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

Master Thesis

Tom Leven

02312706

At the Faculty of Sciences

Ghent University

Main supervisor: Dr. Pilar Tugores

Co-supervisors: Dr. Diego Alvarez-Berastegui & Dr. Miguel Cabanellas-Reboredo

Executive Summary

The executive summary goes here.

Abstract

Abstract goes here.

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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, 2022). 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). 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, bluefin tuna (*Thunnus thynnus*), albacore tuna (*Thunnus alalunga*), and swordfish (*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). 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). The bluefin tuna fishery for example, is the oldest known industrial fishery in the world (Di Natale, 2012).

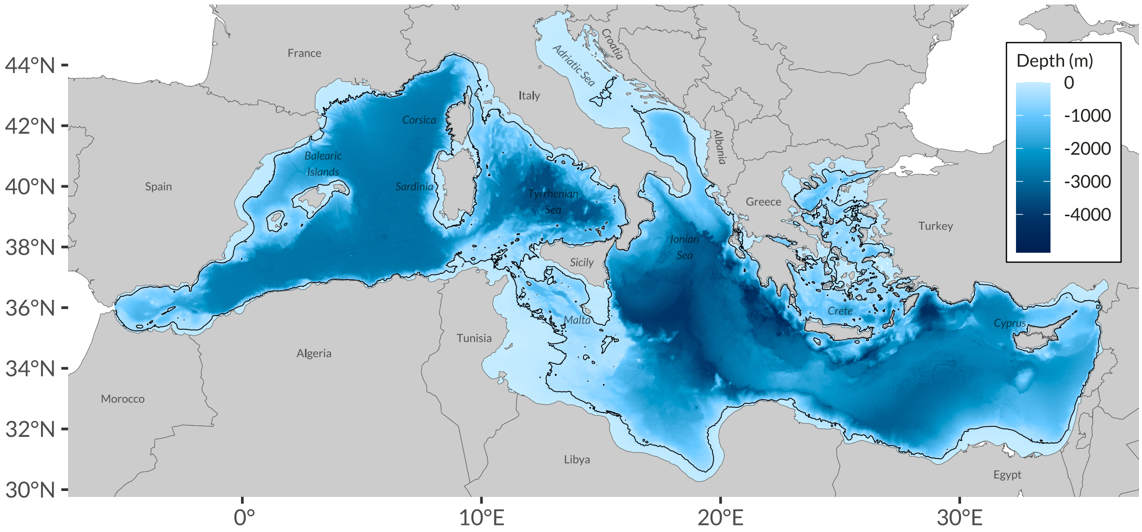

Figure 1: The Mediterranean Sea, study area for this analysis. The black line indicates the 200m isobar.

To sustainably manage these fish stocks 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 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 who, when, where and how much fishing is occurring is necessary (Orofino et al., 2023).

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 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.). This enables the analysis of more complex fisheries behaviours (Natale et al., 2015). Apart from this, AIS data is also publicly accessible and thus, allows 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.

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).

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 a regional analysis, 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, analyse temporal trends, and the relationship of fishing with other environmental features. 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 interannually?

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 and how could we use these as indicators of habitat changes?

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).

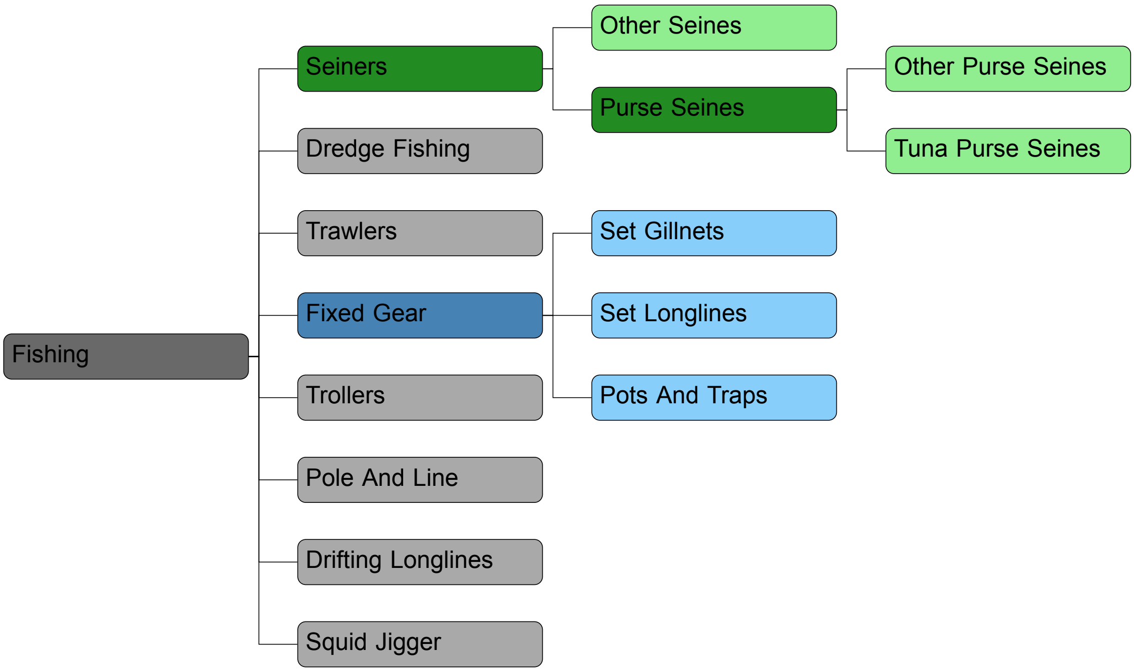

Figure 2: Hierarchy of fishing gears recognised by GFW

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 Europan Fleet Register to obtain it (European Commission, Directorate-General for Maritime Affairs and Fisheries, 2025).

2.2 Data filtering

All data filtering was conducted using R (v4.4.1; R Core Team, 2024) within the RStudio environment (Posit team, 2024). The GFW dataset was first cropped and adjusted to a shapefile of the Mediterranean Sea (Fig. **??**), 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). These gear types were chosen as they are the main *metiers* 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 since 2018 (Taconet et al., 2019).

