Title: Abundance and distribution of the white shark in the Mediterranean Sea

Authors: Moro Stefano[1,2], Jona-Lasinio Giovanna[2], Block Barbara[3], Micheli Fiorenza[3,4], De Leo Giulio[3], Serena Fabrizio[5], Bottaro Massimiliano[6], Scacco Umberto[7], and Ferretti Francesco[8].

[1]Department of Environmental Biology, Sapienza University of Rome, Piazzale Aldo Moro 5, 00185, Rome, Italy
[2]Department of Statistical Sciences, Sapienza University of Rome, Piazzale Aldo Moro 5, 00185, Rome, Italy
[3]Hopkins Marine Station of Stanford University, 120 Ocean View Blvd, 93950, Pacific Grove (CA), USA
[4]Stanford Center for Ocean Solutions, 120 Ocean View Blvd, 93950 Pacific Grove (CA), USA
[5]Italian National Research Council (CNR), Via Luigi Vaccara, 61, 91026, Mazara del Vallo (TP), Italy
[6]Stazione Zoologica Anton Dohrn, Villa Comunale, 80121, Naples, Italy
[7]Institute for Environmental Protection and Research (ISPRA), Via Vitaliano Brancati 48, 00144, Rome, Italy
[8]Department of Fish and Wildlife Conservation, 310 West Campus Drive (MC0321), 24061, Blackburg (VA), USA

Corresponding Author: Stefano Moro, Department of Environmental Biology, Sapienza University of Rome, Piazzale Aldo Moro 5, 00185, Rome, Italy, +39 3338451987, stefano.moro@uniroma1.it

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ABSTRACT

Conservation of apex predators is a key challenge both in marine and terrestrial ecosystems. The white shark is a rare but persistent inhabitant of the Mediterranean Sea and it is currently assessed as “critically endangered” in the region. However, the population trends and dynamics of this species in the area are still unknown. Little is known about white shark distribution, habitat use, and population abundance trends, aspects that are critical for conservation and management. In this study, we built the most comprehensive database of white shark occurrence records in the region. We collected 773 different records from different sources and used them to characterize the spatial and temporal patterns of abundance of Mediterranean white sharks between 1860 and 2016. We analyzed these data by using generalized additive models and used spatially disaggregated information on human population abundance as a proxy of observation effort. Our results suggest a complex trajectory of population change characterized by a historical increase and a more recent reduction (61%, range 58-72%) since the second half of the 20th-century. In particular, analyses reveal a 52% (range 37-88%) to 96% (range 92-100%) overall decline in different Mediterranean sectors and a contraction in spatial distribution. Here, we provide the first reconstruction of abundance trends and offer new hypotheses regarding the drivers of change of white sharks in the Mediterranean. Our approach can be broadly applied to data-poor contexts to reconstruct change and inform the conservation of endangered top predators in the Mediterranean Sea and other intensely used marine regions.

Keywords: Mediterranean Sea, observation effort, opportunistic and sparse data, spatiotemporal patterns, standardized trends, white shark

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INTRODUCTION

The loss of top predators is one of the most challenging forms of global environmental change, with still unrecognized and not well-understood ecosystem effects (Estes et al., 2011). The decline of large predators on land started approximately 50 kya with the great demographic and geographic human expansion (Dirzo et al., 2014; Ripple et al., 2014). In the oceans, recent increases in resource exploitation by high seas industrial fishers as well as artisanal fleets, habitat degradation, and climate change pose unprecedented challenges also to marine predators (Worm & Tittensor, 2011). In the Mediterranean Sea, predator loss is more severe than other ocean sectors due to thousands of years of human impact on marine communities (Coll et al., 2010) and currently high cumulative human pressure on marine ecosystems (Micheli et al., 2013). However, it is only in the last 50 years that systematic data started to be gathered to evaluate the impact of fishing on exploited marine populations and ecosystems (Ferretti et al., 2015; McClenachan et al., 2012). This lack of historical baselines hampers our ability to fully understand the ecology of habitats and species, and consequently, our ability to evaluate the conservation status of Mediterranean ecosystems and marine populations.

Among marine animals, sharks are one of the marine taxa with the highest percentage of threatened species (Dulvy et al., 2014). They are generally vulnerable animals, with very low resilience and biological productivity, strongly susceptible to fishing pressure (Ferretti et al., 2010; Queiroz et al., 2019), though examples of sustainable shark fishery also exist (see for details Simpfendorfer & Dulvy, 2017). Because of these features, in the past decades, many shark populations showed rapid declines in multiple marine regions mostly because of the direct effect of targeted and bycatch fisheries (Baum & Blanchard, 2010). An among global ocean sectors, the Mediterranean Sea showed the worst population declines and conservation statuses for many populations (Cavanagh & Gibson, 2007; Ferretti et al., 2008). In 2016, the International Union for Conservation of Nature (IUCN) compiled the second regional assessment of sharks and rays in the Mediterranean Sea, reporting that after ten years the situation had not improved and the conservation status of these species remained probably the worst in the world (Dulvy et al., 2016). In fact, 39 of the 73 assessed species are still threatened and 13 are still considered Data Deficient (Dulvy et al., 2016). Moreover, for most non-data-deficient species, the risk assessment was based on suspected trends and not adequately supported by quantitative analyses. For instance, the conservation status of the white shark (*Carcharodon Carcharias,* Lamnindae) was raised from Endangered to Critically Endangered in both Mediterranean and European Regional Red Lists (Dulvy et al., 2016; Nieto et al., 2015) solely on the ground of its current sporadic occurrence in the region and suspected declines.

The white shark is one of the largest and most widespread top predators in the ocean. It is broadly distributed between the sub-polar and sub-tropics in both hemispheres, with major coastal aggregation sites in temperate latitudes (Compagno, 2001). Most of the biological and ecological research on white sharks have been carried out in three coastal aggregation sites (Huveneers et al., 2018): California (Chapple et al., 2011; Tinker et al., 2016), southern Australia (Bruce & Bradford, 2012) and South Africa (Kock et al., 2013). Here, satellite and acoustic tagging, genetics, and isotopes analyses have deepened our ecological understanding of the species' migrations, preferred habitats, population structure, abundance, and distribution patterns (Bruce & Bradford, 2012; Carlisle et al., 2012). Even if a general assessment of the white shark abundance trends is challenging to achieve, there have been several attempts in different areas to assess the status of the sharks. Locally, different data sources and modeling approaches have been adopted (Christiansen et al., 2014; Curtis et al., 2014; Dudley & Simpfendorfer, 2006; Lowe et al., 2012; Reid et al., 2011). Most of these attempts showed a slow increase in white shark populations or sub-populations relative abundance in recent years due to the presence of local protecting measures (Curtis et al., 2014; Dudley & Simpfendorfer, 2006; Lowe et al., 2012; Reid et al., 2011). By contrast, relative declines have been detected in regions lacking these measures (Christiansen et al., 2014). Despite both the protecting provisions existing and the actual conservation status, no white shark population trend analyses have been carried out in the Mediterranean basin, so far.

In the Mediterranean Sea, white sharks have been sporadically but regularly detected throughout history. Several authors (Fergusson, 1996; Gubili et al., 2011) hypothesized the existence of a distinct Mediterranean population, and phylogeographic analyses showed a large genetic distance and scarce genetic flow between the Mediterranean and northwestern Atlantic white sharks (Gubili et al., 2011, 2015). However, little is known about the ecology and biology of the Mediterranean population. Studying white sharks in the Mediterranean Sea is challenging because of the low population density and the absence of conventional aggregation sites, such as around pinnipeds colonies (Klimley & Anderson, 1996). This makes it challenging to conduct monitoring studies with the use of electronic tagging, and limits the scope of genetic and isotopic analyses (Gubili et al., 2011). However, opportunistic occurrence records exist (Boldrocchi et al., 2017; De Maddalena & Heim, 2012; Fergusson, 1996; Serena et al., 2008). Regional reviews of these data generated interesting hypotheses on patterns in population structure, movements, and abundance. For example, several catches of young-of-the-year white sharks reported for the Sicilian Channel suggested the presence of a nursery area in this sector (Fergusson, 1996, 2002). The reduction in white shark sightings through the years from areas with a parallel strong decline of tuna populations, combined with recent and historical sightings in and around farm pens and tuna traps (Galaz & De Maddalena, 2004; Storai et al., 2011), suggested a close relationship between Atlantic Bluefin tuna (*Thunnus thynnus,* Scombridae) and white shark occurrence in the Mediterranean Sea (Boldrocchi et al., 2017; De Maddalena & Heim, 2012; Kabasakal, 2016). Yet, more research is needed to understand population structure, size, movements and distribution within the area and their relations with environmental and biological variables.

Mediterranean white shark observation records are opportunistic because they are often collected from fishers' anecdotes or newspaper articles (Pearce & Bouyce, 2006), and, hence, obtained without a specific and systematic sampling effort. Nevertheless, in the absence of systematic surveys, opportunistic data provide valuable insights on species distribution, habitat requirements and population trends (Christiansen et al., 2014; Curtis et al., 2014; Ferretti et al., 2015). For example, McPherson & Myers (2009) used white shark sightings collected between 1868 and 2005 to infer population changes in the Adriatic Sea. They estimated temporal trends of occurrence records under different scenarios of observation effort and estimated an 84% decline (CI: +27% and -98%). These estimates were highly uncertain as the authors had no direct information on observation effort but provided a first quantitative estimate of white shark population change in a sector of the Mediterranean Sea. Here we expand on this approach to produce the first regional assessment at the Mediterranean scale. We assembled the most comprehensive database of white shark's occurrence records currently available for the Mediterranean Sea and estimated trends controlling for observation effort, which was directly estimated with long-term trend models of coastal human population censuses in the region. We used these standardized records to infer trends in population abundance and asked whether, how and how much the white shark population has changed in abundance and spatial distribution over the last two centuries.

METHODS

Shark database construction and exploratory analysis

We built a database containing all the white shark records in the Mediterranean Sea using different sources and multiple search strategies (Supporting Information), also including existing institutional databases, such as MEDLEM (Mediterranean Large Elasmobranchs Monitoring) currently under the auspices of the General

Fisheries Commission for the Mediterranean Sea (GFCM, Serena et al., 2008). We followed through citations in the listed references to delineate the history of each account and to determine whether the record was original or redundant (reporting records from other publications) (Ferretti et al., 2016). For each observation we recorded: date and location; total length; weight; sex; age (adapted from Bruce & Bradford, 2012; Supporting Information); record type (stranding, catch, sighting, signs of predation on other marine animals); stomach contents; fishing gear involved in the capture; and bibliographic reference for published accounts. Then, we performed an exploratory data analysis in order to evaluate the most immediate ecological information, such as the sightings' temporal and spatial distribution, length frequency, length-weight relationship, and a qualitative stomach content analysis (Supporting Information).

