Spatio-temporal fishing risk of large pelagic fish in the Mediterranean Sea

Master Thesis

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‘No data can be taken out of this work without prior approval of the thesis main supervisor(*)’

Executive Summary

This study provides a fine-scale, spatio-temporal assessment of fishing activity targeting large pelagic fishes (LPF) in the Mediterranean Sea from 2015 to 2024. Using data derived from the Automatic Identification System (AIS), the fishing activity of drifting longliners and tuna purse seiners (the two main gear types exploiting LPF in the region) were analysed.

A total of 213 unique fishing vessels were identified across the study period, with fishing effort concentrated along the Spanish Mediterranean coast, around Sardinia and Sicily, the Adriatic, Malta, and off Cyprus. These areas overlap with key spawning and feeding grounds of high-valued LPF, like bluefin tuna (BFT), and swordfish, representing the main risk areas for these species. Purse seine activity peaked in spring, following the BFT spawning migration, while longliners operated predominantly during summer. Hotspot analysis revealed persistent effort in the Balearic Islands and Adriatic Sea. The Balearic purse seine hotspot shifted in location between years, which may correspond to variability in oceanographic frontal systems known to affect BFT spawning.

Fishing grounds remained stable between years, with no large-scale shifts in spatial distribution. However, the longline fishing season showed signs of expansion, potentially due to prolonged warm periods or higher effort needed to meet quotas. Most fishing occurred within 100 km of port, and purse seiners operated in shallower areas compared to longliners. Monitoring depth and distance to port could offer additional indicators of changes in fishing grounds.

AIS data under-represented non-EU fishing activity relative to official catch records, highlighting coverage gaps, particularly for smaller vessels and non-EU fleets. Despite these limitations, AIS proved useful in identifying broad-scale patterns and temporal trends. Results from this study may help inform spatial and seasonal closures, especially in areas where bycatch risk for bycatch species like

sea turtles is high.

The findings underline the value of publicly available AIS data for monitoring fisheries in transboundary regions such as the Mediterranean. They also demonstrate the potential of combining AIS-derived effort estimates with other sources like logbooks or catch data to improve the spatial resolution of stock assessments and support ecosystem-based fisheries management. The hotspots identified here, and potentially the migratory pathways between them, may be useful reference areas for future management initiatives, including spatial protection frameworks such as *Blue Corridors*.

Abstract

This thesis presents a spatio-temporal analysis of fishing activity targeting large pelagic fishes (LPF) in the Mediterranean Sea from 2015 to 2024. Using vessel tracking data from the Automatic Identification System (AIS) fishing effort by drifting longliners and tuna purse seiners, the two main gear types targeting bluefin tuna, swordfish, and albacore tuna, was assessed.

Persistent fishing hotspots were identified around the Balearic Islands, Sicily, the Adriatic, Cyprus, and south of Malta, aligning with known LPF spawning and feeding grounds. Purse seine activity peaked in spring, driven by bluefin tuna migration, while longline fishing showed broader seasonality with a summer peak. The Balearic purse seine hotspot shifted over time, possibly tracking oceanographic variability in bluefin spawning areas. Overall, fishing grounds remained spatially stable, though longline activity expanded seasonally, potentially due to increases in temperature caused by climate change.

AIS data was biased towards larger EU-flagged vessels and did not fully capture non-EU fleets. Despite this, it provides a valuable source of information on effort distribution and potential overlap with sensitive habitats. This study supports the use of AIS in monitoring LPF fisheries and highlights the importance of improving registry transparency and combining data sources to inform ecosystem-based management in the Mediterranean.

Contents

1 Introduction

Large pelagic fishes (LPF) including tunas, swordfish, and pelagic sharks, hold profound ecological and economic importance globally. They are characterized by their highly migratory nature, and their roles as apex predators. Their large-scale migrations are driven by the fact that food resources and suitable breeding grounds are far apart from each other (Fromentin and Powers, 2005; Tracey et al., 2023; Relano and Pauly, 2022a). Through these migrations, LPF form an important biological link between distant areas (trans-ocean migrations), and between coastal and pelagic production (Beamish et al., 2005). As apex predators, they also strongly influence the structure and function of ecosystems and intensive fishing can lead to cascading top-down effects (Baum and Worm, 2009; Young et al., 2015). They also have a high social and global importance for food security. Global catches of LPF, i.e., tuna and tuna-like species (mainly Thunnini, Xiphiidae, and Istiophoridae), amounted to a record 8.3 million t reported landings in 2022, and tuna fisheries alone are worth 40 billion dollars annually (FAO, 2024; McKinney et al., 2020).

In the Mediterranean Sea (Fig. 1), bluefin tuna (BFT; *Thunnus thynnus*), albacore tuna (*Thunnus alalunga*), and swordfish (SWO; *Xiphias gladius*) are the most important LPF (Papaconstantinou and Farrugio, 2000). In 2023, these species alone accounted for approximately 63% of reported catches for all tuna and tuna-like species (in total around 60 thousand tonnes; ICCAT, 2025). Apart from their economic importance, these three species also form an important part of the culture and identity of numerous coastal communities in the Mediterranean, as they have been exploited there since ancient times (Addis et al., 2012; Usai, 2022; Di Natale et al., 2005; Andrews et al., 2022). The bluefin tuna fishery for example, is the oldest known industrial fishery in the world (Di Natale, 2012).

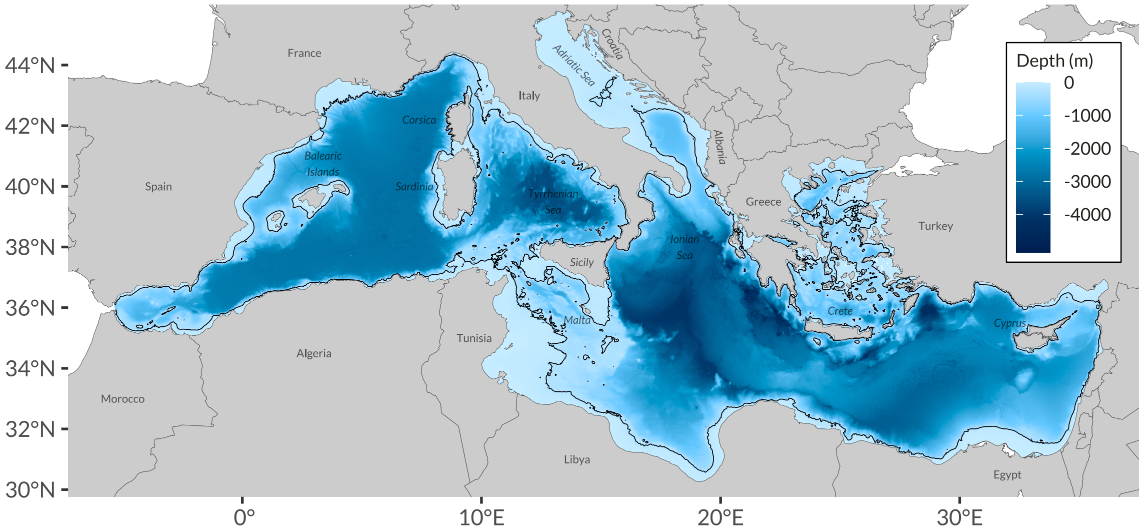

Figure 1: The Mediterranean Sea, study area for this analysis. The black line indicates the 200 m isobar.

To sustainably manage these marine resources and the ecosystems they occur in, it is essential to accurately estimate the location and intensity of fishing pressure (Piet et al., 2006; Russo et al., 2013; Maina et al., 2016). This information is increasingly needed for efficient marine spatial planning, marine protected area designation, conservation of target and non-target species, and ecosystem-based fisheries management (Vespe et al., 2016; Sales Henriques et al., 2024; Tidd et al., 2015; Gerritsen and Lordan, 2010; James et al., 2018; Shea et al., 2023; Bell et al., 2025). Most fisheries management systems for example aim to regulate one or more of the following: catches, gear type, fishing location, seasonality, and effort. To achieve this, information on whom, when, where and how much fishing is occurring is necessary (Orofino et al., 2023).

To deal with the complex task of understanding the spatial distribution of fishing, traditionally, mostly logbooks are used to monitor where and when a vessel is fishing (Hintzen et al., 2012). Compiling logbook data is the responsibility of each skipper and is mandatory for vessels fishing in EU waters (European Commission, 1993). Information of catches is recorded daily at a spatial resolution of 1°

longitude and 0.5° latitude (size of ICES areas). Since the 2000s however, there has been an increase in the usage of automatic monitoring tools. Since 2005, Vessel Monitoring Systems (VMS) are mandatory for fishing vessels >15 m in the EU, to meet the increasing need for fine-scale spatial and temporal information from commercial fleets for compliance with the ecosystem approach to fisheries management (European Commission, 2003; Gerritsen and Lordan, 2010). In the EU, VMS usually have a ping rate between 1-2 hours, aiming at a compromise between appropriate resolution and costs (Shepperson et al., 2017). This data has however traditionally been confined to government regulators and other fisheries authorities, limiting its usage, particularly in the case of migratory species that travel between different countries' jurisdictions (Orofino et al., 2023; Hinz et al., 2013). More recently, the usage of Automatic Identification Systems (AIS) has emerged as a promising tool to monitor the spatio-temporal extent of fisheries and for fisheries Monitoring, Control and Surveillance (MCS; Zhang et al., 2022). Globally, AIS is compulsory for large vessels (over 300 tons), while in the EU it is mandatory for fishing vessels $\geq$15m in length (European Commission, 2011). Originally designed as a collision avoidance tool, it allows analysis at higher spatial and temporal resolution due to the high ping rate of up to 2 seconds (Taconet et al., 2019; Kontas, n.d.). There are however some handicaps that can limit the coverage of this technology. This includes for example intentional turning-off, reception quality, and difficulty of discerning individual messages in areas with very high vessel density (Taconet et al., 2019). The increasing coverage and data availability however, enable the analysis of more complex fisheries behaviours (Natale et al., 2015) and AIS data is also publicly accessible, allowing for a fine-scale spatio-temporal assessment of fisheries between different countries' jurisdictions.

Most studies investigating fishing effort in the Mediterranean Sea have looked at the spatial footprint of bottom trawlers as shown by Ferrà et al. (2018) and Marsaglia et al. (2024). However, monitoring the fisheries on LPF in this area will also provide important information for their management. The International Commission for the Conservation of Atlantic Tunas (ICCAT) is responsible for the sustainable management of LPF in the Mediterranean. Spatio-temporal data on fishing effort are incorporated into stock assessments for bluefin tuna, swordfish, and albacore tuna (ICCAT, 2024b,c,a). However, the data reported by contracting parties are often coarse in resolution (aggregated at 5° x 5° or more rarely 1° x 1°) which limits the capacity to detect fine-scale fishing patterns. Incorporating fishing pressure derived from AIS, could provide an alternative for cross-validation of reported effort data and analysis on a finer spatial scale.

Monitoring fisheries of LPF is also highly relevant in terms of climate change, of which the effects have recently been proposed to be integrated in the species' management (ICCAT, 2022). For this, members of the ICCAT '*Subcommittee of Ecosystems and Bycatch*' have created the '*TunaMed Observatory*' with the aim to '*identify and monitor the variability of environmental processes in the Mediterranean Sea that affects the ecology of large pelagic fishes - with special attention on tunas-, and to investigate the potential role of climate change on this variability*' (ICCAT, 2023). As the spatial footprint of fishing is closely linked to the distribution of target species, changes in the distribution of fishing could thus be indicators of habitat change and climate-driven shifts in species range (Ojea et al., 2020).

One of the most important gear types used in the Mediterranean for the capture of LPF are drifting longlines (FAO, 2025; ICCAT, 2024a,b,c). This gear type is however also associated with high levels of bycatch which includes species of sea turtles, pelagic sharks, and seabirds (Carpentieri et al., 2021). Thus, demonstrating the utility of fine scale fishing data for the conservation of non-target species for example through combining both species distribution models with this data (Welch et al., 2024). Apart from longlines, purse seine nets are used in the Mediterranean mainly for the capture of BFT, targetting schools of these fish during spawning. In the Mediterranean, this method is not associated to large amounts of bycatch but can have big impacts on the targetted fish as it is extracting whole schools (Carpentieri et al., 2021; ICCAT, 2024b)

To address current gaps in the monitoring of large pelagic fisheries in the Mediterranean, this thesis uses fine-scale data on fishing activities derived from AIS and provided by Global Fishing Watch (GFW) to examine spatio-temporal patterns in fishing over the past decade (2015-2024). This approach enables analysis of the whole Mediterranean Sea area, that would not be possible when relying on other effort estimates like VMS and logbooks. The study focuses on the two main gear types targeting LPF, namely drifting longlines and tuna purse seines, to determine '*hotspots*' of fishing activity (as an indicator of high risk areas for LPF), analyse temporal trends, and determine differences in the spatio-temporal distribution pattern by both fleets. More specifically, we aim to answer:

1. Where and when is fishing activity for large pelagic species most intense and have spatial patterns shifted between 2015 and 2024?
2. What are the seasonal patterns of fishing activity by gear type and do temporal patterns differ inter-annually?
3. To what extent does AIS capture the full scope of fishing activity in the Mediterranean?
4. What is the spatial relationship between fishing hours and environmental features such as distance to port and depth?