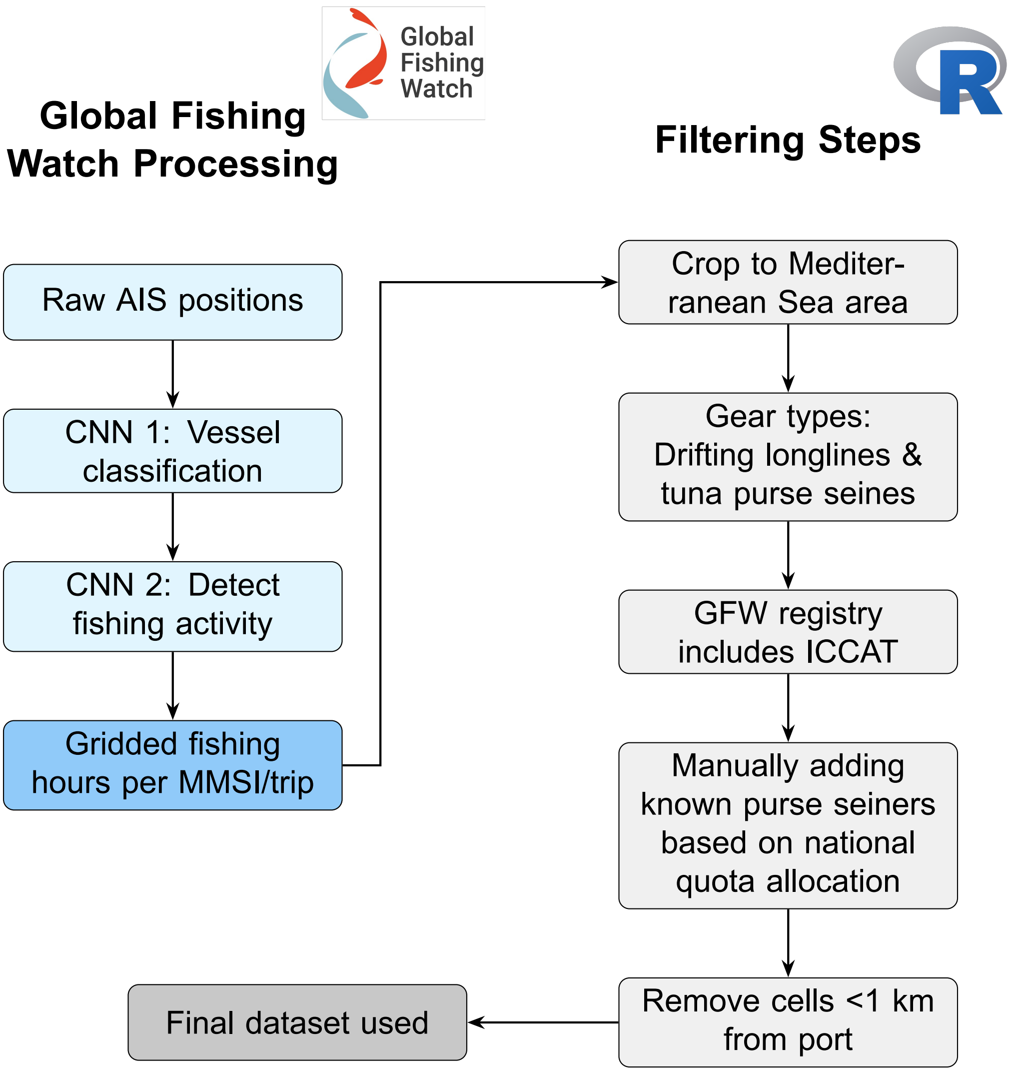

Figure 3: Global Fishing Watch data processing pipeline and filtering steps to obtain the final dataset used in this study. CNN = Convolutional Neural Network

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 (Global Fishing Watch, 2020).

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 (v1.8.18; 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).

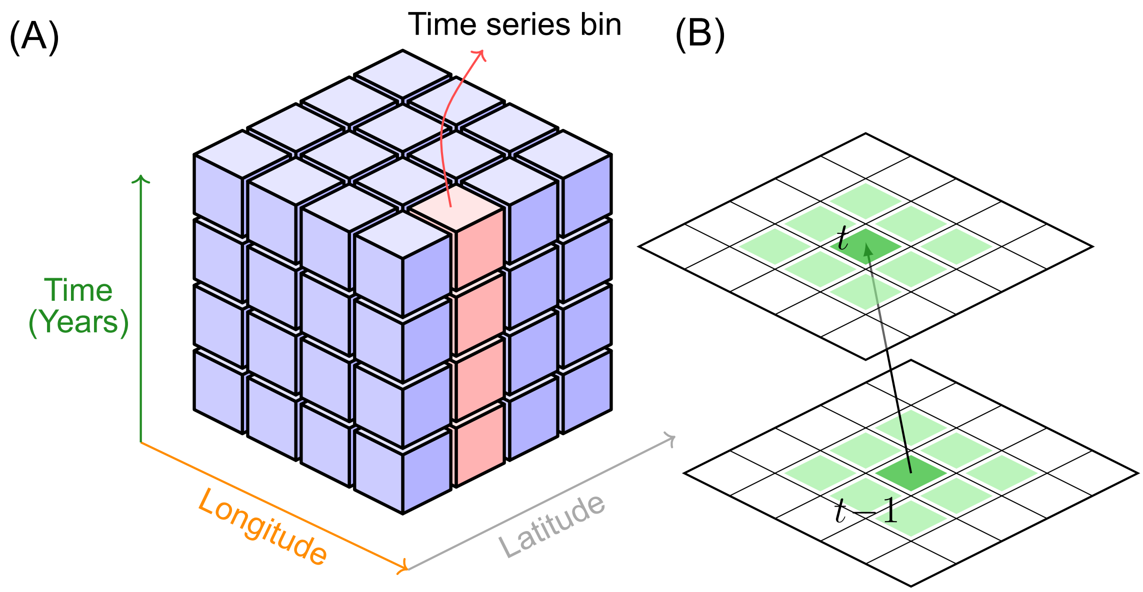

Figure 4: A) Structure of the space-time cube in ArcGIS. Each individual cube corresponds to one *neighbourhood bin*, which is the sum of all coloured cells in B. One *time series bin* corresponds to the same location over time (red). B) Conceptualization of space-time dependency as implemented in the 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.

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 5115 fishing days per year, with an average of 24 days 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).