Model framework

We stratified the Mediterranean sea in spatio-temporal statistical units of different resolution (e.g. FAO or GFCM statistical sectors and year) and following McPherson & Mayers (2009)'s approach, we assumed that the expected number of sightings per statistical unit (year t and geographic sector s) was related to the following variables: number of possible observers (observation effort), O_{ts}, their propensity to report a sighting, P_{ts}, white sharks population abundance, N_{ts}, and shark detectability, D_{ts}. In systematic and dedicated surveys these factors can be controlled. Conversely, this information is incomplete for opportunistic data (McPherson & Myers, 2009). In this work, we chose the human population size (H_{ts}) as a proxy of observation effort. Therefore, we treated O_{ts} and P_{ts} as a joint process, essentially assuming that all observers had a constant probability to report a record (McPherson & Myers, 2009) and that the number of observers is proportional to the human population size ($O_{ts} = cH_{ts}$, where c is constant). Hence, we assumed that detectability, D_{ts}, has a proportional relationship with abundance ($D_{ts} = kN_{ts}$), assuming, in other words, that a specific amount of observation effort is needed to detect a fixed proportion of the individuals present in the study area (McPherson & Myers, 2009). This represents the simplest possible scenario to infer standardized abundance trends of the shark population. In fact, under these assumptions, the probability of a recorded sighting depends only on H_{ts} and N_{ts}. We tested deviations from such an assumption in the following inferential analysis.

Given that Mediterranean white shark sightings are rare and discrete events, we assumed that the expected number of sharks per statistical unit follows either Poisson or Negative Binomial (NB, in case of overdispersed data) distributions where their means are a function of predictors describing N_{ts} and H_{ts}. However, it is important to note that factors other than H_{ts} can affect the observation effort variability over space and time. For example, the marine area covered by the potential observers and the technological innovations in fisheries and boating may have played a pivotal role in changing the sightings probability (fisheries have expanded in distance from shore and overall range over time (Rousseau et al., 2019)). So, the sighting probability may have increased during the 20th-century, but testing this hypothesis was not possible with the available data. Therefore, since this issue arises when interpreting the frequency of occurrence of many other Mediterranean species, we explored the performance of a single, readily available and systematic proxy of observation effort.

Collecting observation effort data

In order to investigate trends in the spatiotemporal distribution of our proxy of observation effort, we divided the Mediterranean coastline into 202 coastal regions, belonging to 23 different countries and retrieved the human population in each coastal region (Supporting Information) (Fig.1a-b). Historical time series of the human population were collected for each coastal region over a time range of 156 years (1860-2016). Multiple sources, such as national census reports or international databases (Eurostat, World Bank), were consulted to rebuild each human population time-series (Supporting Information). As not all considered regions had annual census estimates for the whole time period, we interpolated missing years with a regression approach. Annual population size estimates for each region were obtained by fitting GAMs (Wood, 2011) and log-scale regressions to the historical population censuses data. Then, we selected estimates according to the best fitting model in each region (details are in the Supporting Information).

Estimating standardized shark sighting trends

In order to identify the spatial and temporal patterns characterizing the sighting data, we considered a time range of 156 years (between 1860 and 2016) and different levels of resolution for spatial strata. We chose 1860 as our initial observation year because earlier sightings were scarce and previous human population data in most Mediterranean countries were unavailable. Observation effort and shark occurrences were spatially aggregated using both the GFCM's Mediterranean Geographic Sub-area stratification (GSAs, http://www.fao.org/gfcm/data/map-geographical-subareas/en/) (Fig.2a) and the coarser FAO Major Fishing Area 37's stratification of eight divisions (http://www.fao.org/gfcm/data/map-geographical-subareas/en/) (Fig3b). In order to find the best fitting model, we tested multiple model structures (Supporting Information) with various levels of temporal aggregation, functional relationships between response and predictors (e.g. linear or more complex with polynomials and splines) and the two statistical distributions of the response variable (NB and Poisson). GAMs with 1-year time bins resulted as the best model class in terms of AIC, fitting deviance and residuals analysis. Model fits were performed by using the R package mgcv (Wood, 2011). We fitted a GAM with a Negative Binomial Distribution and a log link function to the annual number of shark occurrences recorded in each GSA, using the observation effort (annual number of people for that GSA) as an offset term and the GSAs as spatial sectors (hereby referred as GSA model). The model structure was

$$log\left(z_{ij}\right) = f(y_i) + [GSA]_j + log\,(H_{ij}) + \varepsilon_{ij} \qquad (1)$$

where z_{ij} is the *i*th observed number of sharks in year y_i (*i*=1,…,156) and GSA *j*, *f* is a smooth function estimated using penalized likelihood maximization (with a smooth parameter estimated by Restricted Maximum Likelihood) (Wood, 2011), $[GSA]_j$ is a factor with 27 levels (*j*=1,…,27), corresponding to the GSAs), $log\,(H_{ij})$ is the offset term and ε_{ij} is the error term for *i*th observation in GSA *j*, assumed to be normally distributed around 0 and with variance to estimate.

In our modeling exercises, we faced several issues. First, in order to verify the assumption of a linear relationship between the response variable and the offset term, we fitted a parallel model with a spline on the human population abundance and compared the two model's prediction errors through RMSEs (Root-mean-square-error, Supporting Information). Second, although we could expect the observation effort to increase with time, we supposed there could be stages in our observation period where sighting effort changed abruptly (i.e. start of ocean use for bathing, interest in marine science, conflicts and epidemics). Therefore, we tested for the effect of these discrete important events dividing our temporal range in bins characterized by different hypothetic sighting effort regimes (Supporting Information). Finally, there was a tradeoff between spatial and temporal resolution. Because of the limited number of sightings from specific Mediterranean sectors, the use of a complex spatial stratification, such as the GSA scheme, with a high temporal resolution, allowed us only to detect a common temporal trend throughout the basin and a sector-specific spatial effect on shark's abundance. It was

$$log\ (z_{ij})\ = f_j(y_i) + [FAO\ Division]_j + log\ (H_{ij}) +\ \varepsilon_{ij} \tag{2}$$

where all terms are the same as in the GSA model except for f_j, which here is sector-specific ($[FAO\ Division]_j$, with $j = 1,\dots,8$). In this way, we obtained sub-regional temporal trends, though with a lower spatial resolution. However, this kind of model parametrization assigns the same number of knots to each sub-regional curve via REML (Restricted Maximum Likelihood). In this way, the trajectories estimated for well-represented sectors (with a high number of records) could have leverage on the others with fewer occurrences recorded. Thus, in order to validate the curves obtained with the FAO Model and to avoid the presence of artifacts related to the sparse nature of data, we chose to fit, parallelly, a single-sector model for each Division (Supporting Information). Finally, we predicted the expected number of sharks in each spatiotemporal model unit considering a fixed amount of observation effort (5 million people), in order to standardize the shark abundance trend on easily interpretable values.

Testing for spatial range contraction

Given its "Critically Endangered" status, it is expected the species went through a range contraction together with a decline in population abundance (Worm & Tittensor, 2011). To test for this scenario, we aggregated the data in two main periods (1945 – 1975, 1976 – 2016), deemed to have the most comparable regimes of observation effort. We excluded from the analysis all the sightings from before 1945 in order to minimize the bias linked to unaccountable variations of the observation effort, such as the two World Wars presence. In addition, our aim was to test for a relatively recent decline associated with a spatial range contraction. Hence, we fitted a Negative Binomial Generalized Linear Model (GLM) (R package MASS, Venables & Ripley, 2002) to the annual number of shark occurrences (considered as replicates) for each time bin in each FAO Division, still maintaining the observation effort as an offset term. The model structure was

$$log\ (z_{ij})\ = \beta_0 +\ \beta_1(T_i)\cdot\beta_2[FAO\ Division]_j + log\ (H_{ij}) +\ \varepsilon_{ij} \qquad (3)$$

where z_{ij} is the observed number of sharks in period T_i and FAO Division *j*, β_0 is the intercept, β_{1-2} are regression coefficients, T_i is the time bin, $[FAO\ Division]_j$ is a factor with eight levels (*j*= 1,…,8, corresponding to the spatial sectors), $log\ (H_{ij})$ is the offset term and ε_{ij} is the error term for *i*th observation in each FAO Division *j*. Hence, we predicted the expected number of sharks in each FAO Division for each period considering a fixed value of observation effort (5 million people) and compared this index for each sector between the two different time bins.

RESULTS

Exploratory data analysis

We identified a total of 773 white shark records within the Mediterranean Sea, spanning from the end of the Middle Ages (1453) to 2016. However, 93% (718) of these occurred after 1860, which is the period when we had the most reliable data and, consequently, was used for our trend analyses. Fisheries catches accounted for 66% of the records, 48% coming from tuna traps, followed by gillnets (23.0%), hand lines (8%), harpoons (6.4%), purse seines (5.6%) and longlines (5.2%) (Fig1e). The remaining portions came from strandings, sightings, recorded predation events, and bites to humans. Records were mainly distributed in the western Mediterranean Sea, in particular, the Northern Adriatic sea (GSA 17, 20.9%), Ligurian and North Tyrrhenian Sea (GSA 9, 13.8%), Southern Sicily (GSA 16, 9.5%) and off the Balearic Islands (GSA 5, 8.5%); and pertained mainly to adults (42.8%), sub-adults (10.5%) and juveniles (9.6%) (adapted from Bruce & Bradford 2012) with the majority of individuals of being from 4 to 6 meters long (Fig1b). However, it is important to emphasize that more than a third (32.8%) of records were lacking length information and, consequently, we could not address the age class. Sex ratio was biased toward females (64.1% of the 142 records having sex), and the individuals that had also information on stomach contents (n = 122) suggested that bony fish were the main prey (27.3%), followed by odontocetes (25.0%), scavenging carcasses of other animals (principally farm animals, pets - 5.7% and humans - 10.2%) and chelonians (6.8%) (Fig1d).

Coastal human population increased six-fold since 1860, rising from 29.6 million to 183.8 million in 2016, though this increase was geographically heterogeneous (Fig1a). The highest increases were detected in the eastern basin sectors, with the maximum rise around the Marmara Sea (319.4-fold). By contrast, the lowest rates of change were observed in the western and central Mediterranean sectors, such as the Northern Adriatic, Southern Sicily, and Corsica, where the human population doubled throughout the same period (Fig1a).

Model fitting results

Temporal trends. Shark observations increased throughout the period (Supporting Information Fig.2), but when we controlled for changes in the potential number of observers (Fig2a), we detected an initial increase, characterized by two peaks in the 1880s and a higher one in the 1980s, followed by a 61% (range 58-72%) decline between 1975-2016. Similarly, to the changes in the human population, this trajectory was not homogeneous throughout the basin. At the FAO Divisions' level, the non-linear smoothing term for year (Fig3a-c) was significant for seven of the eight considered sectors (five with $\alpha = 0.05$ and two considering $\alpha = 0.1$) and five of these six significant trajectories ended in recent declines (Fig3b). These declines began earlier and were more intense in the peripheral sectors, such as the Marmara Sea (1961 – 96.0%, range 92-100%), Adriatic Sea (1883 – 94.1%, range 90-100%) and the Balearic (1954 – 82.5%, range 76-98%) than central Mediterranean sectors (Ionian from 1988 a 52.1% decline, range 37-88%, and Sardinia from 1980 a 76.4% decline, range 75-91%).