2 Material and Methods

2.1 Data sources

2.1.1 Fishing hours

Data on fishing hours was obtained from Global Fishing Watch (GFW). This non-profit organization provides a global dataset of estimated fishing activity derived from AIS data (Global Fishing Watch, 2025). They process data from over 190,000 unique AIS transmitters, each assigned a unique Maritime Mobile Service Identity (MMSI). These AIS devices broadcast a vessel's location as frequently as every 2 seconds (Kontas, n.d.; Taconet et al., 2019). Along with the exact location, each AIS transmission includes a timestamp, speed, and heading of the vessel. GFW then analyses these positional data points, to infer fishing activity, via two different Convolutional Neural Networks (CNN's), which are described in detail in Kroodsma et al. (2018).

A first CNN classifies fishing vessels into one of sixteen fishing gear categories (Fig. 2) and predicts vessel characteristics such as length, tonnage, and engine power. This deep-learning model is trained on a dataset of vessels matched to official vessel registries which are *known* fishing vessels. Vessels without gear information in the registries used are assigned a gear if their movement patterns resemble those of a known vessel class. A second CNN classifies every obtained AIS position as either fishing or non-fishing based on characteristic fishing movement (Kroodsma et al., 2018; Fig. 3). These individual fishing events are then aggregated into grid cells spanning either 0.1° or 0.01° on a side. For the present analysis, 0.1° resolution was chosen, covering the study area (Mediterranean Sea; Fig 1) in sufficient detail.

Unique vessels are identified based on their MMSI number and the dataset contains information on the vessel's registration and flag country. The gear class estimated by the CNN is also compared with the information from different vessel registries, such as the EU fleet register or the ICCAT record of vessels. In case the derived vessel class does not match to the one in the registry, GFW assigns the broadest gear type that allows for agreement. If for example, a vessel is registered as a purse seiner but is inferred to be a tuna purse seiner, it would ultimately be assigned to the purse seiner class (Fig. 2).

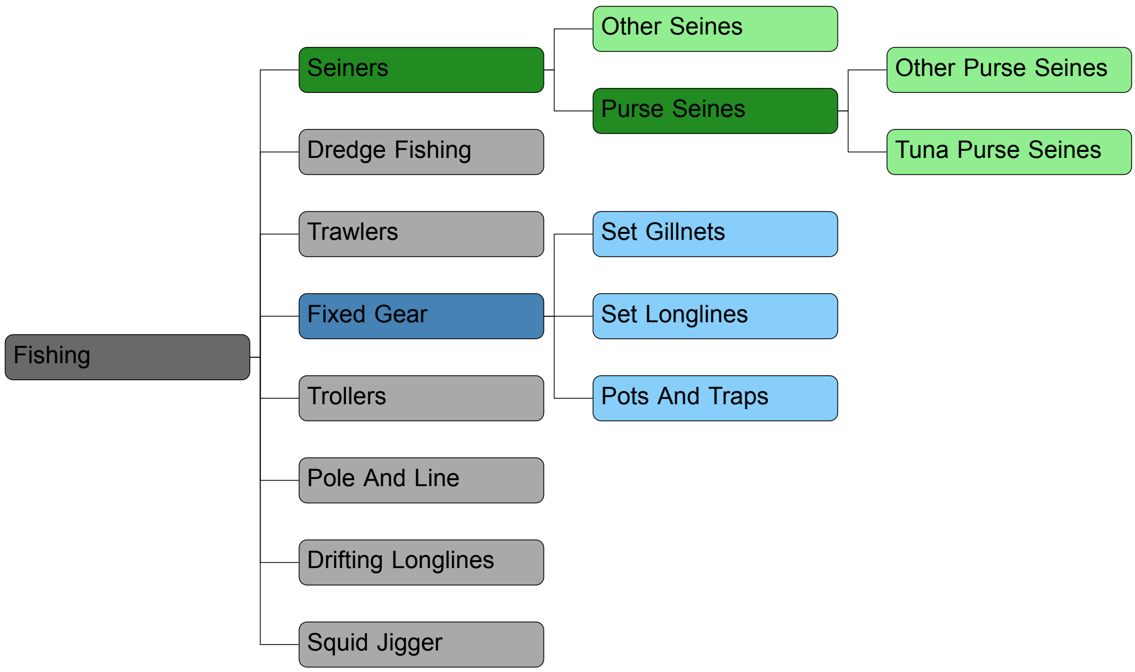

Figure 2: Hierarchy of fishing gears recognized by GFW.

2.1.2 ICCAT catch data

Data on catches of large-pelagic species in the Mediterranean is openly available from the International Commission for the Conservation of Atlantic Tunas (ICCAT). Nominal catch data was obtained for the period 2015-2023 and filtered for the major large pelagic species like tunas and billfishes (ICCAT, 2025).

2.1.3 Bluefin Tuna vessels

Individual purse seine vessels that were assigned a bluefin tuna quota for 2024 were obtained from the corresponding national notices. In France, quotas are allocated and published by the *Ministère de la Transition écologique et de la Cohésion des territoires* (2024). In Spain, by the *Secretaría General de Pesca* (2024) and in Italy by the *Ministero dell'agricoltura, della sovranita'alimentare e delle foreste* (2024). These countries were chosen exemplary because in the period from 2015 to 2023, they made up more than half of the total landings of BFT for all contracting parties to ICCAT, of which close to 90% are fished with purse seine nets (ICCAT, 2024b). Since the national notices did not contain the vessels MMSI number (which is the identifier used by GFW), the vessel names and registration numbers were cross-referenced with the European Fleet Register to obtain it (European Commission, Directorate-General for Maritime Affairs and Fisheries, 2025).

2.2 Data filtering

The GFW dataset was first cropped and adjusted to a shapefile of the Mediterranean Sea (Fig. 1), obtained from the General Fisheries Commission for the Mediterranean (GFCM). Subsequent filtering was based on the assigned gear type and GFW registry information. Only entries with the gear type drifting longlines or tuna purse seines, and that were registered with ICCAT were retained (Fig. 3). All data filtering was conducted using R (v4.4.1; R Core Team, 2024) within the RStudio environment (Posit team, 2024), primarily using the `dplyr` package (Wickham et al., 2023). Longlines and purse seines were chosen as they are the main gear types involved in the exploitation of large-pelagic species in the Mediterranean. Since 2015, on average, 95% of BFT's, and 99% of albacore tunas are caught using either longlines or purse seine nets and close to 100% of swordfish catches use longlines (ICCAT, 2024b,a,c) The GFW dataset is available from the year 2012 until 2024. However, only entries from 2015 were retained, in order to avoid masking *real* fishing dynamics with the increase in adoption of AIS devices, which only became mandatory in the EU in 2014 for all vessels > 15 m in length (European Commission, 2011). It is estimated however, that in the Mediterranean, the EU fishing fleet >15 m is 100% equipped with AIS at least since 2018 (Taconet et al., 2019).

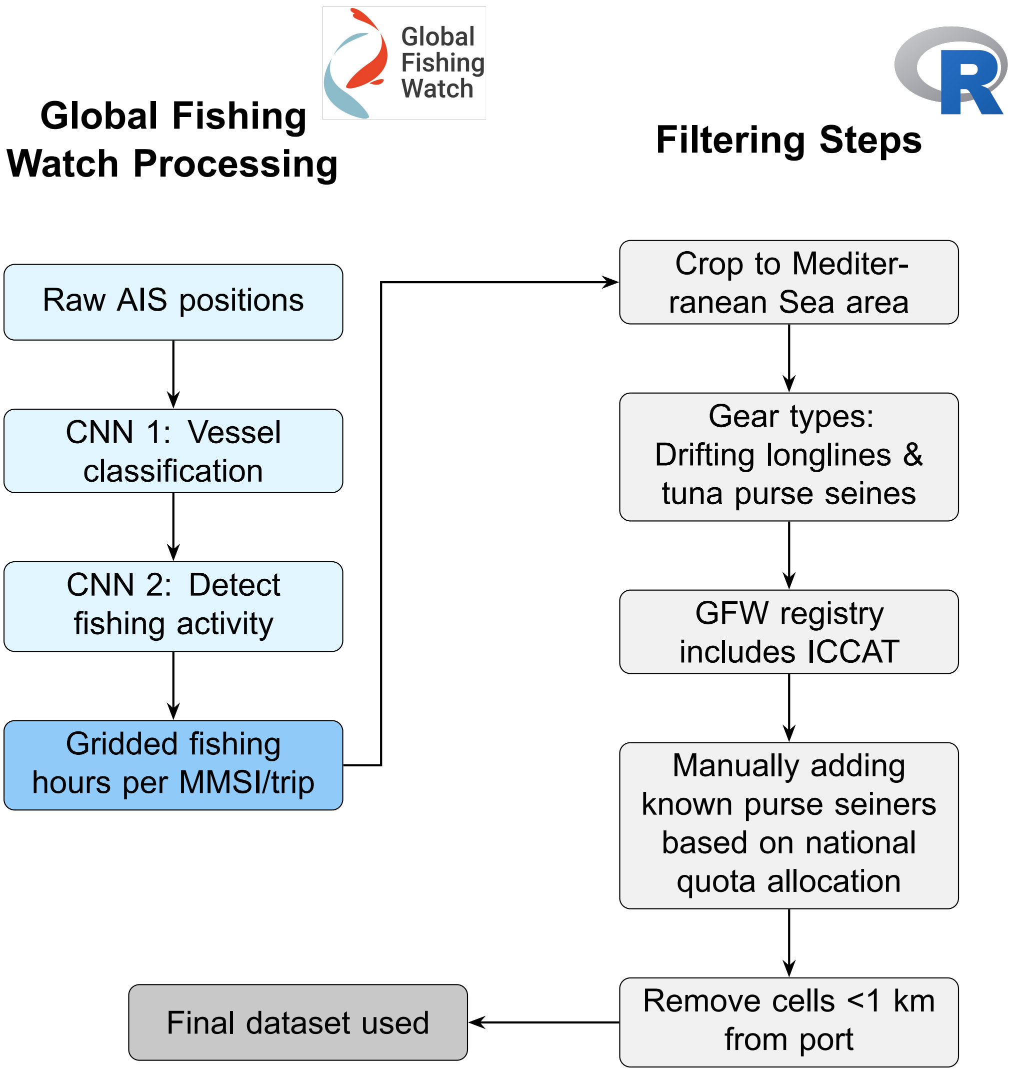

Figure 3: Global Fishing Watch data processing pipeline and filtering steps to obtain the final dataset used in this study. CNN = Convolutional Neural Network.

In case of the tuna purse seiners, these filtering steps also removed some vessels which are known to be fishing for bluefin tuna based on national quota allocations (obtained for Spain, France, and Italy). These vessels were removed by the filtering steps either because GFW assigns them a different gear type, or they are not present in the registry information from ICCAT that GFW uses. For the present analysis, these vessels were thus, manually included after comparison with the information from the national vessel registries.

Irregular vessel movement patterns occurring in or near ports can falsely resemble fishing activity and should therefore be excluded when estimating fishing effort. These movements include cruising towards the harbour to land catches or vessel maintenance (de Souza et al., 2016). Thus, to remove these areas from the analysis, the points inside the 1 km boundary around ports were removed. Distance from port was determined based on a dataset from GFW, which contains anchorages that are either known ports, or that contained at least 20 unique stationary vessels since 2012 (Fig. S1; Global Fishing Watch, 2020). The distance to port of each fishing hour cell was extracted with the `exactextractr` package (Daniel Baston, 2023). Bathymetry was extracted in the same manner and obtained from EMODnet Bathymetry Consortium (2024).

2.3 Data analysis

To identify persistent hotspot areas throughout the one decade study time and analyse spatio-temporal trends, the Emerging Hotspot Analysis (EHA) tool was used in ArcGIS Pro (Esri Inc., 2024). For this, multidimensional netCDF (network common data form) files of the fishing hours data were generated after curation and filtering in R, using the `terra` package (Hijmans, 2025). Subsequently, this data was read in as multidimensional raster files in ArcGIS Pro, with the dimensions corresponding to longitude, latitude and time. Data was aggregated annually, using the sum of fishing hours per year for each cell. From this, a space-time cube, which is the input required for the EHA tool, was created (Fig. 4A).