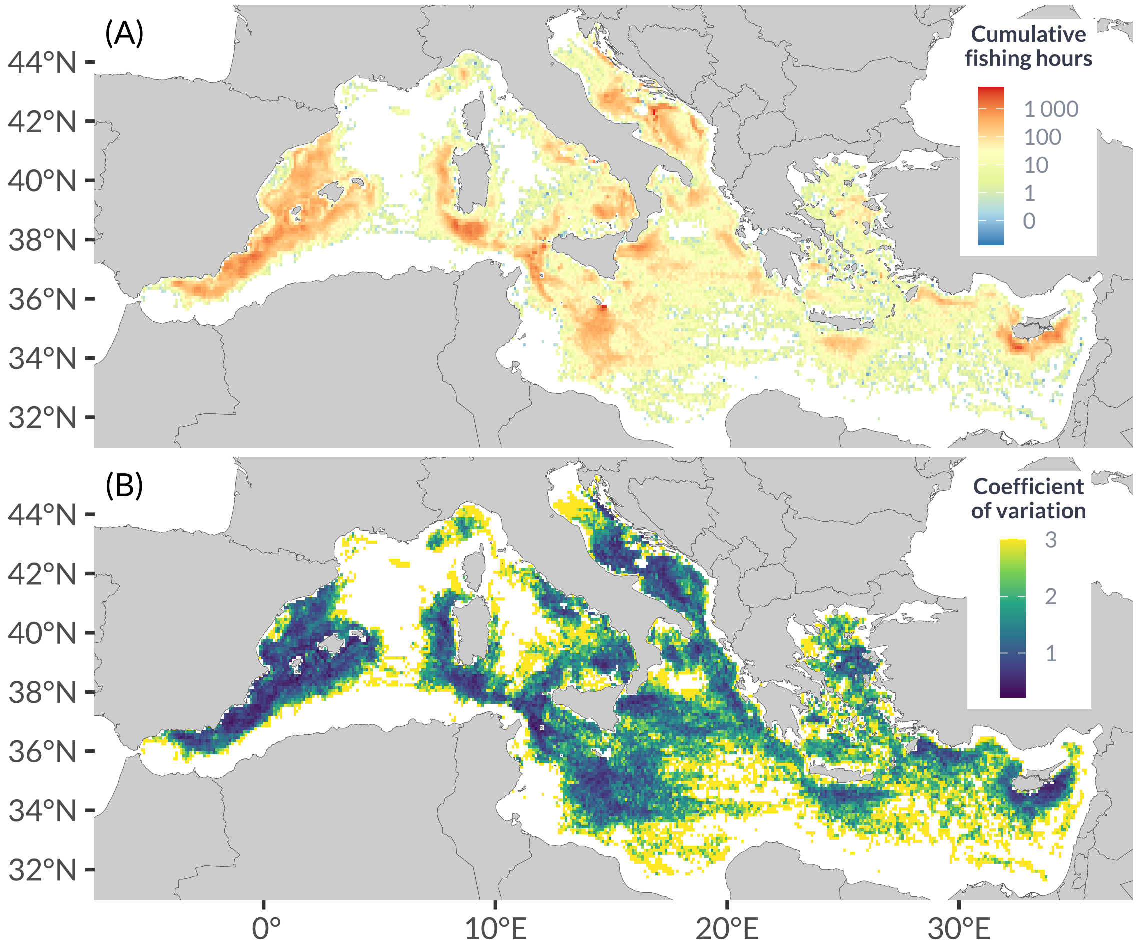

Figure 5: Summary statistics for both longliners and purse-seiners. A) Cumulative fishing hours in the Mediterranean (2015-2024). Colors are on a log-scale. B) Coefficient of variation between years (standard deviation divided by mean) for each cell.

3.2 Hotspot analysis

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).

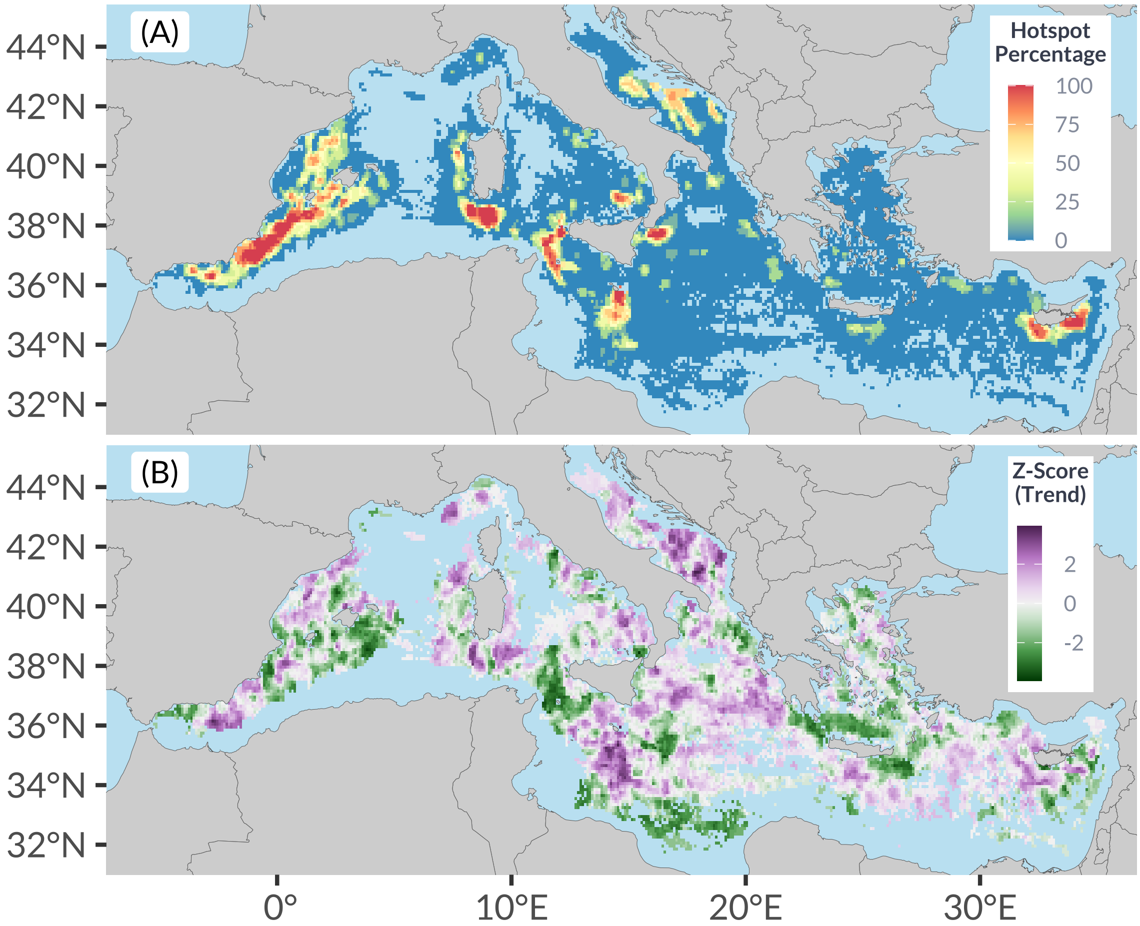

Figure 6: Hotspot percentage and trend scores for longliners in the Mediterranean. The percentage reflects the years in which a given cell was a hotspot based on the Getis-Ord Gi* statistic. The Z-score is derived from the Mann-Kendall statistic.