Spatial patterns and distribution shrinkage. Our standardized indices of shark abundance identified heterogeneous spatial distribution landscapes. The main hotspots were located in the western Mediterranean sectors (Fig2b), especially in the Balearic Islands (0.73, CI 0.51 – 1.05), Maltese waters (0.37, CI 0.21 – 0.64) and Corsica (0.34, CI 0.18 – 0.65). Shark abundance cold spots were in all eastern Mediterranean GSAs, except for the Marmara and Aegean Sea. When we aggregated the records in two time bins (1945 – 1980; 1980 – 2016), we detected a significant contraction of the species' spatial distribution. All the Mediterranean Sea peripheral sectors recorded a decrease in shark abundance in the second period (Fig4c), with the highest difference detected in the Marmara Sea (-96.6%, CI -95.2% – -<99.9%), followed by the Balearic (-73.1%, CI -72.5% – -74.7%) and the Gulf of Lions (-38.0%, CI -41.4% – -18.3%). All the central sectors instead, highlighted an increase in the shark abundance (Fig4c), with the highest value detected in the Ionian Division (+ 222.6%, CI +191.6% – +322.4%).

DISCUSSION

Conservation actions and recovery plans for threatened and endangered marine top predators are broadly limited by a lack of information on the population status and trends at the scale of whole ecoregions and over multi-decadal time scales. By analyzing 156 years of white shark records in the Mediterranean Sea we were able, for the first time, to estimate large-scale and long-term trajectories of white shark abundance indices across the entire region. The use of all the available sources of information, integrated with a proxy controlling for the observation effort change within space and time, permitted us to standardize our trends. These standardized indices of population abundance suggested that the species went through a complex trajectory of change, characterized by an increasing phase followed by a sharp decline since the 1980s. The recent decline, together with a detected range contraction in the spatial distribution of records (Worm & Tittensor, 2011), and stronger and more prolonged declines estimated in peripheral regions compared to central sectors, suggest an overall rapid decline of the white shark population in the region in the last 3-4 decades. Our results are in contrast with population abundance increases inferred in other regions, such as California (Lowe et al., 2012), North-western Atlantic (Curtis et al., 2014), South Africa (Dudley & Simpfendorfer, 2006) and Australia (Reid et al., 2011). Conversely, they are in line with regions where the white shark occurrence data are sparse and infrequent, such as the Northwest Pacific Ocean (Christiansen et al., 2014). These results confirmed earlier evidence of regional declines provided by McPherson & Myers (2009), Boldrocchi et al., (2017), and Ferretti et al. (2008) for a larger taxonomic group, but scaled-down recent Red List assessments carried out by the IUCN, which classified the white shark as critically endangered in the Mediterranean Sea and European waters

(Dulvy et al., 2016; Nieto et al., 2015). Our results suggest instead an overall decline of 61.5% over the last 10 years or three generations, which would classify the species as endangered (EN) "if the reduction causes may not have ceased or well understood", as stated in IUCN Criteria Version 3.1 (A2-bc). Taken together, our results and those of studies conducted elsewhere highlight the importance of regional analyses and the risk of extrapolating trends across different geographies. It is easily perceivable that each region has peculiar characteristics, history of human impact and drivers of change. An informative regional assessment would prevent wastage of both conservation efforts and resources.

Similarly, we confirmed previous evidence of the prevalence of Mediterranean white sharks in western sectors (Boldrocchi et al., 2017), characterized by distinct bio-ecological and physical oceanographic characteristics from the Eastern Mediterranean. The west-east temperature (Bosc et al., 2004) and productivity (Coll et al., 2010) gradients would make the warmer eastern Mediterranean waters a sub-optimal habitat for adult endothermic white sharks (Carey et al., 1982). By contrast, the colder and productive western sectors could represent resource hotspots for the species. These are in fact important breeding and feeding ground for bluefin tunas (Cermeño et al., 2015) and small cetaceans (Gnone et al., 2011; Lauriano et al., 2014), which are important food items for the white sharks (Fig1d, Boldrocchi et al., 2017). This result highlights the critical importance of the western sectors for the persistence of white shark populations.

The white shark ecology in the Mediterranean Sea is still poorly characterized and these analyses are a step forward addressing this important issue. Among the multiple hypotheses that may explain the estimated trajectories of change, we highlight three potential drivers. First, over the last 200 years, coastal fishing in the Mediterranean Sea has notably increased and expanded throughout the region (Piroddi et al., 2015) impacting both juvenile and adult white sharks, but contemporarily increasing the number of occurrence records. Young-of-the-year and juvenile white sharks are vulnerable to inshore gears such as trammel or gill nets (Bruce & Bradford, 2012; Curtis et al., 2014; Lowe et al., 2012), which have been massively used all along the Mediterranean shores also for targeting sharks (Ferretti et al., 2013). Adult individuals were frequently reported in tuna traps (>50% of catches on record, Fig1e), which were fixed gears historically used to catch bluefin tunas on their migratory routes in the Mediterranean Sea (Bombace & Lucchetti, 2011) and could have represented a source of mortality for white sharks for centuries. Since the 1960s, tuna traps ceased to be profitable and most have been closed as an effect of tuna overexploitation by industrial purse seining and other pelagic fisheries (Fromentin & Powers, 2005; ICCAT, 2017; Rouyer et al., 2018). This may have reduced the impact on adult white sharks as well as the number of catches we had on record. Meanwhile, white sharks began to be exposed to offshore fishing, especially tuna and swordfish longlining, which greatly escalated in the region during the last 50 years (Ferretti et al., 2008). In this period white sharks were exposed to both inshore and offshore fishing and could not benefit from sheltering offshore which was practically unexploited historically (Ferretti et al., 2008). Similar patterns have been observed in South Africa and Australia (Dudley & Simpfendorfer, 2006; Ferretti et al., 2010; Reid et al., 2011).

It is also possible that Mediterranean white sharks have followed the population trajectory of Bluefin tuna, one of their most frequent prey in the region (Boldrocchi et al., 2017; De Maddalena & Heim, 2012; Kabasakal, 2016). In our data, 27.3% of the white sharks with stomach content data ate bony fish and 47% of these fishes were tunas (Fig1d, Supporting Information Tab. 6). Tunas are suitable prey for white sharks (Hussey et al., 2012) and the bluefin tuna's overexploitation in the last 50 years may have reduced one of the most important prey resources for this species in the area (ICCAT, 2017; Rouyer et al., 2018). The long-term trajectory we estimated for the white shark records has a temporal phase similar to the time series of Mediterranean bluefin tuna abundance estimated from centuries of tuna trap data (Ravier & Fromentin, 2001). The bluefin tuna decline detected in recent decades (Fromentin & Powers, 2005; Rouyer et al., 2018) coincides with the recent decline of the white shark sighting rate, supporting the plausibility of a predator-prey dynamic between the two species. Yet tuna overexploitation also caused the end of the tuna trap fishery. Therefore, it is unclear whether such a contemporary decline in sighting rate has been caused by the end of an important source of white shark mortality in the region (i.e. decline in catch records from tuna traps), or by an underlining population decline through indirect bottom-up effects (because of the decline of an important prey), or both factors combined. However, no differences in GAM's trajectories were detected by fitting the FAO Model with and without the tuna trap catches (Supporting Information, Fig. 9) in all sectors but the Balearic (Division 1.1), a piece of evidence against the decline in catch record hypothesis. Whereas, the predator-prey hypothesis is corroborated by the fact that adult white sharks' preferential prey, such as pinnipeds and whale carcasses (Hussey et al., 2012), have been much scarcer or essentially absent in the Mediterranean Sea for most of the period considered in this analysis. The only pinniped in the region, the monk seal (*Monachus monachus,* Phocidae), has small remnant populations only in the eastern Mediterranean sectors (Karamanlidis & Dendrinos, 2015) and was considered rare (heavily depleted by centuries of overhunting) in most of the Mediterranean Sea by the 18th century (Johnson, 2004). Whale abundance is also much lower than in other ocean sectors where white sharks occur (Notarbartolo di Sciara, 2002). It is, therefore, possible that adult white sharks adapted to feed mainly on tunas in the Mediterranean Sea; a hypothesis that would make this population unique respect other global populations and should be formally tested in future research.

The above explanations are confounded by the change in observation effort expected from the spatial and temporal expansions of fisheries and other factors affecting the probability to detect records. We used trajectories of human population change along the Mediterranean coasts as a single and practical proxy of observation effort, but human population abundance is one of its multiple components. For example, linguistic barriers and political instability may have limited the number of records we found in North-African and Middle Eastern regions, as well as the two World Wars and the 1918 Flu Pandemic may have acted similarly in Europe during these periods (D'Ancona, 1949; Thurstan et al., 2010). In addition, episodic events, such as a 19th-century reward program issued by the Imperial Maritime Austrian Government to cull white sharks in the Adriatic Sea (De Marchesetti, 1882), could have boosted the probability to have occurrence records independent of human population changes. Similarly, the expansion of the use of the Internet and social networks in the last 20 years has likely increased the probability that a record of a white shark capture is reported. International (CITES, CSM, Barcelona and Bern Conventions) and national legislation (in Malta, Israel, Croatia, Montenegro, and Slovenia) to protect this species may have deterred Mediterranean fishermen in reporting catches, fearing disruptive or legal consequences for their activities. Although these factors may have acted in different direction (i.e. biasing upward or downward the estimated trends), and the probabilistic distribution we used to handle the response variable allows clustered observations, quantifying these sources of bias is now a top priority to further explaining, and reducing uncertainty of the general large-scale spatial and temporal patterns we identified. Nevertheless, our modelling approach represents an innovation in analyzing opportunistic data, by testing observation effort regimes that are not simulated, as done so far (Christiansen et al., 2014; Curtis et al., 2014; McPherson & Myers, 2009), but quantitively estimated through the use of a proper observation effort proxy. Indeed, most of the cited features affecting observation effort are in some ways related to demographical changes of the human population (i.e. fishing pressure, technological development). Hence, adopting an observation effort proportional to the human population mitigates the confusing effects of the mentioned factors.

Reconstruction of the Mediterranean white shark spatio-temporal patterns of abundance, obtained by using all available occurrence records, generated new hypotheses on the species' population structure and predator-prey dynamics in the region. Testing these hypotheses with further dedicated research will further contribute to reconstruct population baselines of this species and deepen our understanding of its life-history, ecology, and biogeography. These aspects are crucial to ensure the conservation of white sharks in the region and across the planet. We also identified occurrence hotspots that would represent important sampling locations for collecting high-quality biological data, including tracking data to directly assess distribution, foraging, and habitat use. These field studies are expensive and require careful planning on where and when white sharks are most likely detected.