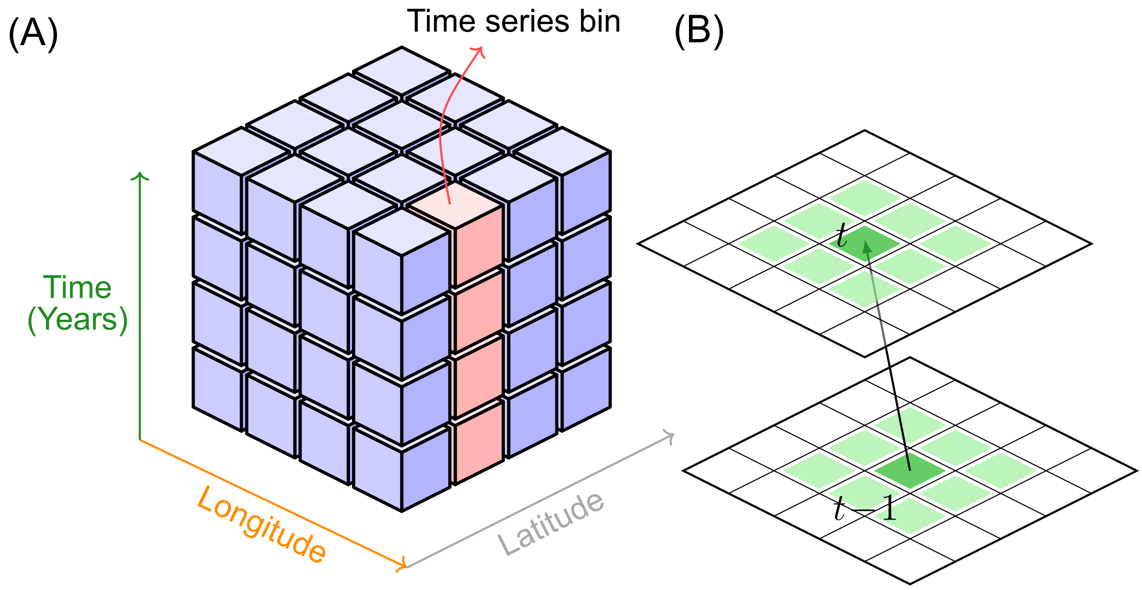

Figure 4: A) Structure of the space-time cube in ArcGIS. Each individual cube corresponds to one *neighbourhood bin*, which is the sum of all coloured cells in B. One *time series bin* corresponds to the same location over time (red). B) Conceptualization of space-time dependency as implemented in the Emerging Hotspot Analysis tool. One *neighbourhood bin* is defined as the cell itself (darkgreen) plus the cells surrounding it (lightgreen), as well as those cells in the previous time step ($t-1$).

EHA uses a combination of two statistical methods. First, the Getis-Ord G_i^* statistic to identify areas where low/high values are spatially clustered (Getis and Ord, 1992). The null hypothesis states that the sum of values of location i and its neighbours, is not significantly different from what would be expected by chance, based on all observations (neighbours are defined as shown in Fig. 4B). Thus, each *neighbourhood* contains the cell itself, plus all cells contiguous with it via edges and corners at time t and $t-1$. Each neighbourhood is compared to all global observations at the current and preceding time step. Based on the neighbourhood definition, a binary spatial weight matrix is constructed, where each entry $w_{i,j}$, is either 1 (if features i and j are neighbours) or 0 otherwise. The G_i^* statistic is then calculated as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2}{n-1}}} \tag{1}$$

where x_j is the value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, and n is the total number of features. The terms $\bar{X}$ and S represent the global mean and standard deviation of the attribute values, respectively, and are given by:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2} \tag{3}$$

The implementation of G_i^* in the EHA tool also applies a False Discovery Rate (FDR) correction to account for multiple testing and spatial dependency in the data. This approach is preferred over methods like Bonferroni correction, which only accounts for multiple testing, as FDR is less conservative and less likely to miss true positives (Caldas de Castro and Singer, 2006). EHA is thus, a spatio-temporal extension of the G_i^* statistic, as it extends each cell not only to its spatial but also to the temporal neighbours.

Second, EHA applies the Mann-Kendall trend test to evaluate whether there is a monotonic upward or downward trend in each time series bin (Mann, 1945; Kendall and Gibbons, 1990). The non-parametric Mann-Kendall statistic S analyses each time series bin. It ranks and compares each point x_i (for $i = 1, 2, \ldots, n-1$) to all subsequent points x_j (for $j = i+1, i+2, \ldots, n$) and is given by (Kendall and Gibbons, 1990, Section 1.9)

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(x_j - x_i) \tag{4}$$

Where the sign function is defined as:

$$\text{sign}(x_j - x_i) = \text{sign}(R_j - R_i) \begin{cases} 1 & x_i < x_j \\ 0 & x_i = x_j \\ -1 & x_i > x_j \end{cases} \tag{5}$$

and R_i and R_j are the ranks of observations x_i and x_j of each time series. Thus, for every time point, it assigns a 1 if the value is higher than the previous one, a 0 if the value is the same, and a -1 if the value is lower. These scores are then summed for each time series bin and under the null hypothesis of no trend, the value of S is zero. To assess the significance of S, the variance V_0^* can be calculated as (Kendall and Gibbons, 1990, Section 4.9)

$$V_0^*(S) = n(n-1)(2n+5)/18 - \sum_{j=1}^{m} t_j(t_j - 1)(2t_j + 5)/18 \tag{6}$$

where n is the total number of observations, and m the number of groups with tied ranks, each with t_j tied observations.

Results of the EHA tool were then exported as tables and visualized using the R package *ggplot2* (Wickham, 2016).

3 Results

3.1 Cumulative apparent fishing hours

A total of 213 unique longliners and purse seiners were recorded for 2015-2024. These vessels together accounted for an average of 122 760 hours per year, with an average of 576 hours per vessel per year. Areas that show the highest effort throughout the study time include the Mediterranean coast of Spain, around Sardinia and Sicily, south of Malta, the Adriatic, and south of Cyprus (Fig. 5A). Areas with high effort generally also show the lowest coefficient of variation (Fig. 5B). There does not appear to be any fishing activity based on AIS around the African Mediterranean coast (Fig. 5).

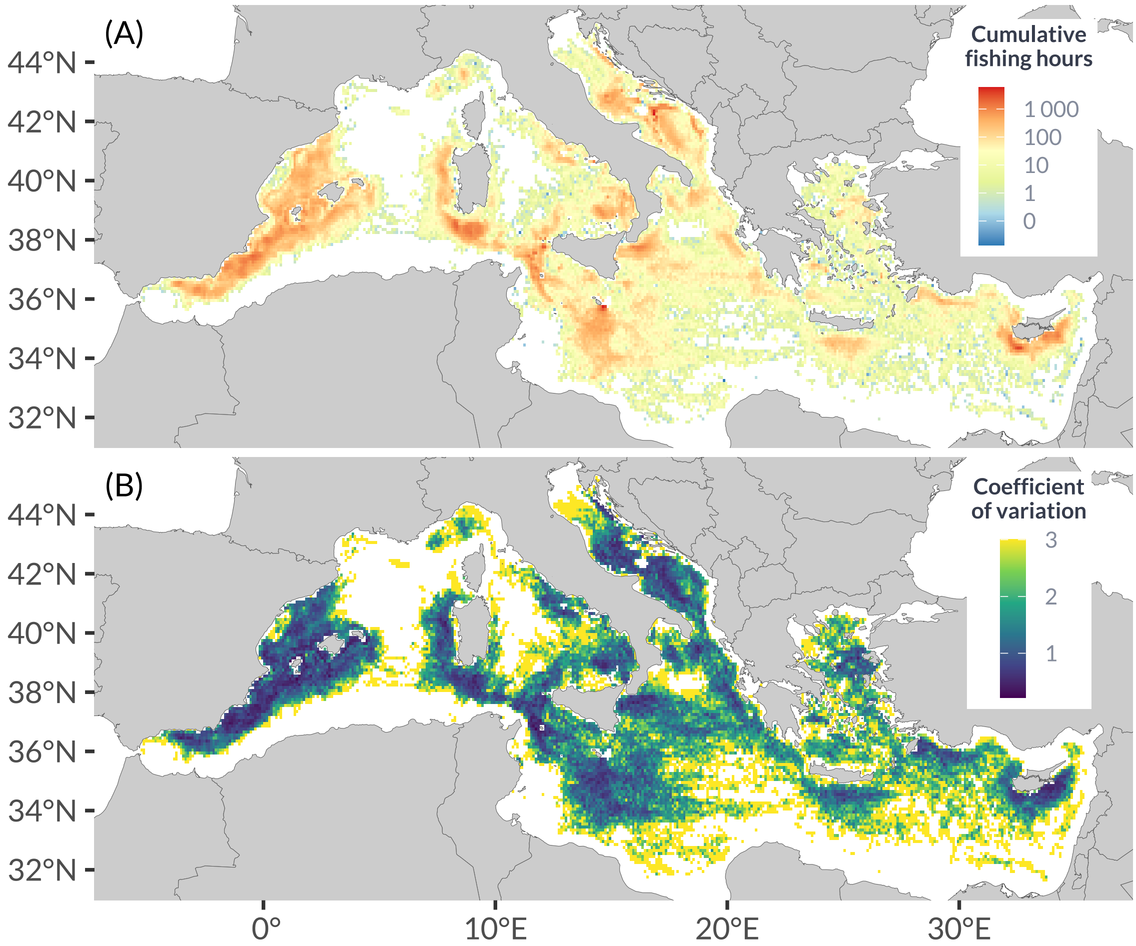

Figure 5: Summary statistics for both longliners and purse-seiners. A) Cumulative fishing hours in the Mediterranean (2015-2024). Colors are on a log-scale. B) Coefficient of variation between years (standard deviation divided by mean) for each cell.

3.2 Fishing hotspots and high risk areas

Numerous persistent longline hotspot areas were identified throughout the Mediterranean including the southern coast of Spain, south of Sardinia, around Sicily and Malta, as well as south of Cyprus (Fig. 6A). These hotspots show however, differing trends. Fishing hours in the south of Malta appear to be increasing throughout, with a similar trend of increase in the Adriatic Sea. Other areas that appear to be consistent hotspots, like the east of Sicily, show a decreasing trend (Fig. 6B).

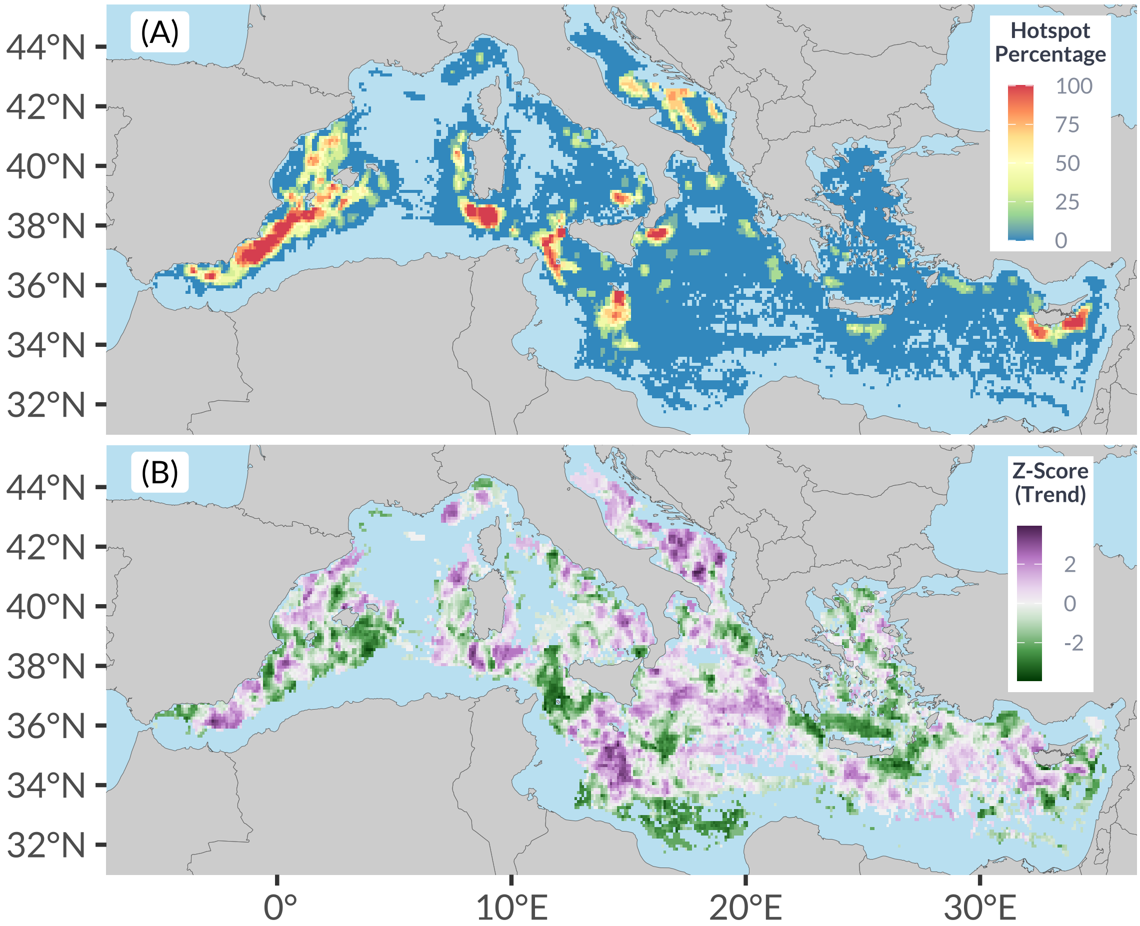

Figure 6: Hotspot percentage and trend scores for longliners in the Mediterranean. The percentage reflects the years in which a given cell was a hotspot based on the Getis-Ord Gi* statistic. The Z-score is derived from the Mann-Kendall statistic.

Purse seine hotspots appear persistent around the Balearic Islands, in the Adriatic Sea, and along the Calabrian coast in Italy (Fig. 7A). Trends in these areas show a clear increase around Ibiza and in the central Adriatic, while areas around the coast in the Adriatic show a decrease (Fig. 7B). The hotspot area along Calabria shows no clear trend.