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.

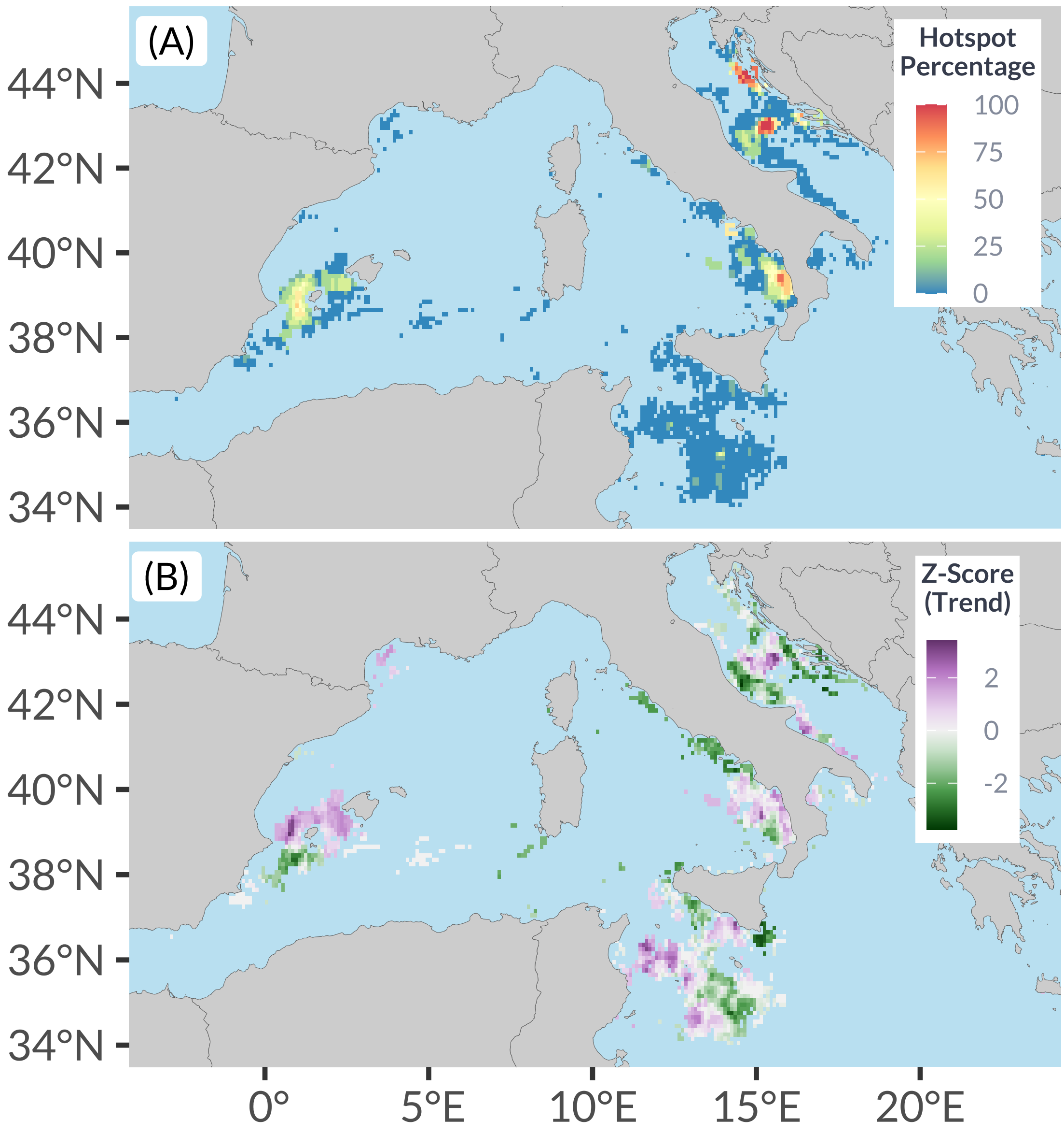

Figure 7: Hotspot percentage and trend scores for purse seiners in the Mediterranean. The percentage reflects the years in which a given cell was a hotspot based on the Getis-Ord Gi* statistic. The Z-score is derived from the Mann-Kendall statistic.

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). Daily fishing shows a similar seasonal trend, although the intensity varies between years. The highest annual longline fishing hours throughout the study time were recorded for 2022 and the lowest for 2015 (Tab. 1).

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

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 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).