Globally, there are multiple species of conservation concern with a similar scantiness of abundance data that would benefit from our approach of combining all available occurrence data. Our study shows that a careful examination of these data, even if opportunistic, can reveal important ecological patterns, particularly regarding trends in abundance and spatial distribution, that are critical to inform adequate conservation actions and science-based recovery plans.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author (stefano.moro@uniroma1.it) upon reasonable request.

SUPPORTING INFORMATION

Data collection and management, detailed description of the models, exploratory analysis (Appendix S1), human population size trends (Appendix S2).

LITERATURE CITED

Baum, J. K., & Blanchard, W. (2010). Inferring shark population trends from generalized linear mixed models of pelagic longline catch and effort data. Fisheries Research, 102(3), 229–239. https://doi.org/10.1016/j.fishres.2009.11.006

Boldrocchi, G., Kiszka, J., Purkis, S., Storai, T., Zinzula, L., & Burkholder, D. (2017). Distribution, ecology, and status of the white shark, Carcharodon carcharias, in the Mediterranean Sea. Reviews in Fish Biology and Fisheries, 27(3), 515–534. https://doi.org/10.1007/s11160-017-9470-5

Bombace, G., & Lucchetti, A. (2011). Elementi di biologia della pesca. Edagricole.

Bosc, E., Bricaud, A., & Antoine, D. (2004). Seasonal and interannual variability in algal biomass and primary production in the Mediterranean Sea, as derived from 4 years of SeaWiFS observations. Global Biogeochemical Cycles, 18(1). https://doi.org/10.1029/2003GB002034

Bruce, B. D., & Bradford, R. W. (2012). Habitat use and spatial dynamics of juvenile white sharks, *Carcharodon carcharias*, in eastern Australia. In M. L. Domeier (Ed.), Global perspectives on the biology and life history of the white shark (pp. 225–254). Boca Raton:CRC Press.

Carey, F. G., Kanwisher, J. W., Brazier, O., Gabrielson, G., Casey, J. G., & Pratt Jr, H. (1982). Temperature and activities of a white shark, *Carcharodon carcharias*. Copeia, 1982(2), 254–260.

Carlisle, A. B., Kim, S. L., Semmens, B. X., Madigan, D. J., Jorgensen, S. J., Perle, C. R., … Block, B. A. (2012). Using Stable Isotope Analysis to Understand the Migration and Trophic Ecology of Northeastern Pacific White Sharks (*Carcharodon Carcharias*). PLOS ONE, 7(2), e30492. https://doi.org/10.1371/journal.pone.0030492

Cavanagh, R. D., & Gibson, C. (2007). Overview of the conservation status of cartilaginous fishes (Chrondrichthyans) in the Mediterranean Sea. IUCN.

Cermeño, P., Quílez-Badia, G., Ospina-Alvarez, A., Sainz-Trápaga, S., Boustany, A. M., Seitz, A. C., … Block, B. A. (2015). Electronic Tagging of Atlantic Bluefin Tuna (*Thunnus thynnus*, L.) Reveals Habitat Use and Behaviors in the Mediterranean Sea. PLOS ONE, 10(2), e0116638. https://doi.org/10.1371/journal.pone.0116638

Chapple, T. K., Jorgensen, S. J., Anderson, S. D., Kanive, P. E., Klimley, A. P., Botsford, L. W., & Block, B. A. (2011). A first estimate of white shark, *Carcharodon carcharias*, abundance off Central California. Biology Letters, 7(4), 581–583. https://doi.org/10.1098/rsbl.2011.0124

Christiansen, H. M., Lin, V., Tanaka, S., Velikanov, A., Mollet, H. F., Wintner, S. P., … Hussey, N. E. (2014). The Last Frontier: Catch Records of White Sharks (*Carcharodon carcharias*) in the Northwest Pacific Ocean. PLOS ONE, 9(4), e94407. https://doi.org/10.1371/journal.pone.0094407

Coll, M., Piroddi, C., Steenbeek, J., Kaschner, K., Ben Rais Lasram, F., Aguzzi, J., … Voultsiadou, E. (2010). The Biodiversity of the Mediterranean Sea: Estimates, Patterns, and Threats. PLOS ONE, 5(8), e11842. https://doi.org/10.1371/journal.pone.0011842

Compagno, L. J. (2001). Sharks of the world. An annotated and illustrated catalogue of shark species known to date, vol 2. Bullhead, mackerel and carpet sharks (*Heterodontiformes*, *Lamniformes* and *Orectolobiformes*). FAO Species Catalogue for Fishery Purposes, 1, viii+ 1-269.

Curtis, T. H., McCandless, C. T., Carlson, J. K., Skomal, G. B., Kohler, N. E., Natanson, L. J., … Pratt, H. L., Jr. (2014). Seasonal Distribution and Historic Trends in Abundance of White Sharks, *Carcharodon carcharias*, in the Western North Atlantic Ocean. PLOS ONE, 9(6), e99240. https://doi.org/10.1371/journal.pone.0099240

D'Ancona, U. (1949). Rilievi statistici sulla pesca nell'alto Adriatico. Atti Istituto Veneto Scienze Lettere Ed Arte, 108, 41–53.

De Maddalena, A., & Heim, W. (2012). Mediterranean great white sharks: A comprehensive study including all recorded sightings. McFarland.

De Marchesetti, C. (1882). La pesca lungo le coste orientali dell'Adria. Tipografia di Lod. Herrmanstorfer.

Dirzo, R., Young, H. S., Galetti, M., Ceballos, G., Isaac, N. J. B., & Collen, B. (2014). Defaunation in the Anthropocene. Science, 345(6195), 401. https://doi.org/10.1126/science.1251817

Dudley, S. F. J., & Simpfendorfer, C. A. (2006). Population status of 14 shark species caught in the protective gillnets off KwaZuluNatal beaches, South Africa, 1978-2003. Marine and Freshwater Research, 57(2), 225–240.

Dulvy, N. K., Allen, D. J., Ralph, G. M., & Walls, R. H. L. (2016). The conservation status of sharks, rays and Chimaeras in the Mediterranean Sea. IUCN, Malaga, Spain.

Dulvy, Nicholas K., Fowler, S. L., Musick, J. A., Cavanagh, R. D., Kyne, P. M., Harrison, L. R., … Francis, M. P. (2014). Extinction risk and conservation of the world's sharks and rays. Elife, 3, e00590.

Estes, J. A., Terborgh, J., Brashares, J. S., Power, M. E., Berger, J., Bond, W. J., … Wardle, D. A. (2011). Trophic Downgrading of Planet Earth. Science, 333(6040), 301. https://doi.org/10.1126/science.1205106

Fergusson, I. K. (1996). Distribution and autecology of the white shark in the eastern North Atlantic Ocean and the Mediterranean Sea. In A. P. Klimley & D. G. Ainley (Eds.), Great White Sharks: The Biology of *Carcharodon carcharias* (pp. 321–345). San Diego: Academic Press.

Fergusson, I. K. (2002). Occurrence and biology of the great white shark, *Carcharodon carcharias*, in the Central Mediterranean Sea: A review. Proc. 4th European Elasmobranch Association Meeting Livorno, Italy, 7–23.

Ferretti, F., Jorgensen, S., Chapple, T. K., De Leo, G., & Micheli, F. (2015). Reconciling predator conservation with public safety. Frontiers in Ecology and the Environment, 13(8), 412–417. https://doi.org/10.1890/150109

Ferretti, F., Morey Verd, G., Seret, B., Sulić Šprem, J., & Micheli, F. (2016). Falling through the cracks: The fading history of a large iconic predator. Fish and Fisheries, 17(3), 875–889. https://doi.org/10.1111/faf.12108

Ferretti, F., Myers, R. A., Serena, F., & Lotze, H. K. (2008). Loss of Large Predatory Sharks from the Mediterranean Sea. Conservation Biology, 22(4), 952–964. https://doi.org/10.1111/j.1523-1739.2008.00938.x

Ferretti, F., Osio, G. C., Jenkins, C. J., Rosenberg, A. A., & Lotze, H. K. (2013). Long-term change in a meso-predator community in response to prolonged and heterogeneous human impact. Scientific Reports, 3, 1057.

Ferretti, F., Worm, B., Britten, G. L., Heithaus, M. R., & Lotze, H. K. (2010). Patterns and ecosystem consequences of shark declines in the ocean. Ecology Letters, 13(8), 1055–1071. https://doi.org/10.1111/j.1461-0248.2010.01489.x

Fromentin, J.-M., & Powers, J. E. (2005). Atlantic bluefin tuna: Population dynamics, ecology, fisheries and management. Fish and Fisheries, 6(4), 281–306. https://doi.org/10.1111/j.1467-2979.2005.00197.x

Galaz, T., & De Maddalena, A. (2004). On a Great White Shark, *Carcharodon carcharias*(Linnaeus, 1758), trapped in a tuna cage off Libya, Mediterranean Sea. Annales Series Historia Naturalis, 14, 159–164.

Gnone, G., Bellingeri, M., Dhermain, F., Dupraz, F., Nuti, S., Bedocchi, D., … Wurtz, M. (2011). Distribution, abundance, and movements of the bottlenose dolphin (*Tursiops truncatus*) in the Pelagos Sanctuary MPA (north-west Mediterranean Sea). Aquatic Conservation: Marine and Freshwater Ecosystems, 21(4), 372–388. https://doi.org/10.1002/aqc.1191

Gubili, C., Kalkan, E., Karhan S. Ünsal, Jones Catherine S., Sims David W., Kabasakal Hakan, … Noble Leslie R. (2011). Antipodean white sharks on a Mediterranean walkabout? Historical dispersal leads to genetic discontinuity and an endangered anomalous population. Proceedings of the Royal Society B: Biological Sciences, 278(1712), 1679–1686. https://doi.org/10.1098/rspb.2010.1856

Gubili, Robinson CEC, Cliff G, Wintner SP, de Sabata E, De Innocentiis S, … Jones CS. (2015). DNA from historical and trophy samples provides insights into white shark population origins and genetic diversity. Endangered Species Research, 27(3), 233–241.

Hussey, N. E., McCann, H. M., Cliff, G., Dudley, S. F., Wintner, S. P., & Fisk, A. T. (2012). Size-based analysis of diet and trophic position of the white shark (*Carcharodon carcharias*) in South African waters. Global Perspectives on the Biology and Life History of the White Shark, 27–49.

Huveneers, C., Apps, K., Becerril-García, E. E., Bruce, B., Butcher, P. A., Carlisle, A. B., … Werry, J. M. (2018). Future Research Directions on the "Elusive" White Shark. Frontiers in Marine Science, 5, 455. https://doi.org/10.3389/fmars.2018.00455

ICCAT. (2017). Report of the 2017 ICCAT Bluefin Tuna Stock Assessment Meeting (No. Document SCRS/2017/10; p. 106). Retrieved from ICCAT, Madrid, Spain 20-28 July, (2017) website: https://www.iccat.int/Documents/SCRS/DetRep/BFT_SA_ENG.pdf

Johnson, W. M. (2004). Monk seals in post-classical history. The Netherlands Commission for International Nature Protection, Mededlingen, 39, 91.