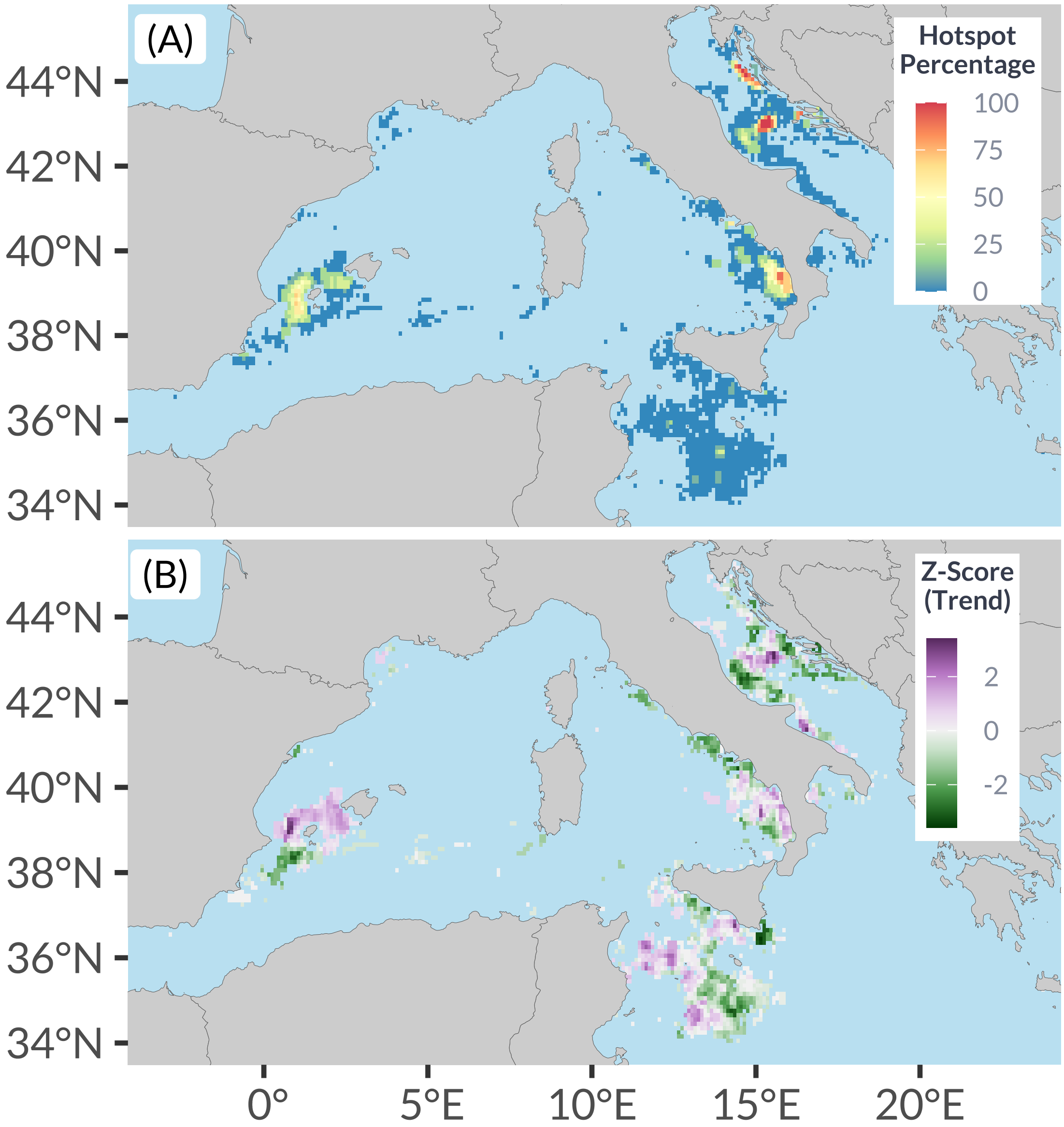

Figure 7: Hotspot percentage and trend scores for purse seiners in the Mediterranean. The percentage reflects the years in which a given cell was a hotspot based on the Getis-Ord Gi* statistic. The Z-score is derived from the Mann-Kendall statistic.

3.3 Temporal changes

Longline fishing hours show a clear seasonal trend where activity is highest during warmer months (mainly in the summer) and lowest in the colder months around winter (Fig. 8A). Some areas show high effort earlier in the season in spring (for example south of Malta) and others are more persistent later in the season in fall (for instance around Ibiza). The time series show a similar seasonal trend, although the intensity varies between years, and it appears that the longline season is expanding between years (Fig. 8B). The highest annual longline fishing hours throughout the study time were recorded for 2022 and the lowest for 2015 (Tab. 1).

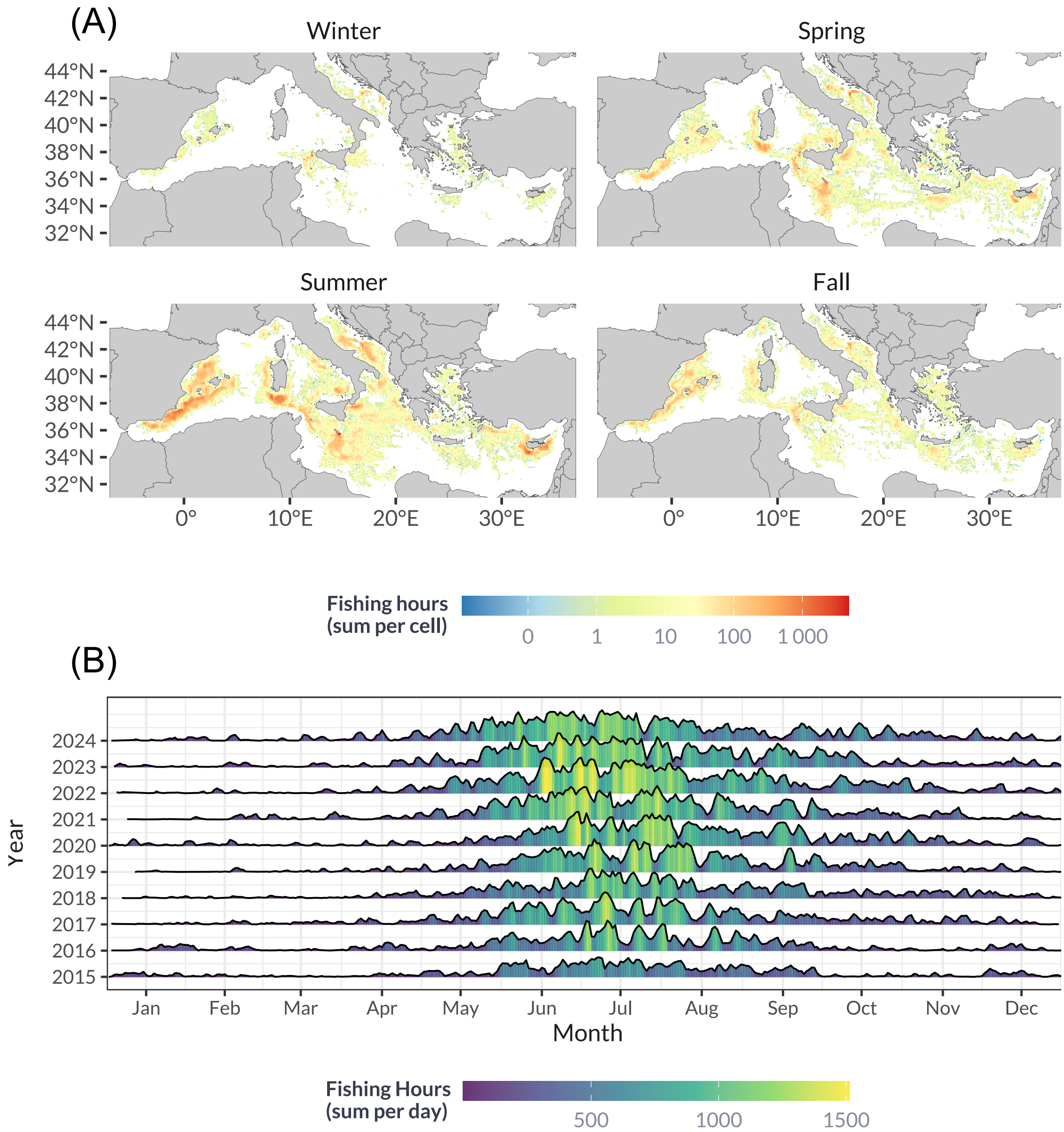

Figure 8: Temporal changes in longline fishing hours. A) Spatial differences between seasons. Hours are summed per season and cell and colour is on a log-scale. Seasons are defined based on calendar dates: winter (Dec 21 - Mar 19), spring (Mar 20 - Jun 20), summer (Jun 21 - Sep 21), and fall (Sep 22 - Dec 20). B) Time series of fishing hours, summed per year and day.

Regarding the purse seine fleet, fishing hours show a very pronounced seasonal trend with a peak in spring (Fig. 9). The core areas of the fishery during spring are the Balearic Islands, along the coast of Calabria (south-west Italy), and the central

Table 1: Annual sum of fishing hours for purse seiners and longliners.

Year	Fishing hours	
	Purse seiners	Longliners
2015	4,193	71,846
2016	5,313	89,136
2017	5,901	107,345
2018	6,128	106,130
2019	5,931	113,261
2020	5,636	124,927
2021	5,706	133,361
2022	5,675	149,059
2023	5,085	139,068
2024	6,661	137,406

Adriatic. In the Adriatic, there appears to be purse seine activity throughout the whole year (Fig. 9A). The purse seine season for large-pelagic species is limited to the months of May and June and is consistent between years (Fig. 9B). Highest annual fishing hours for purse seiners were recorded in 2024 and the lowest in 2015 (Tab. 1).

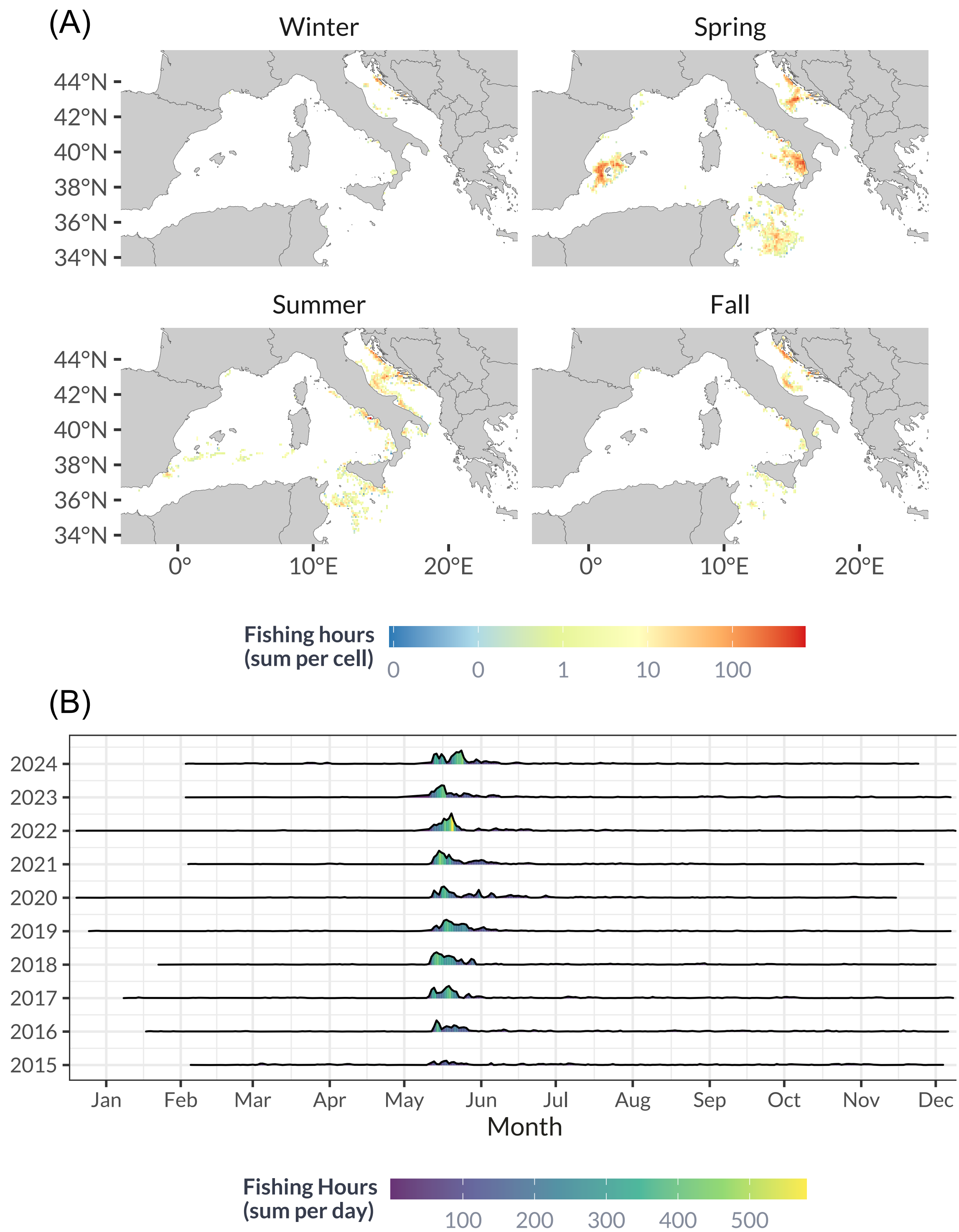

Figure 9: Temporal changes in purse seine fishing hours. A) Spatial differences between seasons. Seasons are defined based on calendar dates: winter (Dec 21 - Mar 19), spring (Mar 20 - Jun 20), summer (Jun 21 - Sep 21), and fall (Sep 22 - Dec 20). Hours are summed per season and cell and colour is on a log-scale. B) Time series of fishing hours, summed per year and day.