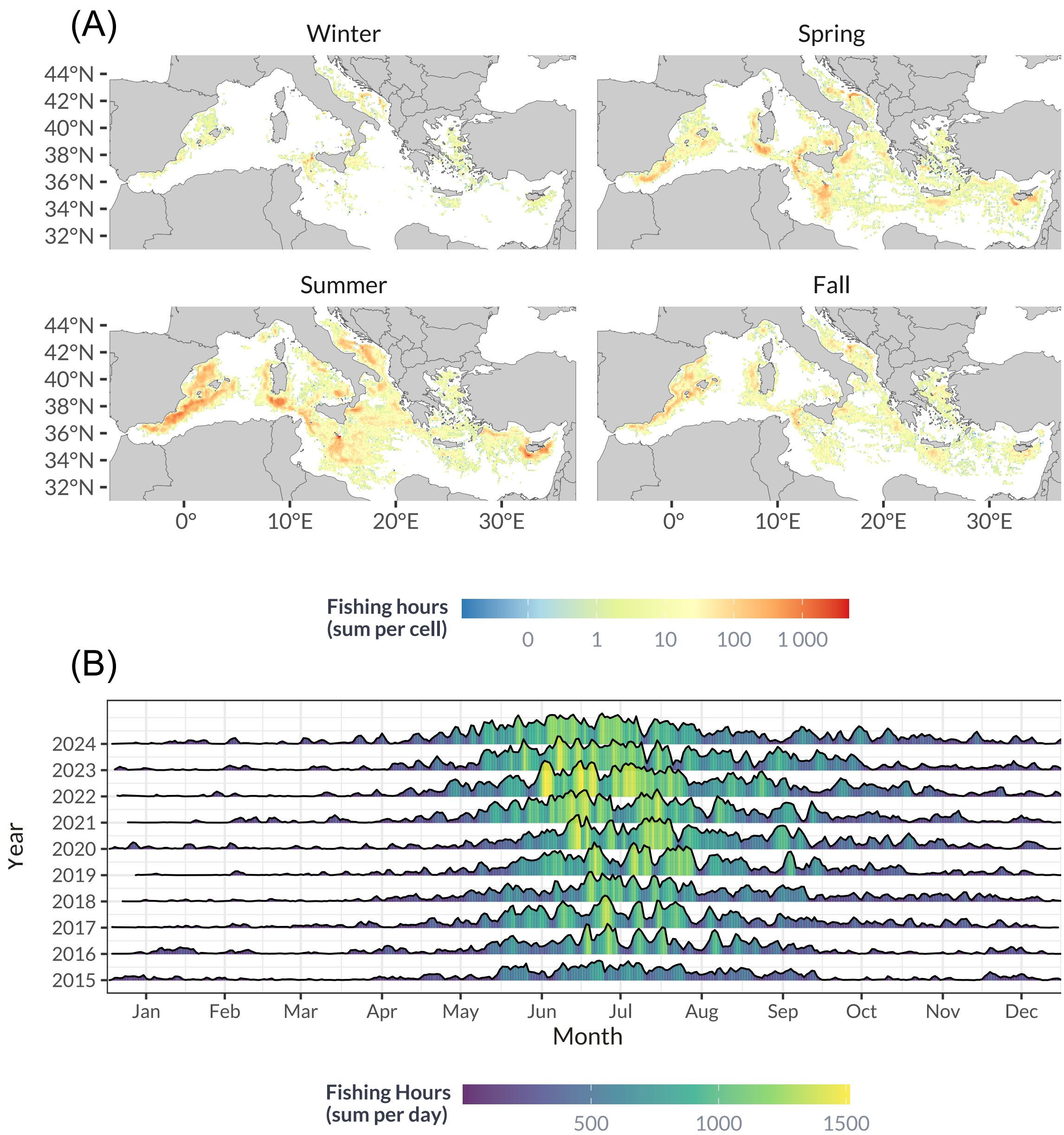

Figure 8: Temporal changes in longline fishing hours. A) Spatial differences between seasons. Hours are summed per season and cell and colour is on a log-scale. B) Time series of fishing hours, summed per year and day.

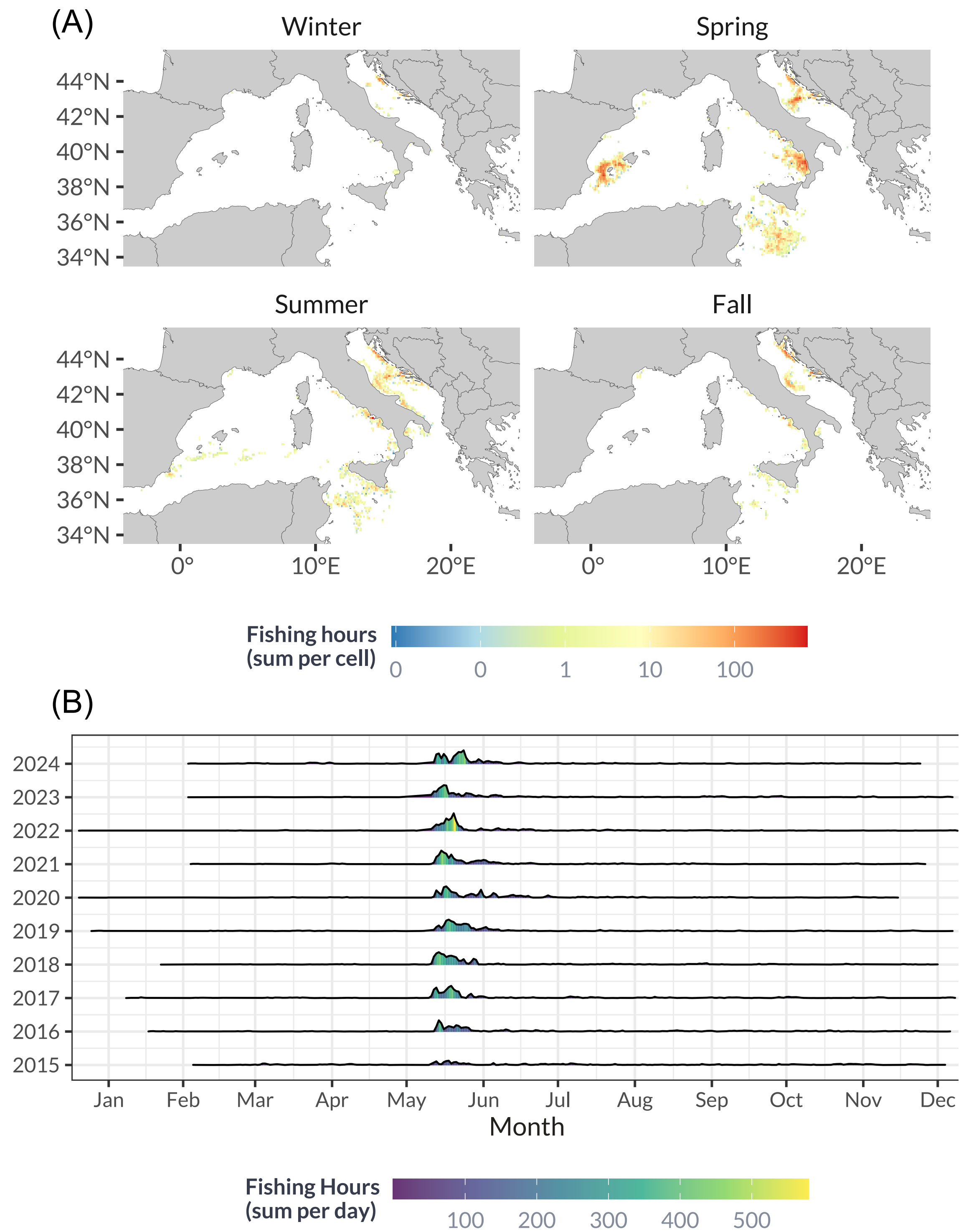

Figure 9: Temporal changes in purse seine fishing hours. A) Spatial differences between seasons. Hours are summed per season and cell and colour is on a log-scale. B) Time series of fishing hours, summed per year and day.