Kabasakal, H. (2016). Historical dispersal of the great white shark, *Carcharodon carcharias*, and bluefin tuna, *Thunnus thynnus*, in the Turkish waters: Decline of a predator in response to the loss of its prey. Annales Series Historia Naturalis, 26, 213.

Karamanlidis, A., & Dendrinos, P. (2015). Monachus monachus. The IUCN Red List of Threatened Species.

Klimley, A. P., & Anderson, S. D. (1996). Residency patterns of white sharks at the South Farallon Islands, California. In A. P. Klimley & D. G. Ainley (Eds.), Great White Sharks: The Biology of *Carcharodon carcharias* (pp. 365–373). San Diego: Academic Press.

Kock, A., O'Riain, M. J., Mauff, K., Meÿer, M., Kotze, D., & Griffiths, C. (2013). Residency, Habitat Use and Sexual Segregation of White Sharks, *Carcharodon carcharias* in False Bay, South Africa. PLOS ONE, 8(1), e55048. https://doi.org/10.1371/journal.pone.0055048

Lauriano, G., Pierantonio, N., Donovan, G., & Panigada, S. (2014). Abundance and distribution of *Tursiops truncatus* in the Western Mediterranean Sea: An assessment towards the Marine Strategy Framework Directive requirements. Large Marine Vertebrates as Sentinels of GES in the European MSFD, 100, 86–93. https://doi.org/10.1016/j.marenvres.2014.04.001

Lowe, C. G., Blasius, M. E., Jarvis, E. T., Mason, T. J., Goodmanlowe, G. D., & O'Sullivan, J. B. (2012). Historic fishery interactions with white sharks in the Southern California Bight. Global Perspectives on the Biology and Life History of the White Shark'.(Ed. ML Domeier.) Pp, 169–186.

McClenachan, L., Ferretti, F., & Baum, J. K. (2012). From archives to conservation: Why historical data are needed to set baselines for marine animals and ecosystems. Conservation Letters, 5(5), 349–359. https://doi.org/10.1111/j.1755-263X.2012.00253.x

McPherson, J. M., & Myers, R. A. (2009). How to infer population trends in sparse data: Examples with opportunistic sighting records for great white sharks. Diversity and Distributions, 15(5), 880–890.

Micheli, F., Halpern, B. S., Walbridge, S., Ciriaco, S., Ferretti, F., Fraschetti, S., … Rosenberg, A. A. (2013). Cumulative Human Impacts on Mediterranean and Black Sea Marine Ecosystems: Assessing Current Pressures and Opportunities. PLOS ONE, 8(12), e79889. https://doi.org/10.1371/journal.pone.0079889

Nieto, A., Ralph, G. M., Comeros-Raynal, M. T., Kemp, J., García Criado, M., Allen, D. J., & Williams, J. T. (2015). European Red List of marine fishes. Luxembourg: Publications Office of the European Union.

Notarbartolo di Sciara, G. (2002). Cetacean species occurring in the Mediterranean and Black Seas. In G. Notarbartolo di Sciara (Ed.), Cetaceans of the Mediterranean and Black Seas: State of knowledge and conservation strategies (p. 17). A report to the ACCOBAMS Secretariat, Monaco, February 2002.

Pearce, J. L., & Boyce, M. S. (2006). Modelling distribution and abundance with presence-only data. Journal of Applied Ecology, 43(3), 405–412. https://doi.org/10.1111/j.1365-2664.2005.01112.x

Piroddi, C., Gristina, M., Zylich, K., Greer, K., Ulman, A., Zeller, D., & Pauly, D. (2015). Reconstruction of Italy's marine fisheries removals and fishing capacity, 1950–2010. Fisheries Research, 172, 137–147. https://doi.org/10.1016/j.fishres.2015.06.028

Queiroz, N., Humphries, N. E., Couto, A., Vedor, M., da Costa, I., Sequeira, A. M. M., … Sims, D. W. (2019). Global spatial risk assessment of sharks under the footprint of fisheries. Nature, 572(7770), 461–466. https://doi.org/10.1038/s41586-019-1444-4

Ravier, C., & Fromentin, J.-M. (2001). Long-term fluctuations in the eastern Atlantic and Mediterranean bluefin tuna population. ICES Journal of Marine Science, 58(6), 1299–1317.

Reid, D. D., Robbins, W. D., & Peddemors, V. M. (2011). Decadal trends in shark catches and effort from the New South Wales, Australia, Shark Meshing Program 1950–2010. Marine and Freshwater Research, 62(6), 676–693.

Ripple, W. J., Estes, J. A., Beschta, R. L., Wilmers, C. C., Ritchie, E. G., Hebblewhite, M., … Wirsing, A. J. (2014). Status and Ecological Effects of the World's Largest Carnivores. Science, 343(6167), 1241484. https://doi.org/10.1126/science.1241484

Rousseau, Y., Watson, R. A., Blanchard, J. L., & Fulton, E. A. (2019). Evolution of global marine fishing fleets and the response of fished resources. Proceedings of the National Academy of Sciences, 201820344. https://doi.org/10.1073/pnas.1820344116

Rouyer, T., Kimoto, A., Kell, L., Walter, J. F., Lauretta, M., Zarrad, R., … Sharma, R. (2018). Preliminary 2017 stock assessment results for the Eastern and Mediterranean Atlantic bluefin tuna stock. ICCAT Col. Vol. Sci. Pap, 74, 3234–3275.

Serena, F., Mancusi, C., & Barone, M. (2008, September 15). The MEDLEM database application: A tool for storing and sharing data about by-catch and incidental catches of large cartilaginous fishes in the Mediterranean basin. 12. FAO HQs, Rome (Italy).

Simpfendorfer, C. A., & Dulvy, N. K. (2017). Bright spots of sustainable shark fishing. Current Biology, 27(3), R97–R98. https://doi.org/10.1016/j.cub.2016.12.017

Storai, T., Zinzula, L., Repetto, S., Zuffa, M., Morgan, A., & Mandelman, J. (2011). Bycatch of large elasmobranchs in the traditional tuna traps (tonnare) of Sardinia from 1990 to 2009. Fisheries Research, 109(1), 74–79. https://doi.org/10.1016/j.fishres.2011.01.018

Thurstan, R. H., Brockington, S., & Roberts, C. M. (2010). The effects of 118 years of industrial fishing on UK bottom trawl fisheries. Nature Communications, 1, 15.

Tinker, M. T., Hatfield, B. B., Harris, M. D., & Ames, J. A. (2016). Dramatic increase in sea otter mortality from white sharks in California. Marine Mammal Science, 32(1), 309–326.

Venables, W. N., & Ripley, B. D. (2002). Modern applied statistics with S (Springer-Verlag, New York).

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 73(1), 3–36. https://doi.org/10.1111/j.1467-9868.2010.00749.x

Worm, B., & Tittensor, D. P. (2011). Range contraction in large pelagic predators. Proceedings of the National Academy of Sciences, 108(29), 11942–11947.