3.4 Flag countries

Vessels were flagged to a total of 10 countries and the majority of vessels analysed were longliners (Tab. 2; see Fig. S2 and S3 for a spatial overview by country). Italy shows the highest amount of both purse seiners and longliners identified in the GFW data.

Table 2: Number of vessels by country and gear type in 2024 from our detections compared to vessels with drifting longlines currently registered with the GFCM and tuna purse seine vessels currently registered with ICCAT (June, 2025). '–' indicates no recorded vessels for that gear. PS = purse seiners, LL = longliners

Country	**Detected PS**	**Reg. PS**	**% PS**	**Detected LL**	**Reg. LL**	**% LL**
Albania	–	2	0.0%	–	–	–
Algeria	3	39	7.7%	–	–	–
EU-Croatia	2	3	66.7%	–	–	–
EU-Cyprus	–	1	0.0%	14	15	93.3%
Egypt	–	2	0.0%	–	–	–
EU-France	13	21	61.9%	–	4	0.0%
EU-Greece	–	–	–	8	24	33.3%
EU-Italy	16	19	84.2%	60	83	72.3%
EU-Malta	–	2	0.0%	19	17	111.8%
Libya	–	15	0.0%	–	–	–
Morocco	1	5	20.0%	–	–	–
EU-Spain	5	7	71.4%	22	30	73.3%
Tunisia	–	59	0.0%	–	–	–
Turkey	–	36	0.0%	–	–	–
Total / Mean	**40**	**213**	**30.1%**	**123**	**173**	**58.6%**

Most regions with high fishing activity are fishing grounds shared by multiple countries (Fig. 10). Regions with high overlap between flag countries for longliners include the Balearic Islands, south of Crete, and south of Malta, which are also areas with high fishing hours (Fig. 5A). For purse seiners, fishing generally is more concentrated and thus, overlap is also higher, as seen in the core fishing areas of the Balearic Islands and south of Malta (Fig. 10).

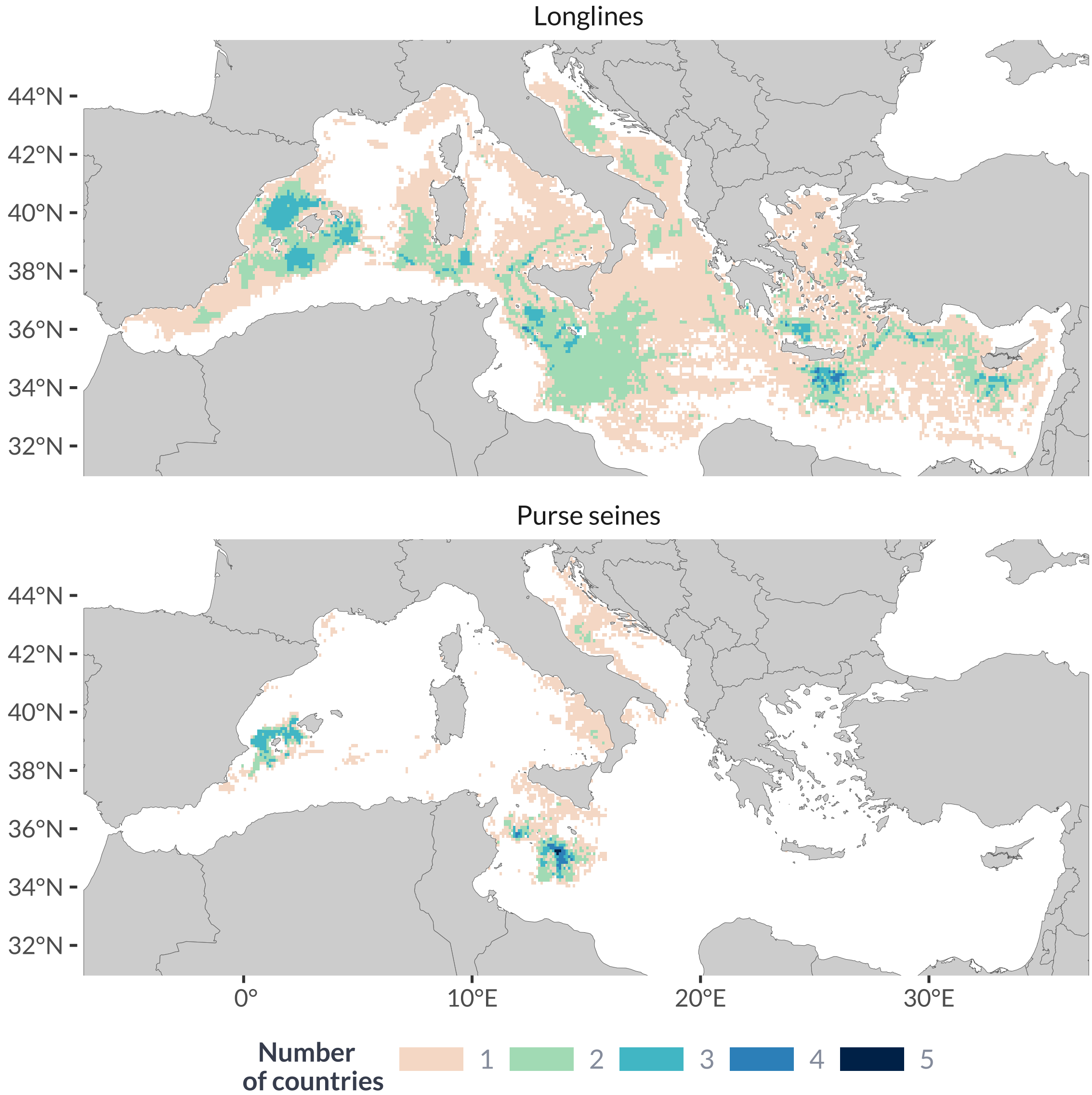

Figure 10: Number of countries fishing per cell for longliners and purse seiners between 2015-2024.

A comparison of fishing hours from the GFW data with catch data from ICCAT shows that AIS under-represents fishing activity by non-EU countries relative to EU countries (Fig. 11). Even though, many non-EU countries account for a substantial share of the total reported catches. Notably, AIS also does not capture any French longline vessels.

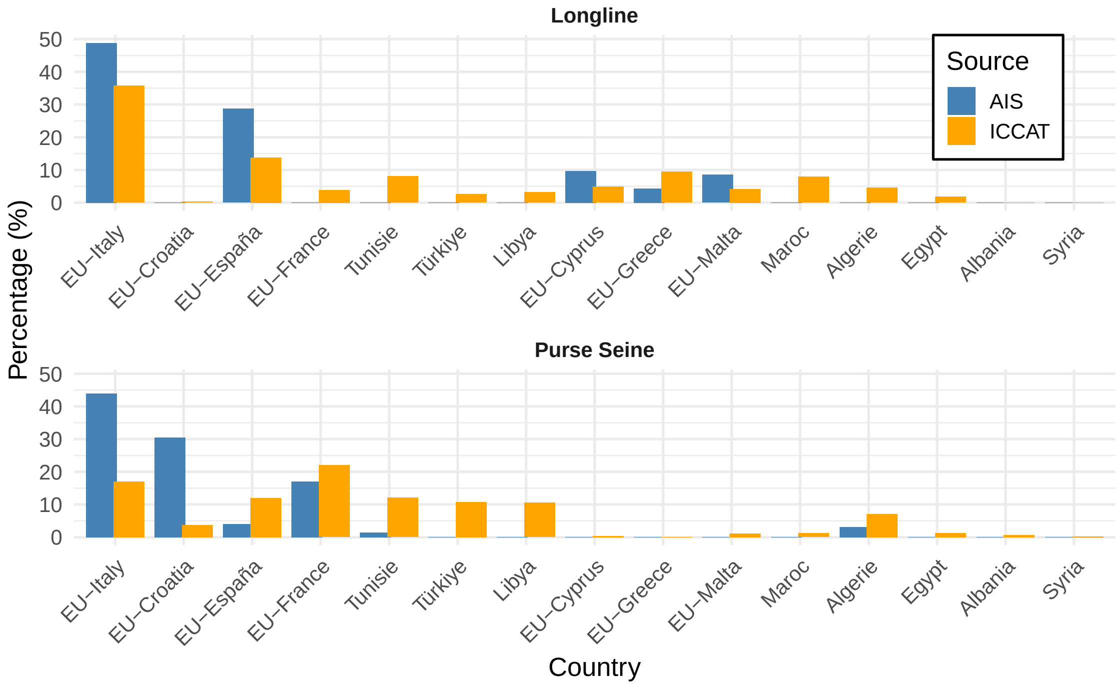

Figure 11: Comparison of relative percentages between GFW AIS data and ICCAT catch data. AIS percentages are relative to the total fishing hours between all countries. ICCAT percentages are relative to the total weight of catches between all countries.

3.5 Depth and distance to port

The relationship between the cumulative proportion of fishing hours and the distance to port reveals that most fishing activity of both gear types is concentrated less than 100 km from the closest port (Fig. 12A). The trend for the depth is different between gear types, where most purse seine fishing occurs at shallower depths (> 1000 m; 50% above 500 m depth) and longline fishing takes place over much greater depth ranges (Fig. 12B; 50% above 1600 m depth).

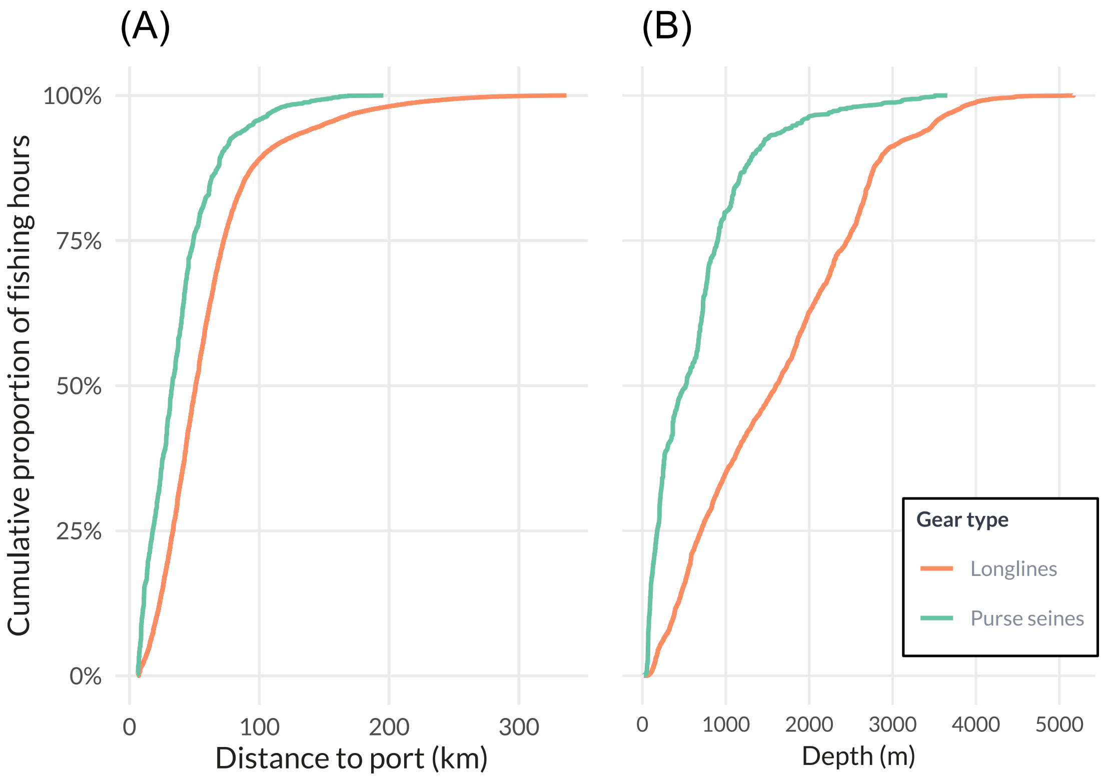

Figure 12: Cumulative proportion of fishing hours with A) Distance to port and B) Depth.

4 Discussion

The fishing activity targeting large pelagic fishes (LPF) across the whole Mediterranean Sea was analysed for the first time by means of fishing activity derived from AIS data. Strong spatio-temporal patterns in how fishing is distributed, as well as regional hotspots were identified. Such dynamic responses in fleet distribution are related not only to ecological cues (e.g., due to focused fishing in spawning and feedings grounds of targeted species) but also to socio-economic aspects (e.g., quotas and seasonal closures). Most fishing occurred within 100 km from port in both fleets, while purse seiners operated in shallower waters when compared to longliners. This is most likely related to the difference in fishing strategy conducted by each fleet. AIS data proved to be a useful tool to monitor industrial LPF fleets from EU countries. Conversely, increasing the uptake of AIS technology in the Southern Mediterranean countries would aid in providing a fuller picture of fishing activity.