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. S1 and S2 for an 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 based on GFW data and national registry information. '–' indicates no recorded vessels for that gear.

Country	**Number of vessels**	
	Purse seiners	**Longliners**
Algeria	4	–
Croatia	2	–
Cyprus	–	25
France	14	–
Greece	–	9
Italy	16	79
Malta	–	21
Morocco	1	–
Spain	5	35
Tunisia	2	–
Total	**44**	**169**

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).

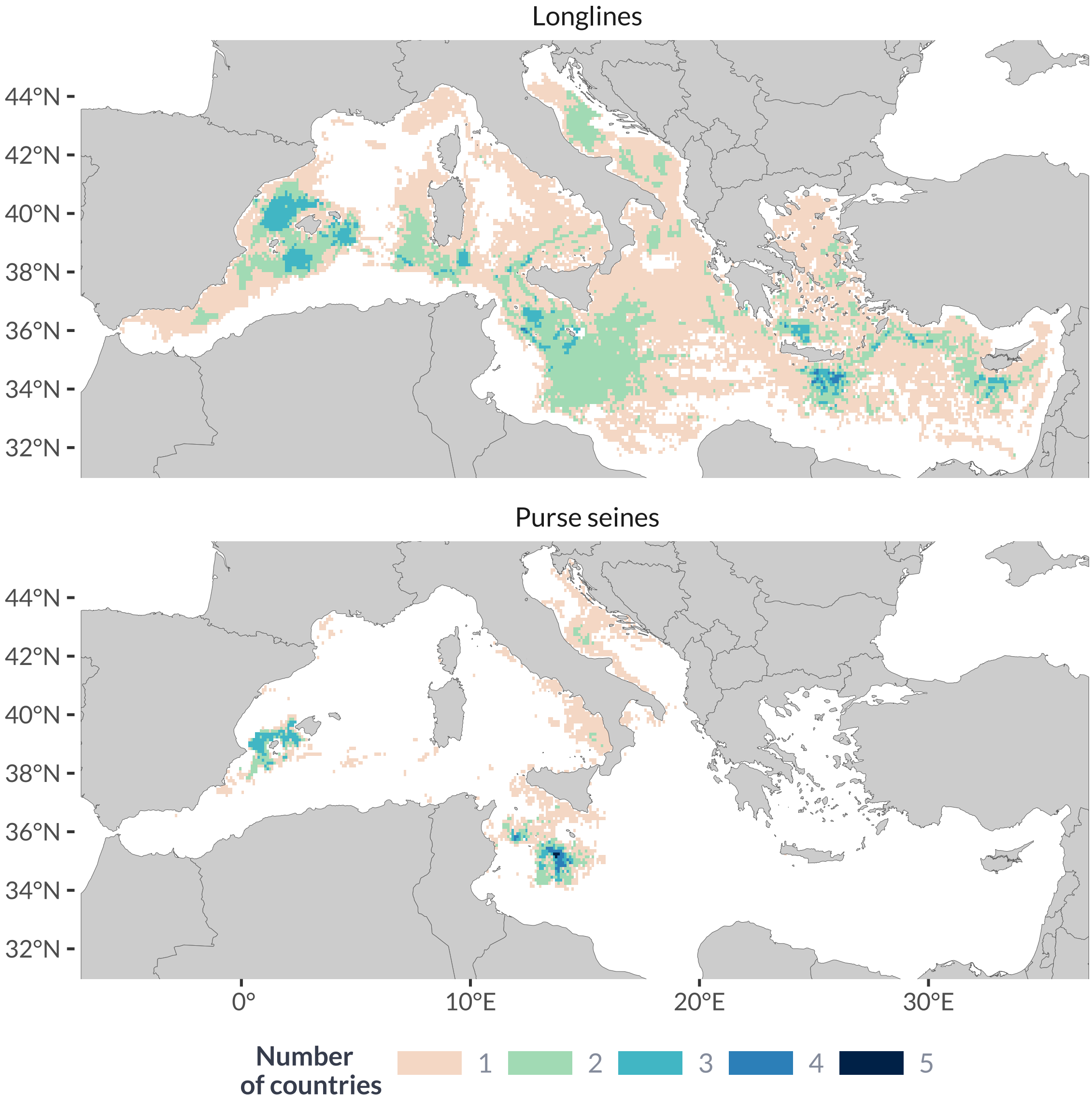

Figure 10: Number of countries fishing per cell for longliners and purse seiners between 2015-2024.

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.