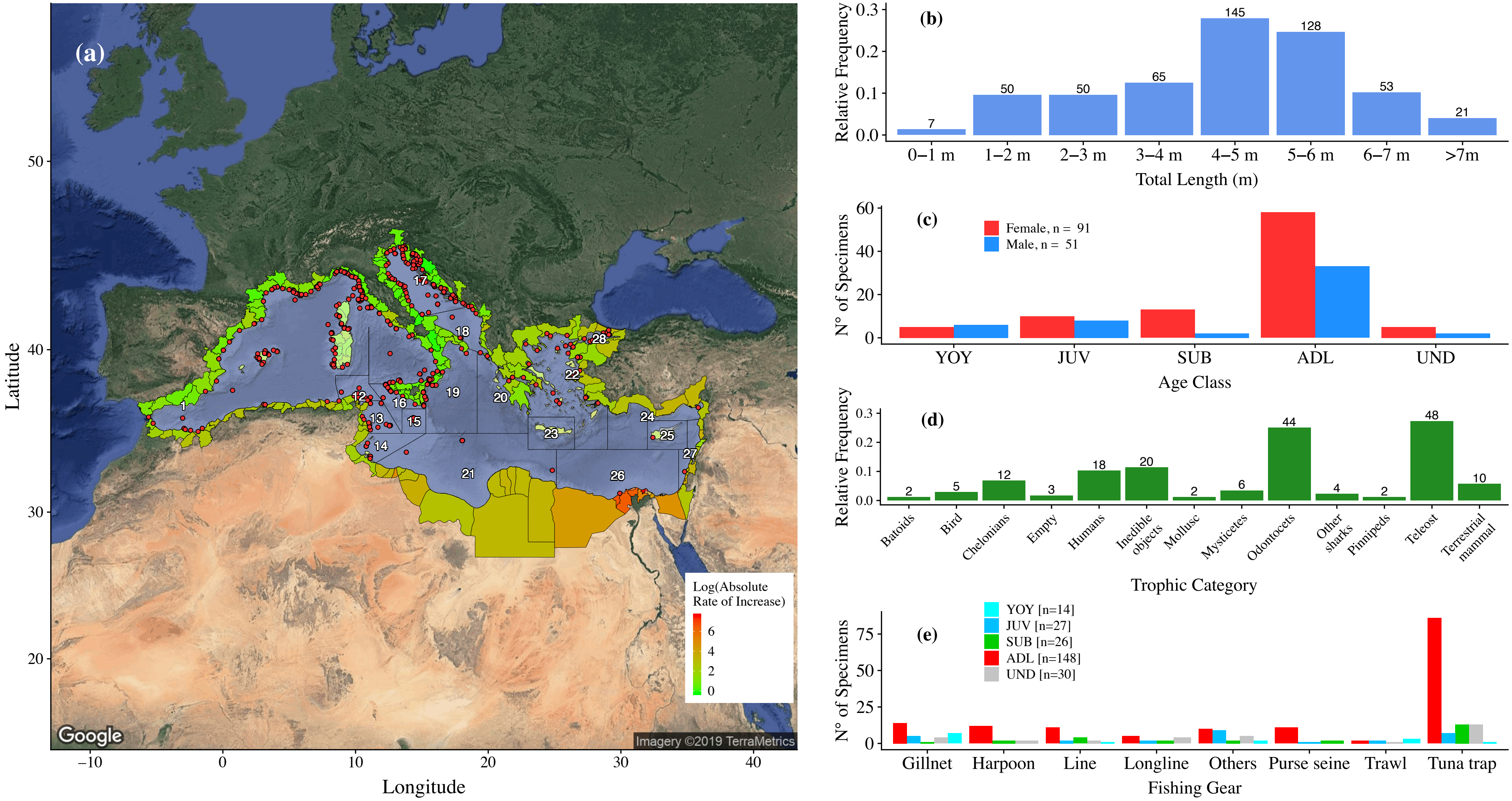
Figure legends

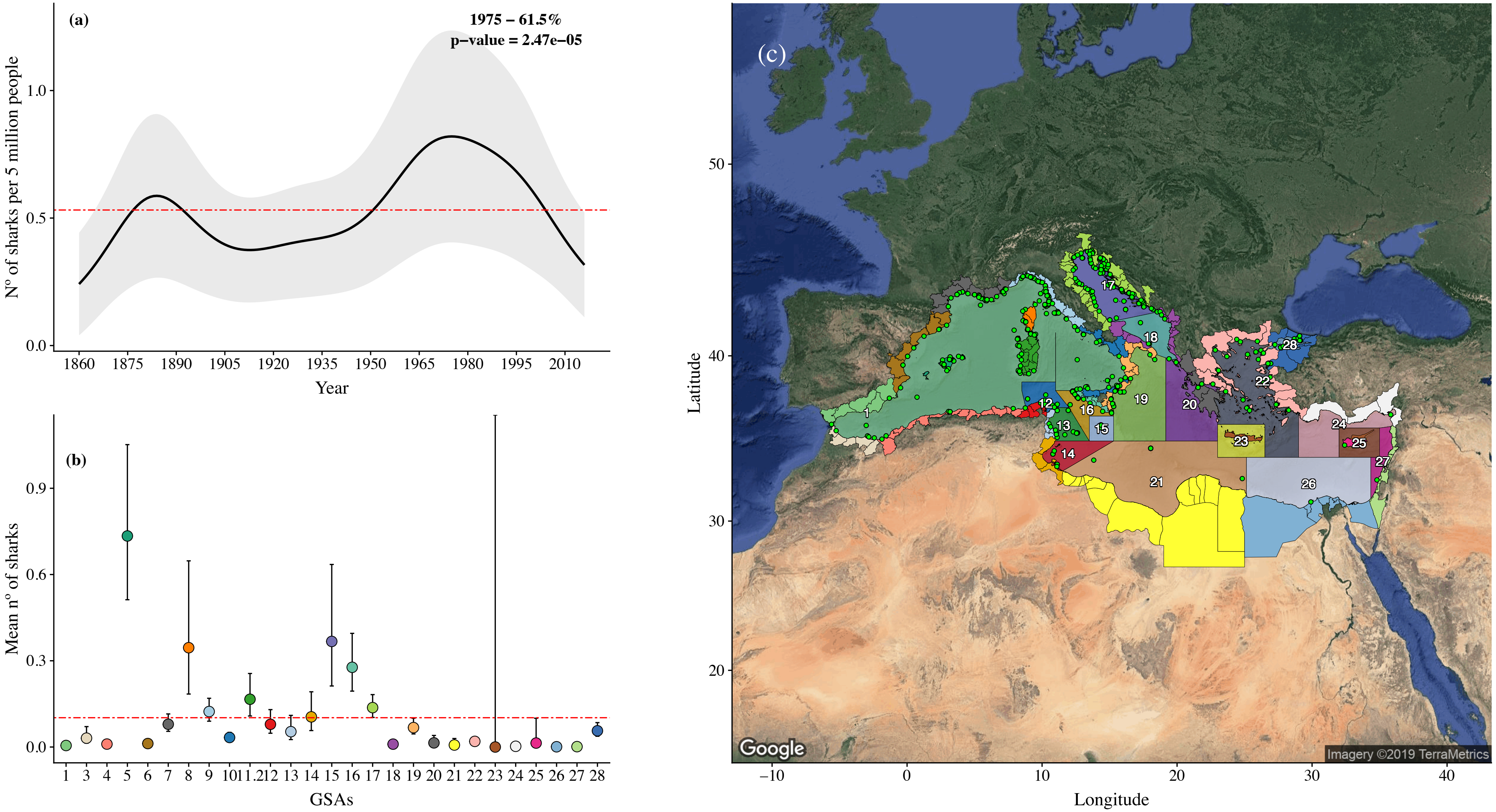
Fig.1 Observation effort and exploratory analysis. (a) Absolute variation of coastal regions human population size calculated between 1860 and 2016 and expressed in logarithmic scale. The red dots correspond to the white sharks sighting locations. (b) Length frequency. The absolute frequency is reported over each bar. (c) Sex distribution within age classes (YOY = young-of-the-year, JUV = Juveniles, SUB = Sub-adults, ADL = Adults, UND = Undetermined). (d) Diet composition. The absolute frequency is reported over each bar. (e) N° of specimens caught by each fishing gear category per age class.

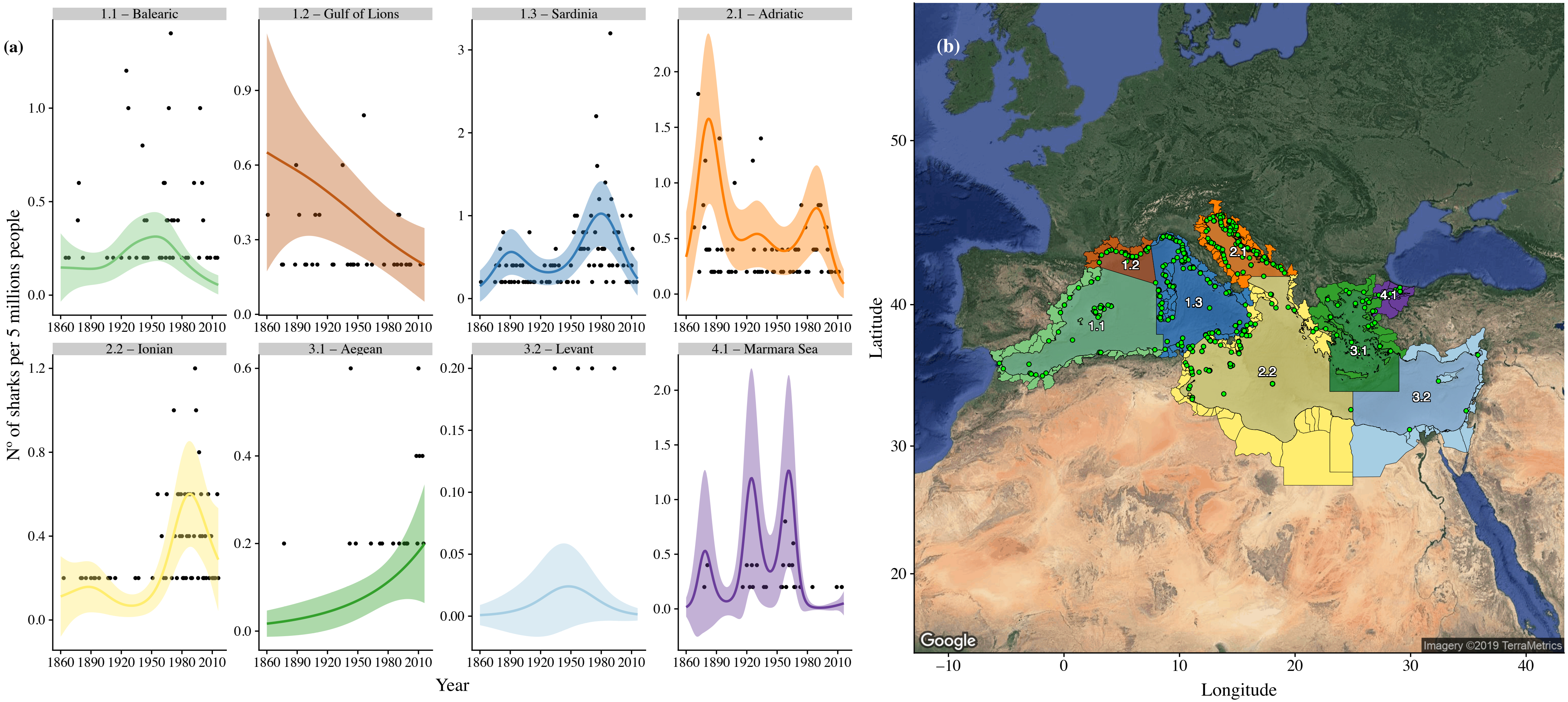
Fig.2 Temporal and spatial changes of sighting rate estimated by the GSA Model. (a) Temporal effect: expected shark sighting rate between 1860 and 2016 predicted by using a fixed observation effort of 5 million people. Magnitude of the detected decline, starting year, and p-value for the smooth term are shown in the top-right corner. The red line is the overall mean sighting rate. (b) Spatial effect: dots are the average variations in mean n° of shark detected in each GSA. Point color matches colors in the map. Segments indicate the confidence boundaries. (c) Spatial unit used in the model: GFCM Geographic Sub-Areas (as indicated in the Res. GFCM/33/2009/2). The green dots in the map correspond to the white sharks sighting locations extracted from a variety of source observations.

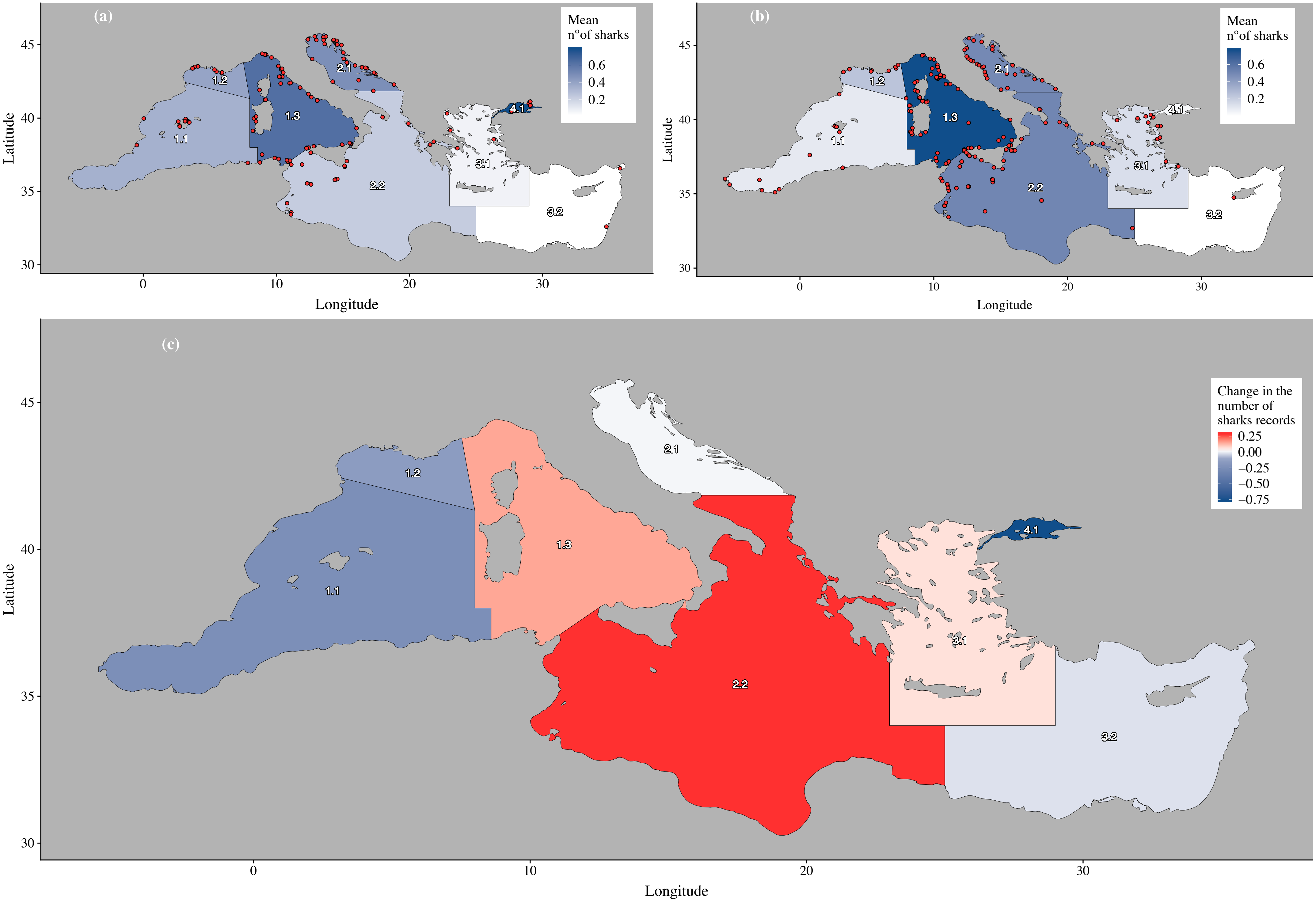
Fig.3 FAO Model. (a) Mediterranean white shark temporal abundance trend (1860-2016) predicted by the FAO model in each FAO Division, considering a fixed observation effort value (5 million people). The black dots represent the actual sighting rates (expressed as n° of sightings per 5 million people) (b) Spatial unit used in the model: FAO Major Fishing Area 37 (Mediterranean and Black Sea) Divisions. The green dots in the map correspond to the white sharks sighting locations.