4.1 Main risk areas (hotspots)

Fishing hotspots and thus, the main risk areas for LPF, aligned with the species' known aggregation sites, particularly around the Balearic Islands, the Tyrrhenian Sea, the Adriatic Sea, and off the coasts of Cyprus and Malta. These hotspot regions overlap with key spawning and feeding areas identified in previous studies (Medina, 2020; Arocha, 2007). A prime example of this is the migration of large (>150 kg) bluefin tuna (BFT) from the Atlantic towards their spawning regions in the Mediterranean between mid-May until mid-July, which drives intense seasonal purse seine activity (Fromentin and Lopuszanski, 2013). However, some smaller individuals remain resident in the Mediterranean the whole year-round (Cermeño et al., 2015; Heinisch et al., 2008). The presence of this all-year-round stock as well as the fisheries changing target species, might explain the extended season of longliners. The spatio-temporal distribution of the purse seiners in the Balearic Islands, and the Tyrrhenian Sea indicates that they might be targeting known BFT spawning grounds (Medina, 2020). Interestingly, the spawning area around the Strait of Sicily was not consistently identified as a purse seine hotspot even though this area is frequented by fleets of up to 5 countries. This could be because of a lack in the adoption of AIS by non-EU countries, which is one potential handicap of AIS derived fishing activity (Taconet et al., 2019; Paolo et al., 2024).

The Adriatic Sea appeared to be the most consistent purse seine hotspot identified in our study and is frequented by purse seiners from Italy and Croatia (Fig. 7 and S3). In contrast to the rest of the Mediterranean, where purse seine activity is restricted to a narrow temporal window coinciding with the spawning aggregations and the authorized fishing seasons, the Adriatic fleet operates during all seasons, particularly Croatian-flagged vessels (Fig. 9 and S3). This continued fishing activity may be largely due to ecological aspects, i.e., the consistent presence of smaller individuals throughout the year. In addition, socio-economic aspects may also play a key role, with regulatory permission for Croatia and Italy to catch individuals weighing less than 30 kg for their use in tuna farms (Fig. S4; Jelić Mrčelić et al., 2023)

Apart from this, the purse seine hotspot in the Balearic Islands showed variation between years. In the earlier years of the study period, it was focused in the southern part of Ibiza, and subsequently moved more towards the north-east and the Mallorca channel (Fig. S8). This could relate to the position of a frontal region which has been shown to be spatially dynamic over time, and important for the spawning location of BFT (Balbín et al., 2014; Reglero et al., 2012).

The relatively stable longline hotspots in combination with no clear temporal trends in most, could be likely due to the use of different types of longlines targeting various species, which are all analysed together in our study. As a result, it is difficult to link observed fishing patterns within each hotspot to the specific dynamic habitat use of individual species, as we were able to do for the purse seine fishery targeting BFT around the Balearic Islands.

Monitoring the fine-scale spatio-temporal dynamics of the longline fishery is still particularly valuable, for example in cases where species' different ontogenetic stages occupy different habitats as is the case for swordfish. Juveniles of this species tend to remain in coastal waters, while adults are more associated with deeper, pelagic zones (Damalas and and, 2014) which could also be the case for BFT, as has been shown in other regions (Patterson et al., 2018). This spatial segregation by life stage offers an opportunity for more targeted monitoring and management. AIS data can for example help identify when and where longline fishing activity occurs close to shore, potentially indicating higher risks of juvenile bycatch. Such information could be used to assess compliance with existing regulations, guide the implementation of spatial or seasonal closures, and evaluate whether these are effectively protecting juvenile habitats. For swordfish, juvenile catch rates remained high prior to the 2017 implementation of a minimum size limit of 100 cm lower jaw fork length, and since its introduction, discards have increased as many individuals caught fall below this threshold (Di Natale et al., 2002). This not only raises conservation concerns but also forces fishers to exert greater effort to meet quotas (García-Barcelona et al., 2020). In this context, spatially explicit monitoring tools like AIS could help inform more adaptive and targeted management by identifying areas with higher juvenile presence and guiding spatial or seasonal restrictions accordingly.

Hotspots in general however, are quite consistent along our study period (2015-2024), and the main fishing grounds stay the same (Fig. S7 and S8). This might be related to the large-scale stability of the spawning and feeding grounds of the LPF targeted. This should however be closely monitored in the future considering the big impacts of climate change on the Mediterranean Sea (Lejeusne et al., 2010; Ben Lamine et al., 2023). Tracking fisheries spatially and comparing data between different years might provide early signs of changes in the distribution of these species, especially when combined with logbook catch data (e.g., Campos et al., 2023). In this context, the monitoring of environmental features in relation to fishing activity, like distance to port and depth, might also provide additional indicators of changes in the fishing grounds or even gears used. The clear seasonality of the purse seine fleet occurs in response to socio-ecological cues. These fleet dynamics can be attributed to the timing of BFT migration into the Mediterranean and the implemented seasonal closures and Total Allowable Catches decided upon by ICCAT, which are usually reached in a very short amount of time.

The fleets investigated in the present study and especially longliners, not only have an important impact on target species but also on other species caught as bycatch (Carpentieri et al., 2021), Bycatch in Mediterranean longline fisheries is a concern for among others, seabirds, pelagic elasmobranchs, and sea turtles (Barcelona, Salvador García et al., 2010; Kleitou et al., 2017; Báez et al., 2013). Drifting longlines for example are estimated to be responsible for the bycatch of about 27 000 individual sea turtles annually in the Mediterranean alone (Carpentieri et al., 2021). Loggerhead turtle *Caretta caretta* is one of the main bycatch species in some Mediterranean longline fisheries (Báez et al., 2019; Burgess et al., 2010) and their estimated areas of high abundance overlap with some of the longline hotspots identified in the present work (DiMatteo et al., 2022). There is significant interest from both conservation and fisheries to mitigate bycatch (Ayers and Leong, 2022) and there have been recent advances in mitigating turtle bycatch for some fleets through targetted management and/or changes in the gear used (Báez et al., 2019 and ICCAT Reg. 22-12). The results and methodology employed here, could be a starting point to identify high risk areas overlapping with important turtle and other bycatch species' habitats, to better target the deployment of onboard observers. This is just an example for one species group, but further studies could look into fine-scale spatial overlap between non-target species and longlines, to better estimate the risk for specific species groups.

Our analysis is likely to miss a significant number of vessels due to inconsistencies between the vessel registries used by Global Fishing Watch (GFW) and the way the gear types are assigned. Since GFW assigns a gear class based not only on the registry, but also on vessels' movement, so there can be discrepancies between them, especially if vessels use multiple gears over time. This is why we decided to include BFT purse seiners identified from national vessel registries, irrespective of the gear type assigned by GFW. The national notices are however published by each country in their respective language and are not easily accessible for cross-country analyses. The ICCAT record of vessels contains details on currently active vessels and their quota allocation, as well as their historic fishing authorizations for specific species. Further improvements to this resource could be to add historic quota allocation for each vessel to the downloadable files, and also add information on historic quotas to the inactive vessel list, which would simplify analyses like this study and provide a more complete picture of fishing activity.

In addition to EU regulations, ICCAT mandates the usage of VMS for all fishing vessels above 24 m LOA (ICCAT Reg. 18-10) and fishing vessels above 15 m length overall (LOA) that are authorized to fish species managed by ICCAT in waters beyond their flag countries jurisdiction. Additionally, all vessels authorized to fish BFT by ICCAT are required to use VMS and share this data with ICCAT (ICCAT Reg. 21-16). This data is however, not made public due to concerns about privacy. Incorporating this information into stock assessments and making it publicly available could however greatly aid in increasing the transparency of these fisheries that are often linked to Illegal, Unreported, and Unregulated (IUU) fishing (Öztürk, 2015; ICCAT, 2008).

4.2 Data caveats

Although AIS was not originally designed for the estimation of fishing effort and there are some persistent challenges in deriving fishing effort from these tracking devices, they provide a very valuable, publicly and readily available source of information for scientists, conservationists and fishery authorities (Taconet et al., 2019). Analyses of fine-scale spatial fisheries data derived from vessel tracking technologies like AIS or VMS have indeed been a revolution in fisheries science and a great step towards increasing the transparency of all human activity at sea (Russo et al., 2019, 2014). However, to advance towards a better application of AIS data for fisheries monitoring, various improvement could be made, such as reducing the variability in AIS reception, which depends on a combination of terrestrial, satellite, and dynamic onboard receivers. Additionally, temporal coverage is not uniform, and has changed over time, which can lead to apparent changes in fishing activity that may reflect improved signal reception rather than actual shifts in effort. GFW is however working on a dataset that quantifies AIS coverage for each vessels' trip, which will reduce uncertainty in analysing time series data (D. Kroodsma, personal communication, May 27, 2025).

AIS data is also biased towards vessels larger than 15 m and countries where its use is mandatory, limiting its ability to fully represent fishing activity in regions dominated by small-scale fleets or in fleets operating without AIS. This bias was evident for example, in the lack of French longline vessels from the Gulf of Lions which are mainly below 15 m LOA (Farrugio, 2013) and in the fact that there seems to be no purse seine or longline activity in the southern Mediterranean. Additionally, differences in gear types and fishing strategies are not always captured by AIS-based models. For example, longliners and purse seiners measure effort differently (e.g., number of hooks vs. number of sets), while GFW's general fishing detection model uses fishing hours as a unified metric. This can lead to potential overestimation of absolute effort, though the geographic accuracy of fishing locations remains high (Hintzen et al., 2025).

Finally, AIS alone cannot distinguish between métiers, which limits species-specific analyses. Future research could combine AIS with catch or logbook data to estimate catch per unit effort (CPUE), allowing a more accurate evaluation of fishing operations and thus, resource abundance (Niu et al., 2024).

Despite the aforementioned limitations, and considering the precise number of fishing hours with caution, this study offers a reliable picture of the broad distribution of fishing in almost the whole Mediterranean Sea. These findings can contribute to the sustainable exploitation of migratory LPF. The methods used here could be combined with other data like log books to get a more detailed information on changes in relative abundance of target species. This would provide more details on fishing fleets to management, which is necessary for the implementation of ecosystem-based management strategies. The areas we identified as fishing hotspots, and potentially also the migratory routes between them, are essential areas for migratory species and could be prime targets for management purposes, for example to implement seasonal or spatial closures. Relano and Pauly (2022b) proposed to protect migratory LPF through *Blue Corridors*, essentially protected areas along the species' migratory pathways, and our findings could help in identifying these areas. Mapping fishing intensity also has other direct implications for conservation, such as protecting bycatch species, of which rates can be substantial for Mediterranean longliners.

5 Conclusion

This study provides a comprehensive, spatially explicit assessment of LPF fisheries in the Mediterranean using AIS data from 2015 to 2024. Linking fishing activity to known ecological features, such as spawning grounds and migratory pathways, offers valuable insights for spatial management and conservation. While spatial distributions have remained broadly consistent, evolving patterns in timing, and precise location, suggest that fisheries are responding to both regulatory and environmental pressures. Our results underscore the importance of integrating fine-scale spatial data into fisheries management frameworks to enhance resilience, sustainability, and bycatch mitigation in a rapidly changing ocean, highlighting the potential of AIS data as a valuable tool for these purposes.

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6.1 Declaration of generative AI and AI assisted technologies

During the creation of this manuscript the author, Tom Leven, used ChatGPT, an AI language model developed by OpenAI, to improve coding, and clarity. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content.

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A Supplementary Material

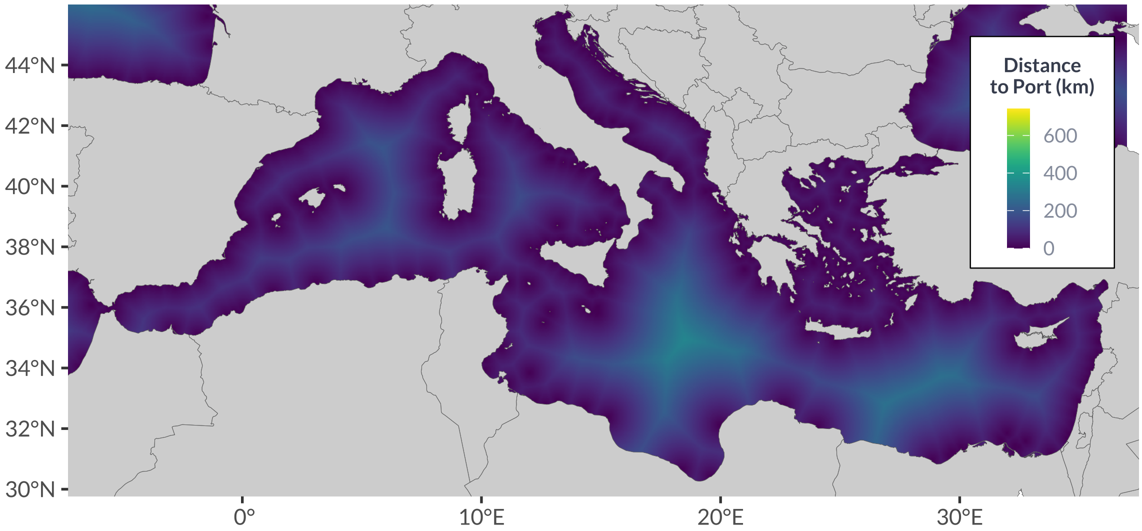

Figure S1: Distance to port in km throughout the Mediterranean.