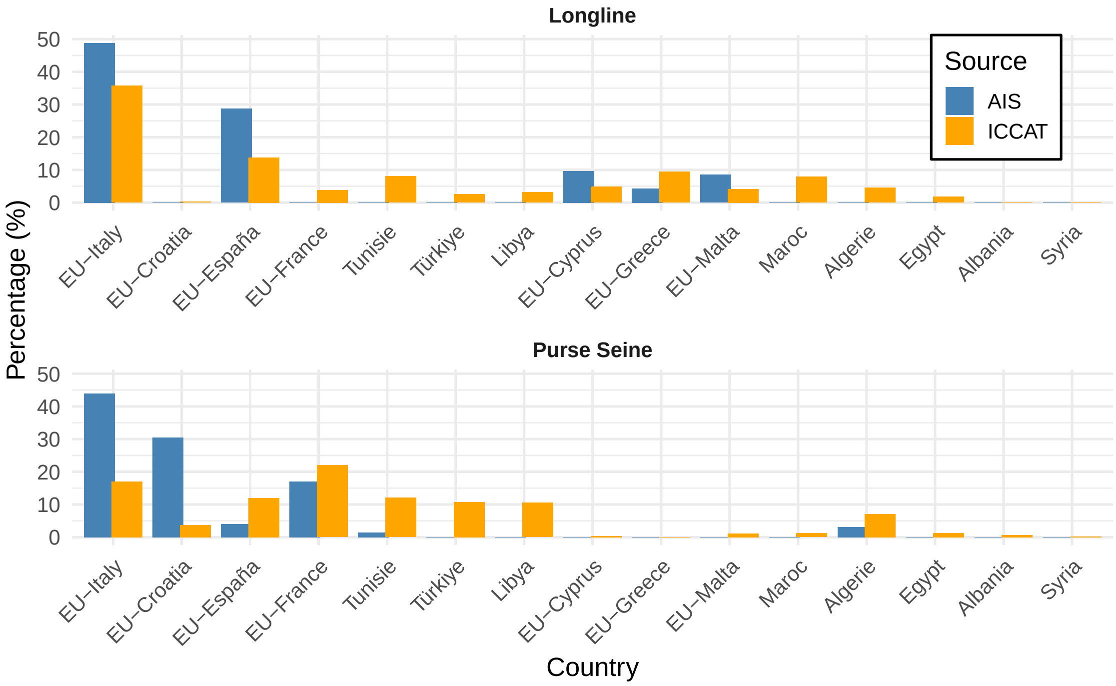

Figure 11: Comparison of relative percentages between GFW AIS data and ICCAT catch data. AIS percentages are relative to the total fishing hours between all countries. ICCAT percentages are relative to the total weight of catches between all countries.

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).

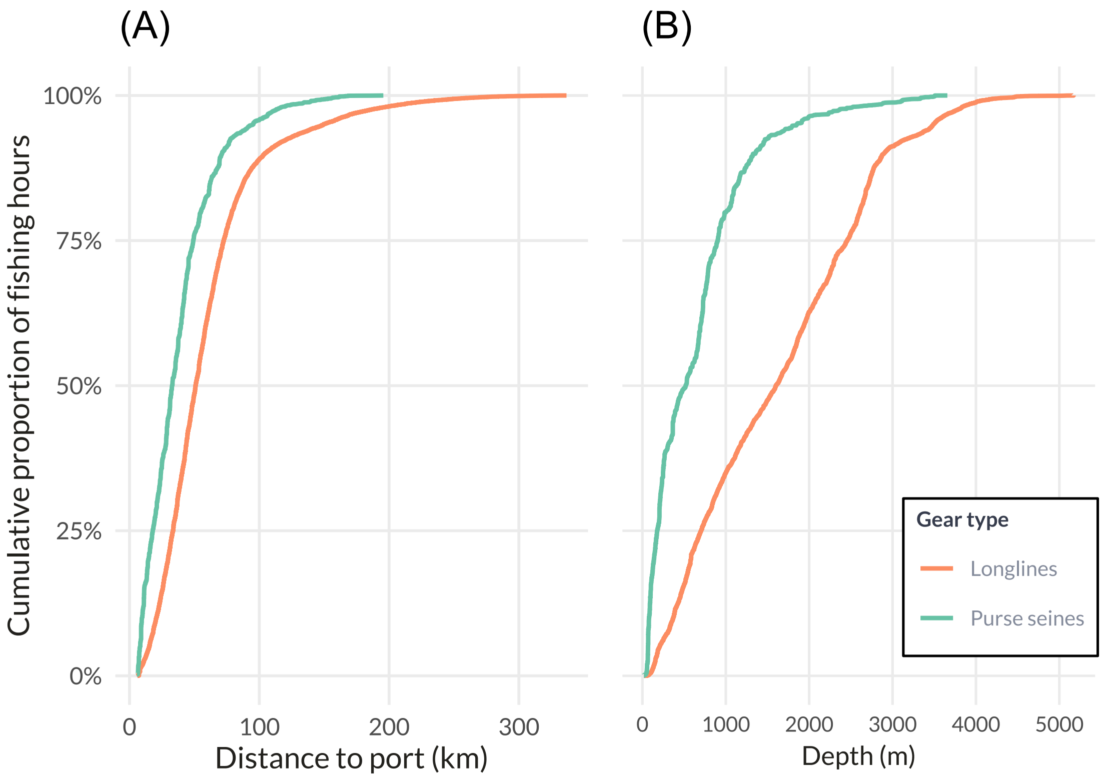

Figure 12: Cumulative proportion of fishing hours with A) Distance to port and B) Depth.

4 Discussion

- Summarize findings and methods
- Compare with other studies looking into effort of these gear types
  - Not possible to get effort per metier with AIS (at least with GFW methods right now) -> problematic
- Shortcomings of AIS
  - What are the caveats identified during the study?
  - Which different methods exist to analyse AIS data? Which one is suitable when and for what?
- What can we infer from AIS derived fishing activity and what not?
- Future perspectives

5 Conclusion

Conclusion goes here.