Fig.4 Spatial range contraction. Predicted mean annual n° of sharks every 5 million people for each FAO Division in time intervals: (a) 1945-1975, (b) 1976-2016. The red dots in the maps show the white sharks sighting locations in each period. (c) Variation between 1945-1975 and 1976-2016 time bins. Red sectors correspond to abundance rise, while blue sectors correspond to abundance decline.


(a)
Latitude
Longitude
50
40
30
20
−10
0
10
20
30
40
1
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
Log(Absolute Rate of Increase)
6
4
2
0
Google
Imagery ©2019 TerraMetrics
(b)
Relative Frequency
0.3
0.2
0.1
0.0
7
50
50
65
145
128
53
21
0–1 m
1–2 m
2–3 m
3–4 m
4–5 m
5–6 m
6–7 m
>7m
Total Length (m)
(c)
N° of Specimens
60
40
20
0
Female, n = 91
Male, n = 51
YOY
JUV
SUB
ADL
UND
Age Class
(d)
Relative Frequency
0.3
0.2
0.1
0.0
2
5
12
3
18
20
2
6
44
4
2
48
10
Batoids
Bird
Chelonians
Empty
Humans
Inedible objects
Mollusc
Mysticetes
Odontocets
Other sharks
Pinnipeds
Teleost
Terrestrial mammal
Trophic Category
(e)
N° of Specimens
75
50
25
0
YOY [n=14]
JUV [n=27]
SUB [n=26]
ADL [n=148]
UND [n=30]
Gillnet
Harpoon
Line
Longline
Others
Purse seine
Trawl
Tuna trap
Fishing Gear


(a)
1975 – 61.5%
p–value = 2.47e–05
Nº of sharks per 5 million people
0.0
0.5
1.0
1860
1875
1890
1905
1920
1935
1950
1965
1980
1995
2010
Year
(b)
Mean nº of sharks
0.0
0.3
0.6
0.9
1
3
4
5
6
7
8
9
10
11.2
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
GSAs
(c)
Latitude
20
30
40
50
Longitude
−10
0
10
20
30
40
1
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
Google
Imagery ©2019 TerraMetrics


(a)
1.1 – Balearic
1.2 – Gulf of Lions
1.3 – Sardinia
2.1 – Adriatic
2.2 – Ionian
3.1 – Aegean
3.2 – Levant
4.1 – Marmara Sea
N° of sharks per 5 millions people
Year
1860 1890 1920 1950 1980 2010
(b)
1.1
1.2
1.3
2.1
2.2
3.1
3.2
4.1
Latitude
Longitude
50
40
30
20
−10
0
10
20
30
40
Google
Imagery ©2019 TerraMetrics


(a)
Mean
n°of sharks
0.6
0.4
0.2
1.1
1.2
1.3
2.1
2.2
3.1
3.2
4.1
Latitude
30
35
40
45
Longitude
0
10
20
30
(b)
Mean
n°of sharks
0.6
0.4
0.2
1.1
1.2
1.3
2.1
2.2
3.1
3.2
4.1
Latitude
30
35
40
45
Longitude
0
10
20
30
(c)
Change in the
number of
sharks records
0.25
0.00
−0.25
−0.50
−0.75
1.1
1.2
1.3
2.1
2.2
3.1
3.2
4.1
Latitude
30
35
40
45
Longitude
0
10
20
30

SUPPORTING INFORMATION

Shark data

Data collection

Mediterranean white shark database was built up using multiple sources and different strategies. First, we reviewed all available historical and actual bibliographic references, including books and scientific papers. Second, we referred to the MedLem (Mediterranean Large Elasmobranchs Monitoring) database (Serena et al. 2006) and collected all the records referring to *C. carcharias*. MedLem is a monitoring program, coordinated by the FAO's General Fisheries Commission for the Mediterranean Sea (GFCM), of large elasmobranch captures and sightings, collected by a network of Mediterranean research institutions, coastal enforcement and monitoring bodies (Serena et al. 2006). Third, we sifted through local news and fishing specialized websites (such as www.sharkyear.com), well-known online portals such as YouTube (www.youtube.com) and Facebook (www.facebook.com), and personal communications of shark sightings from local scientists, in order to identify unpublished records.

We validated each record by cross-checking each source reference. Furthermore, accordingly with other historical ecology bibliographic researches (Ferretti et al. 2016), we followed through each observation history to determine whether a record was original or redundant meaning that it was not reporting an undetected record but existing bibliographic references. Throughout this validation we have been able to erase all source-less observations and duplicates, assuming that each record of the dataset was referred to a unique specimen. After all, differences in size estimates joined with the fact that most of the shark sighted had been caught and then killed, reduce the likelihood that any single shark caused multiple records per year (McPhearson & Myers 2009).

Data management

Now, we will present all the variables included in the database and all criteria used to assemble them.

ID – Identification number. As assumed above, any record is referred to a single specimen. Consequently, we appointed each record to a specific identification number.

Date and Season. If available in the sources, year, month and day have been collected. Sighting date was not precisely reported from the original in most of the records referring to more than 150 years-old observations. Consequently, in such cases, the date has been approximated with the following criteria:

a) if original reference reported *"before"* – year, 1 year has been subtracted to referenced date; b) both in the case that original reference reported a time interval (instead of a specific year) and there were incongruities between sources, an average value has been taken in account.

The year was divided into four different seasons: winter (January through March), spring (April through June), summer (July through September) and fall (October through December).

Specimen size. Considering both the anecdotal nature characterizing the majority of our data and the long time passed from the direct observation for the oldest records, it may be expected that just in few cases size measurements have been taken using rigorous and modern techniques. Length and weight values, thus, has overall to be considered as approximations. However, although we do not have any control over the approximation degree used at the record collection time, it is necessary to explain the criteria we used to approximate the size data of our database. We used the following criteria:

1. We applied simple arithmetic mean to measurement values to solve source conflicts (sources indicating different values for the same specimen).
2. In case of measurement information associated with ">" or "<", we added or subtracted one centimeter to the reported value.
3. If length or weight values were reported as "ca." (circa), we assumed the source value as precise information.
4. If specimen length was measured using a different length type than Total Length (PRC – Precaudal Length, FOR – Fork Length, TOT – Total Length taken with caudal fin upper lobe lying on the main body axes), we converted it in Total Length through methods shown in

Country	Regional Data Source	National Data Source
Albania	INSTAT; worldbank; populstat.info	populstat.info
Algeria	worldbank; populstat.info	populstat.info
Bosnia and Herzegovina	worldbank; populstat.info	populstat.info
Croatia	eurostat; populstat.info	eurostat; populstat.info
Cyprus	eurostat; populstat.info	
Egypt	worldbank; populstat.info	populstat.info
France	INED; populstat.info	INED; populstat.info
Gibraltar	Gibraltar Government	
Greece	eurostat; populstat.info	eurostat; populstat.info
Israel	citypopulation.de; populstat.info	populstat.info
Italy	ISTAT	
Lebanon	worldbank; populstat.info	populstat.info
Libya	populstat.info	populstat.info
Malta	eurostat; populstat.info	
Monaco	eurostat; populstat.info	
Montenegro	worldbank	worldbank
Morocco	populstat.info	worldbank
Palestina	populstat.info; ONU (for Gaza Strip)	
Slovenia	eurostat; populstat.info	eurostat; populstat.info
Spain	INE; populstat.info	
Syria	citypopulation.de; populstat.info	populstat.info
Tunisia	INS; populstat.info	INS; populstat.info
Turkey	eurostat; worldbank; populstat.info	eurostat; populstat.info

5. .

Predicting total length and weight missing values

We investigated the length-weight relationship to predict missing values belonging to these two variables. This relationship tends to have two main characteristics in a fishing stock. First of all is not linear. This can be easily understood considering length as a linear measure, while weight is related to a volume. Second, the variance of weight increases with fish development. Thus, mainly for these two features, length-weight data use to violate the linearity and homoscedasticity assumption of a simple linear model. Commonly the relationship is modeled as a two-parameter power function with a multiplicative error term, as:

$$W_i = aL_i^b e^{\epsilon_i} \tag{1}$$

where a and b are constants and ϵ_i is the multiplicative error term for ith measurement. This model (1) can be linearized applying a logarithmic transformation in both side of the equation, as:

$$\log(W_i) = \log(a) + b\log(L_i) + \epsilon_i \tag{2}$$

Thus, with $y = log\ (W)$, $x = log\ (L)$, slope = b, e intercept = a, the model assumes the form of a simple linear regression. The other benefits of this transformation, beyond of linearity, is to make the errors additive and stabilizing the variance about the model. We used our observed length and weight data to examine the Mediterranean white shark length-weight relationship (Fig. 5c). Furthermore, the obtained regression line has been used to predict the total length and weight missing values included in the database. Normally, back-transforming the estimates on the log scale with a simple exponentiation use to underestimate the value in the original scale. Indeed, the back-transformed mean value from the log scale corresponds to the geometric mean values on the original scale. The geometric mean is always less than the arithmetic one, thus, a correction factor is needed to obtain rigorous estimates. The most common "correction" used for log-transformed data is that suggested by Baskerville (1972), multiplying the exponentiated back-transformed value by:

$$e^{\frac{s^2{}_{Y|X}}{2}} \tag{3}$$

Finally, the "observed" data regression line has been compared with the already existing regression lines describing the same relationship for other white sharks populations worldwide (Fig. 5a-b-d).