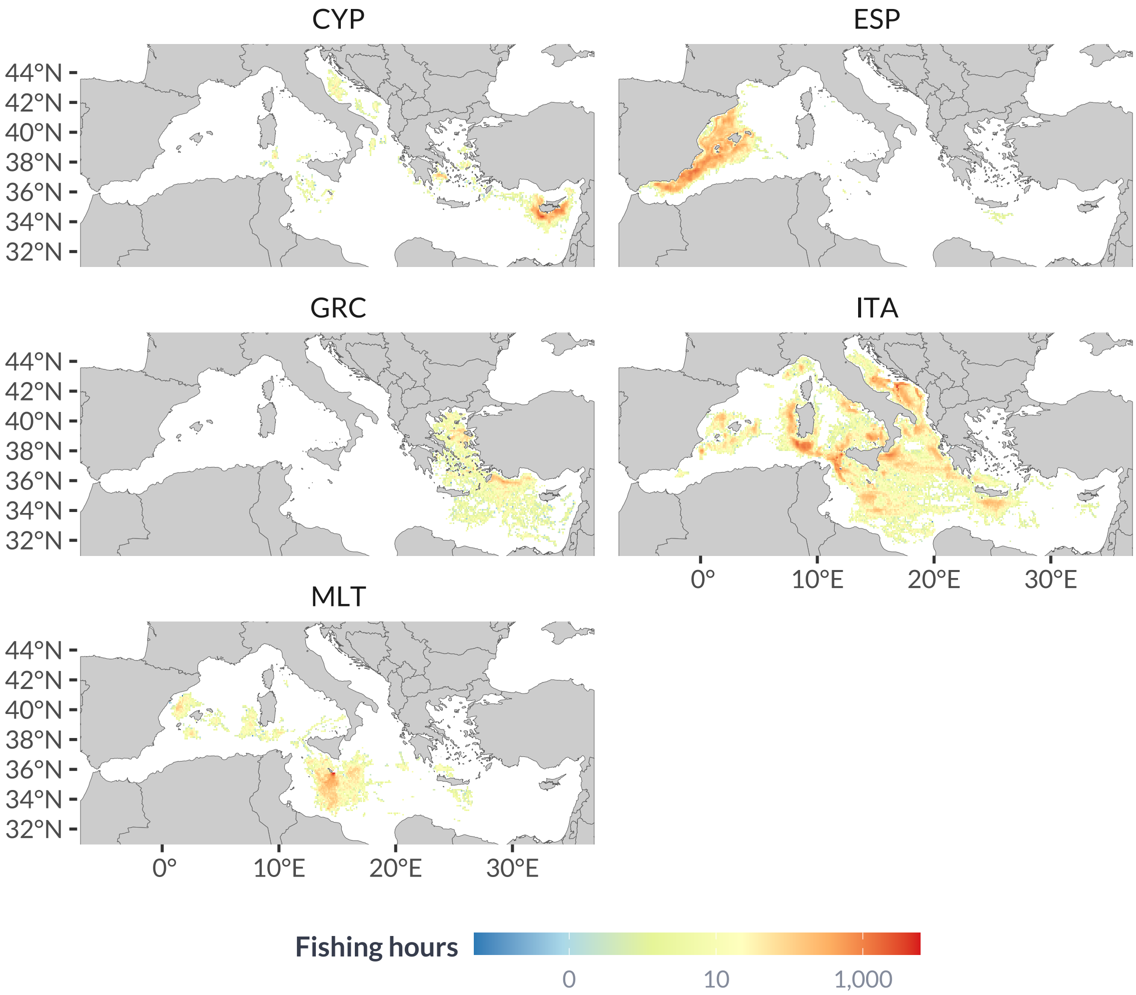

Figure S2: Sum of longline fishing hours per flag country (2015-2024). CYP = Cyprus; ESP = Spain, GRC = Greece, ITA = Italy, MLT = Malta

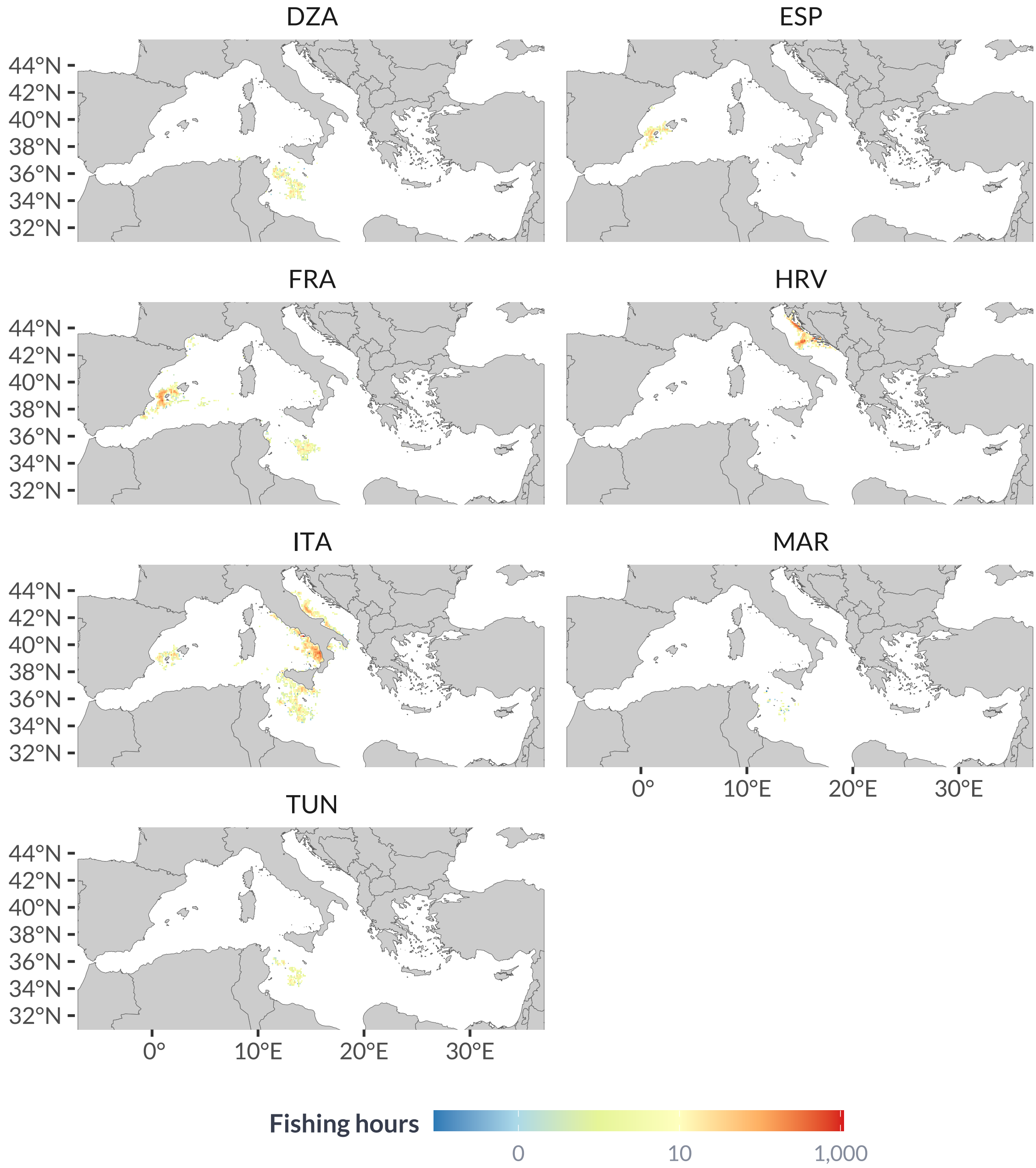

Figure S3: Sum of purse seine fishing hours per flag country (2015-2024). DZA = Algeria, ESP = Spain, FRA = France, HRV = Croatia, ITA = Italy, MAR = Morocco, TUN = Tunisia.

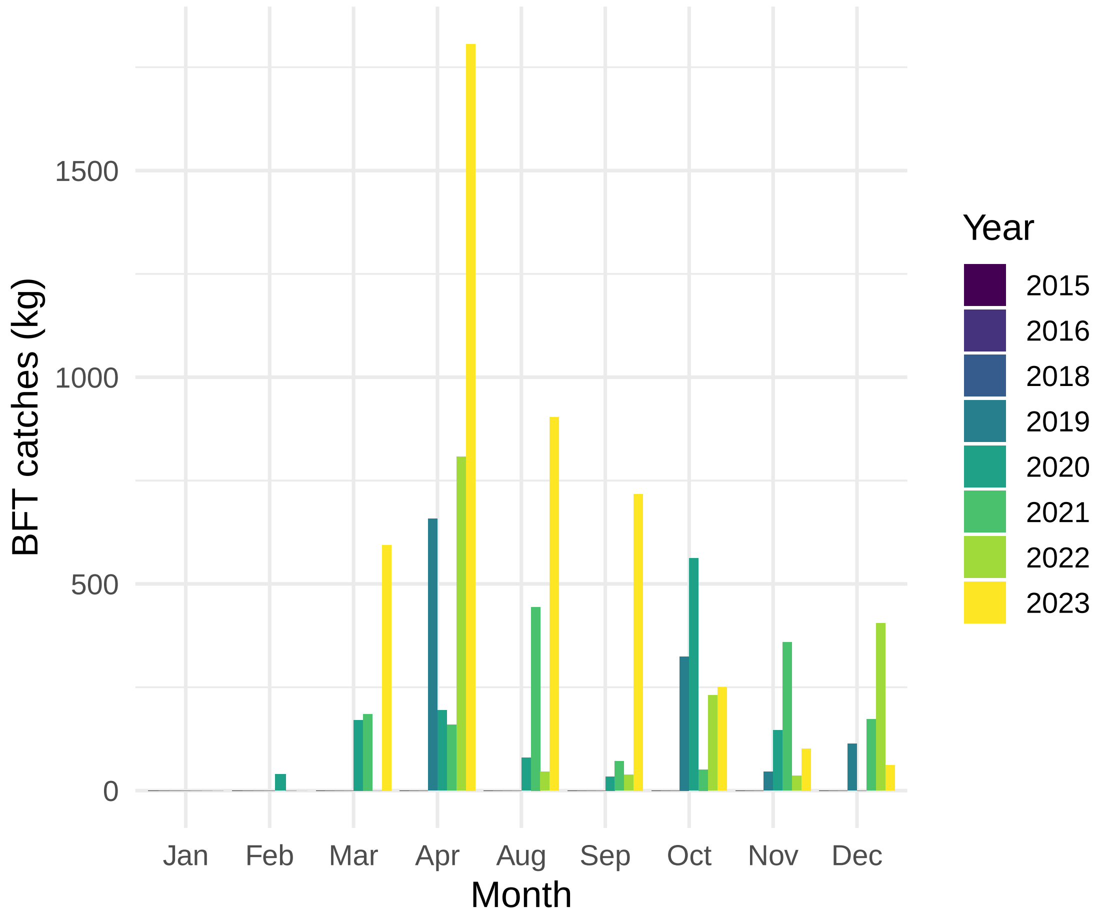

Figure S4: Reported bluefin tuna (BFT) purse seine catches of Croatia from the ICCAT task 2 catch/effort data. May, June, and July were excluded as they are orders of magnitude higher and did not allow for graphic comparison between months with lower activity.

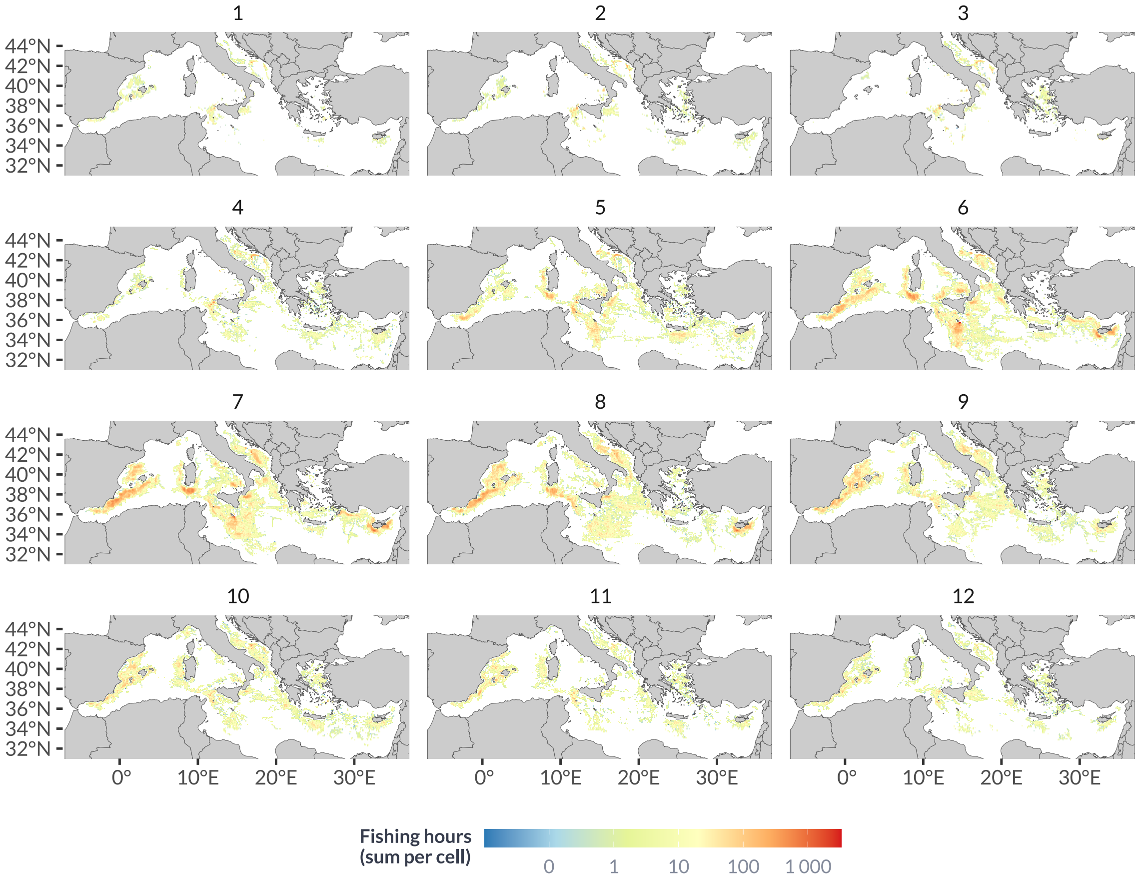

Figure S5: Sum of longline fishing hours per cell for each month between 2015-2024. Colours are on a log-scale.