6 Acknowledgements

Thank you to…

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A Supplementary Material

Annex 1

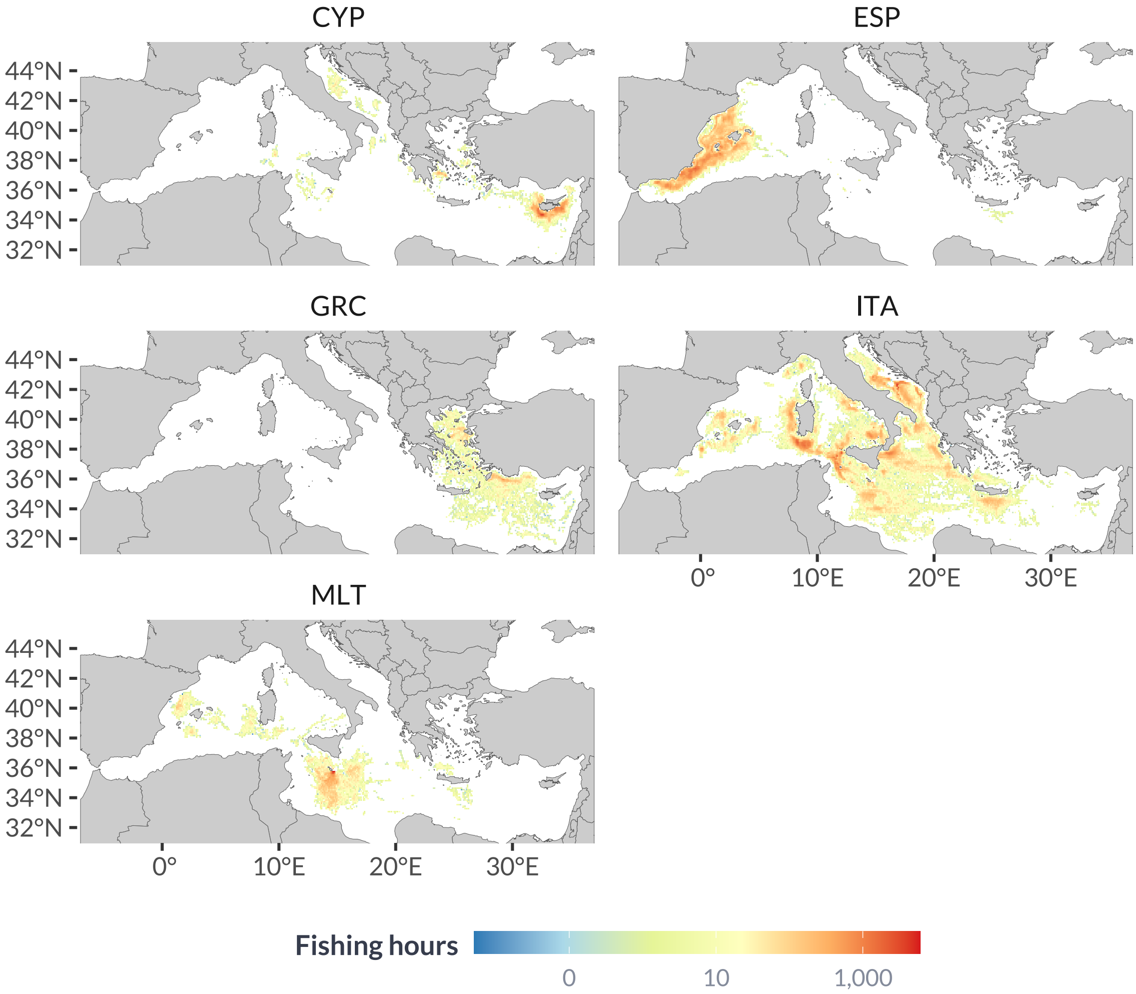

Figure S1: Sum of longline fishing hours per flag country (2015-2024). CYP = Cyprus; ESP = Spain, GRC = Greece, ITA = Italy, MLT = Malta

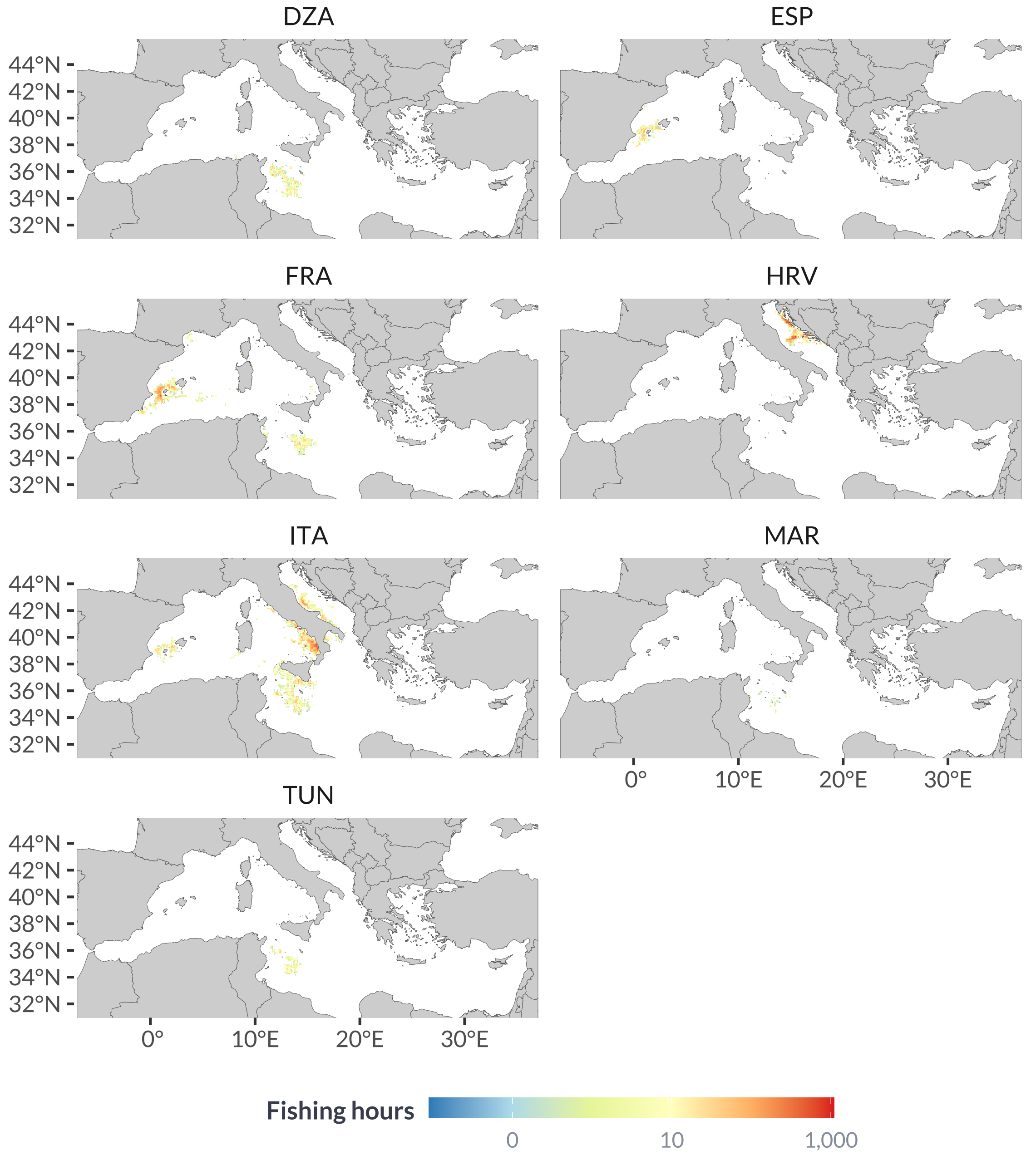

Figure S2: Sum of purse seine fishing hours per flag country (2015-2024). DZA = Algeria, ESP = Spain, FRA = France, HRV = Croatia, ITA = Italy, MAR = Morocco, TUN = Tunisia.