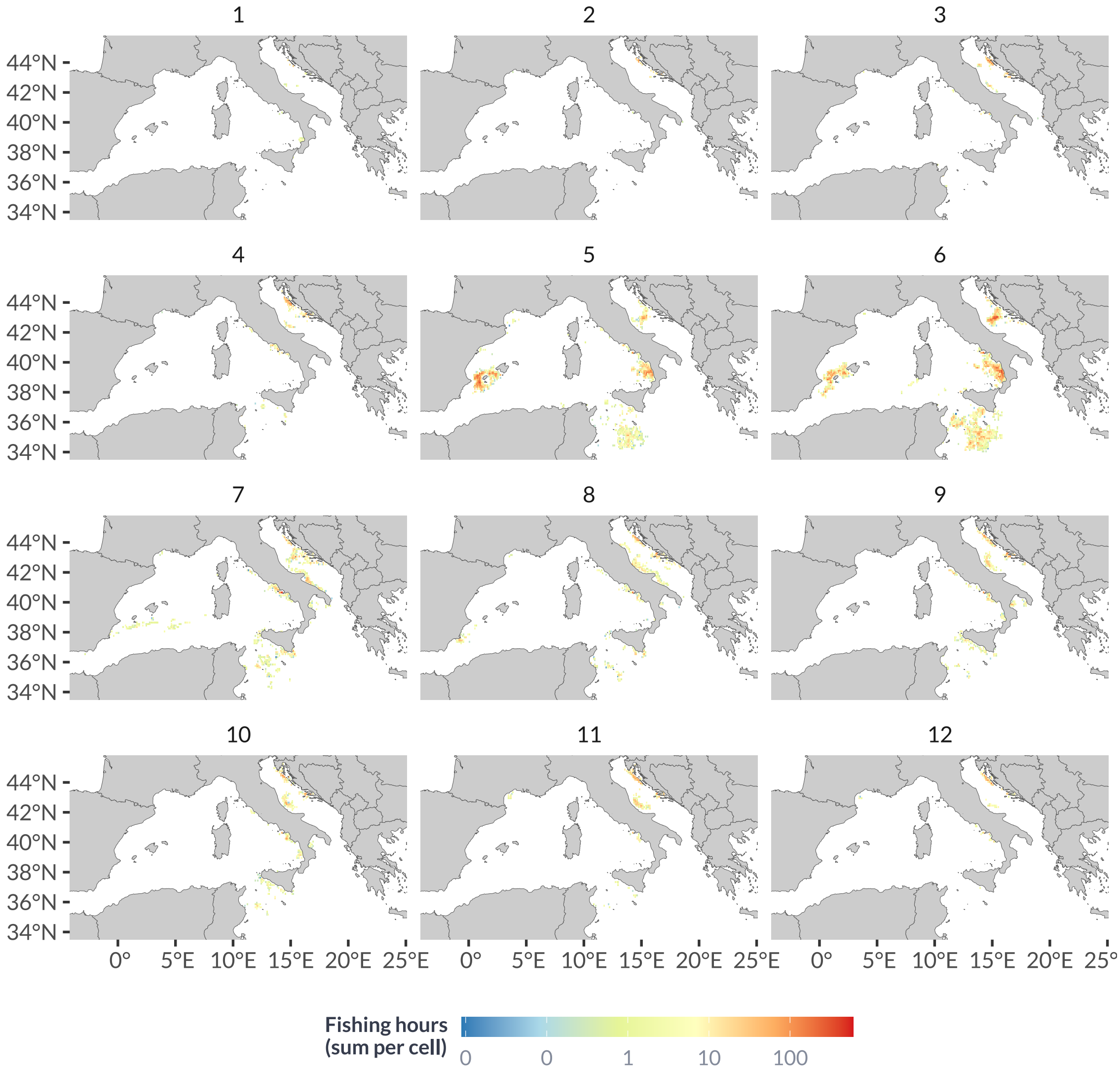

Figure S6: Sum of purse seine fishing hours per cell for each month between 2015-2024. Colours are on a log-scale.

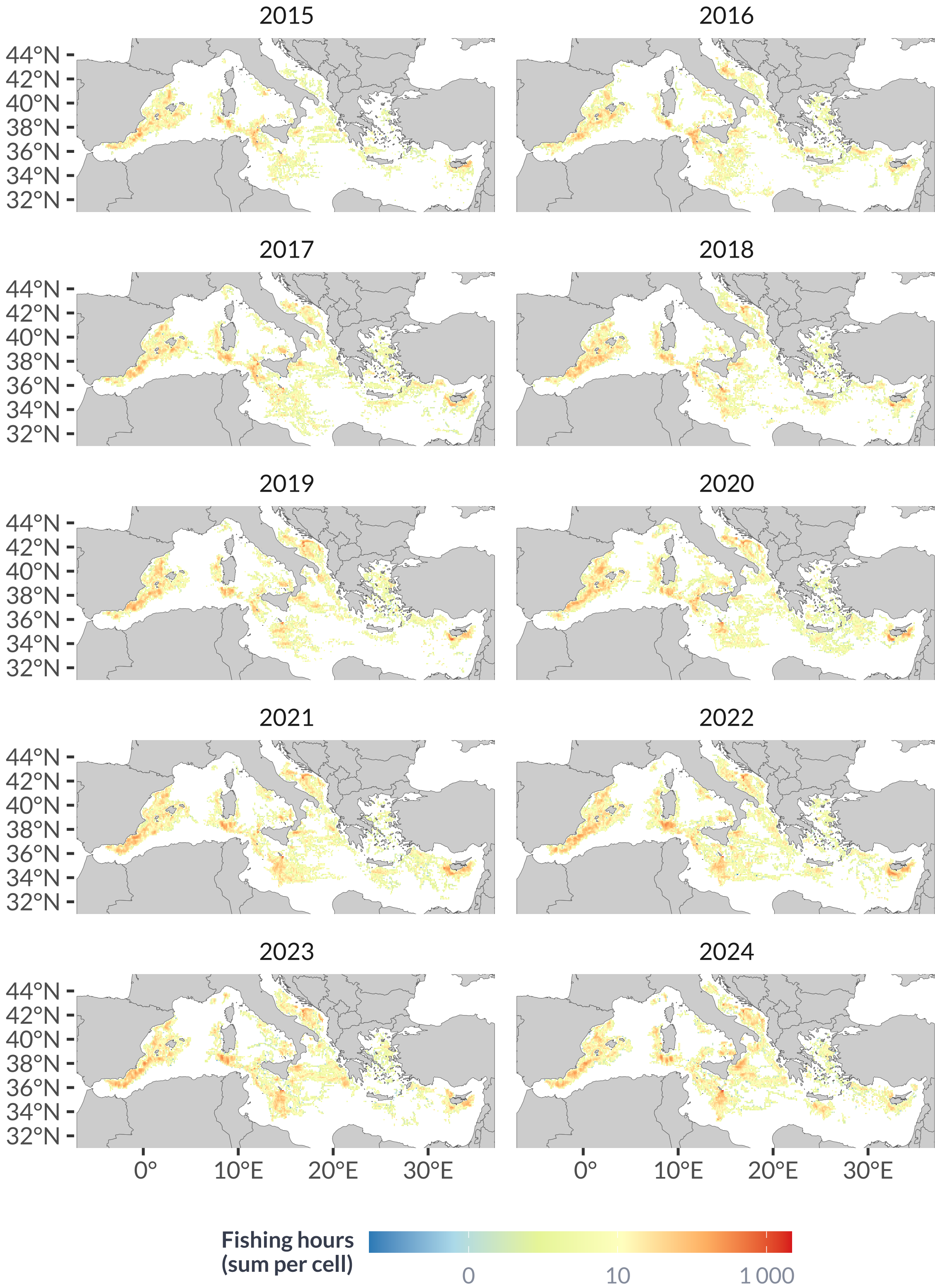

Figure S7: Sum of longline fishing hours per cell for each year. Colours are on a log-scale.

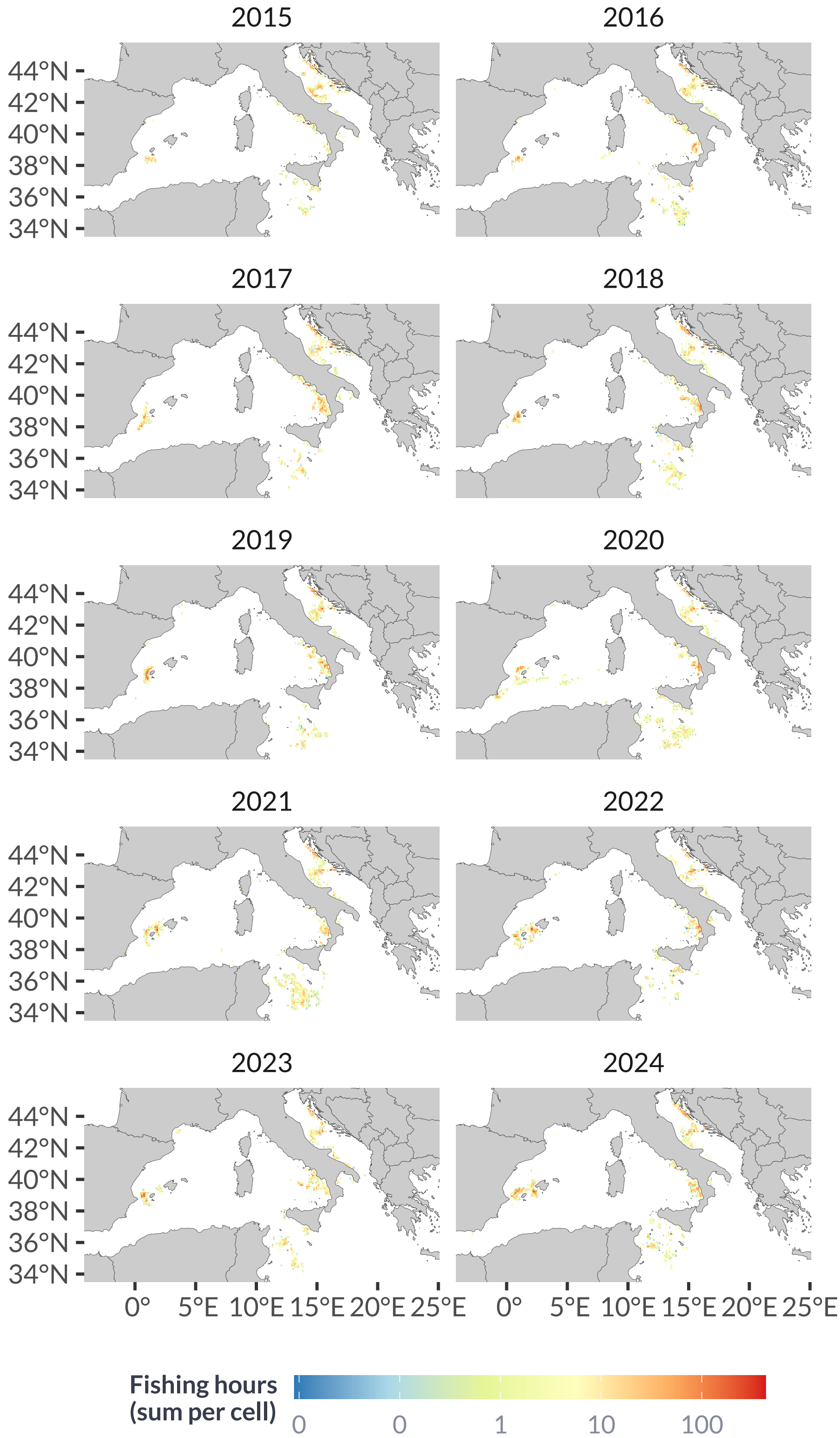

Figure S8: Sum of purse seine fishing hours per cell for each year. Colours are on a log-scale.