Gender and Age. We reported, if available, the specimen sex collected by the original source. In the case of source conflicts, gender information has not been considered reliable and, consequently, it has not included in the dataset.

Age distribution has been assessed using both predicted and observed length values. Four age classes have been established on the basis of Bruce and Bradford (2012) categorization: young-of-the-year (YOY - ≤1.75 m total length, TL), juvenile (JUV - >1.75-3.0 m TL), subadult (SUB - >3.0-3.6 m TL for males and >3.0-4.8 m TL for females), adult (ADL - >3.6 m TL for males and >4.8 m TL for females). When sex was not recorded, sexual maturity threshold was set to the average value between males and females (>4.2 m TL). All records lacking length estimate were classified as "Undetermined".

Geographic position. Coordinates of sightings or catch were sometimes included in the record. In most cases, landing harbor or sighting location was reported. When precise coordinates were not available, we geocoded the occurrences using the Google Map Geocoding API and searching for location reported as text strings (eg "Capo Testa, Sardinia, Italy").

Record type. We distinguished between six different occurrence type: sighting, catch, catch and release, stranding, attack on humans or boats, signs of predation on other marine species.

Fishing gear. To facilitate the analysis, in addition to the fishing gear reported by the original source, we aggregated fishing techniques in macro-categories, as follows: trawl, purse seine, gill nets (included trammel net), longline, tuna trap, harpoon, line (rod and line; hand-line), others.

Stomach contents. This variable includes all information reported by the original source: species (if identified) or common name; quantity (if reported); weight (if reported).

Museum collections. We collected museum of provenance and catalog number of each Mediterranean white shark item hosted in European museums.

Source and Reference. Record origins have been distinguished in two different variables. Reference is referred to the scientific publication or database which record has been taken from, while source indicates all other authors reporting the same occurrence. In addition, a third variable reporting direct sighting observers' names was attached to the data table. All records lacking one of this information have been rejected.

Additional information. For each record, if available, the following information has been collected: pregnancy, distance from the shore, depth, availability of photographic or video material, any additional information reported in original sources.

Exploratory Analysis

Here we report the main additional patterns showed by the exploratory analysis. First, we analyzed the temporal distribution of the sightings for the entire temporal range spaced by the data. As expected, the sighting rate increased significantly in the last 150 years and consequently, we considered time bins not homogeneously distributed. Temporal classes were subdivided in the following way: 100 years between 1500 – 1700; 25 years between 1700 – 1800; 10 years after 1800. Data showed an asymmetric distribution with most of the observations concentrated in the last 100 years. From 1900 to today 617 specimens were recorded, which corresponds to 79.81% of the total observations in the database. The nineteenth century counted for 140 observations, corresponding to 18.11% of the total records, while only 16 were attributable to the previous 300 years, representing 2.07% only. Decades with the highest number of observations corresponds to the period 1960 – 2000. The sum of the sightings recorded during this 40-year bin accounts for 44.63% of the total number of sightings. Referring to the 19th century, decades 1870 – 1880 showed the highest number of observations, corresponding to 35% of all sightings recorded in that century. Decades 1910 – 1920 and 1940 – 1950 exhibited a lower number of specimens recorded which could indicate a contemporary reduction of the observation effort in the area due to historical reasons (World Wars, 1918 Flu Pandemic).

Aggregating sightings in function of different Mediterranean countries, data showed a heterogeneous frequency distribution, with most of the records referring to just a few countries. For example, records located in Italian waters accounted for almost half of the total sightings. The sum of observations of the first six most represented countries (Italy, Croatia, Spain, France, Tunisia, and Turkey) corresponded to the 92.2% of the whole number of sightings. Consequently, the ten countries left accounted for less than 8%, with 2.5% of it formed by just the sightings recorded in Greek waters.

The descriptive analysis also showed a rare but constant presence of the species in the area throughout all seasons. Summer (36.57%) and Spring (30.74%) accounted for almost two-thirds of the observations, while Winter (19.26%) and Fall (13.42%) for the remaining third. In terms of monthly distribution, August (16.84%), May (12.06%), September (12.06%) and June (11.43%) were the most represented. The increase in the sighting rate detected during summer is probably imputable to touristic movements and a generalized increase of all ocean anthropogenic activities during these months.

We investigated the length-weight relationship of observed values through the linearization shown in equation 2. The high R^2 (0.78) underlined a good adaptation of data to the model. The regression line was described by the following equation:

$$y = -8.31 + 2.48x \tag{5}$$

where y is the log(Total Length) and x is the log(Total Weight). Our results seemed to indicate that Mediterranean white sharks could be on average bigger than other conspecifics inhabiting the oceans worldwide. However, this result is likely partially biased by the fact that our database is unbalanced toward adult and sub-adult specimens.

Stomach Content Analysis

Normally, the stomach content analysis constitutes an important component of ecological investigation and is performed on the basis of robust both quantitative and qualitative data. Given the opportunistic nature of our data, we could count excursively on qualitative data. First, we extracted from data all information regarding 122 specimens reporting stomach content data (n = 95), direct hunting episodes and opportunistic scavenging on carcasses (n = 27) (Tab. 6). We identified 45 different prey item typologies, rarely identified to species level, and in 3 cases the stomach was empty. To simplify the analysis prey items have been gathered in main trophic categories, as follows: odontocetes, mysticetes, teleosts, other sharks, batoids, chelonians, terrestrial mammals (human being included), pinnipeds, birds, empty, inorganic matter.

Observation effort data

We collected historical population time series referring to 202 coastal regions included in our sampling design. First, we listed all administrative regions belonging to the 23 different Mediterranean countries, considering both the first and second level of administrative division. Administrative divisions correspond to the entire nation, regions, provinces, governorates, depending on the specific country. In order to obtain spatial strata spacing as much as possible the same surface, we selected different administrative levels for different countries, including, for example, the entire country extension for small nation (e.g. Monaco, Malta, Gibraltar), whereas provinces or regions were considered for large nations like Spain, France or Italy.

A time bin of 156 years has been taken into account, ranging between 1860 and 2016. Data has been collected using different sources (Tab. 2) that include both national census data and international databases.

As expected, considering the long time range we chose for our model, many regional time-series were largely incomplete, reporting regional census data just for recent years. By contrast, national census data were more complete, reporting data even for the earliest part of the time series. Consequently, in order to obtain better estimates, if possible, we inferred the regional population size starting from the national census data, assuming a simple proportional relationship between them, with the following method:

$$P = \frac{P_r}{P_n} \tag{4}$$

where P_r is the regional population size of the earliest year available in the series, P_n is the national population size of the same year and P is the ratio between the two terms. We assumed that this ratio was constant in time and inferred the regional population size for all the previous years where national census data were available. Hence, we fitted a log-scale linear regression and a GAM (Generalized Addictive Model) to a dataset including all the 202 regional time series, to obtain annual estimates of human population size in each coastal region. In this way, the model guarantees the same error term for any regional time series. Both models were set to estimate a different trajectory for each coastal region. GAM models have been performed using “mgcv” R package. Restricted Maximum Likelihood (REML) was used to determine the number of GAM knots and AIC (*Akaike Information Criterion*) as the overall model selection criterion. Despite a little over-fit in some splines, GAM performed the best approximation in all regions but Gaza Strip (Palestine). GAM predictions previous to 1936 in this region were remarkably close to zero and, consequently, we preferred, in this case, log-regression predicted values.

Then, we aggregated the regional time series following the spatial stratification included in the shark abundance models, obtaining human population size trends between 1860 and 2016 both for Geographic Sub-Areas and FAO Divisions (**Errore. L'origine riferimento non è stata trovata.**).

Trend Models in details

In order to evaluate the best fitting model, we considered various methods and different strategies. The investigated parameters are:

Temporal units. We started using an annual time bin to evaluate the population abundance trajectory. Then we considered time bins of 5yr and 10yr. Two years bins were rejected because not significantly different from 1yr bins.

Spatial units. In our models, we considered two different spatial stratifications.

1) **Mediterranean Geographic Sub-Areas (GSA) (**http://www.fao.org/gfcm/data/map-geographical-subareas/en/) - First, we took into account 27 of the 31 Mediterranean GSA, excluding GSAs 2-11.1-29-30 from the analysis. The first two are entirely surrounded by other GSAs and, consequently, the absence of coastline made impossible to associate them with an observation effort value. The latter two represent the Black Sea and Azov Sea, where no sightings were recorded. The only record belonging to GSA 2 was moved to GSA 3, while all records of GSA 13 spotted around the Pelagie Islands were moved to GSA 16 as part of the Italian territorial waters and, hence, related to the Agrigento province human population size.
2) **FAO Fishing Area 37 Divisions** (http://www.fao.org/gfcm/data/map-geographical-subareas/en/) - In order to increase the spatial aggregation level, we used eight of ten Mediterranean FAO Divisions as new spatial grids, excluding Black and Azov Sea areas as above.

Model selection procedure. In our modelling exercise we started from the simplest possible choice, then going towards more complex functions. Our main goal was to select a model framework supporting the finest possible spatiotemporal resolution. Firstly, we investigated linear relationships, considering Poisson and Negative Binomial as representative distribution and fitting GLMs, zero-inflated regressions (ZIP and ZINB) and Hurdle models to our data. Hence, we explored non-linear relationships, still maintaining the same reference distributions, through Generalized Additive Models (GAM). AIC, fitted deviance, R^2, log-likelihood, residuals analysis, and dispersion parameter have been computed as criteria to assess the overall model performance. We repeated this procedure for each temporal and spatial aggregation unit. Negative Binomial GAMs with 1-year as spatial resolution returned the best fitting results in terms of fitted deviance, residuals analysis, and AIC. Details of the fitting criteria of the best models are reported in Tab. *3*.

Relationship between response and observation effort. In all our models we considered the observation effort as an offset term, assuming a linear relationship with the response variable. To verify this assumption, we fitted a second model including a spline on the human population abundance. We proceeded by dividing the dataset into training and testing sets, where the latter was obtained by building a simple random sample of 10% of the entire dataset. This resampling procedure was carried out 150 times and RMSEs were computed on the test sets for both models. Eventually, we compared the average RMSEs in order to evaluate the prediction errors of both models. Given that the two means differed at the third decimal figure (Tab. 5), we chose to include the observation effort as an offset term as it is the simpler model structure and would not entail any serious prediction loss. Furthermore, this model setting permitted us to estimate a standardized index of abundance for the Mediterranean white shark population (#records/coastal people).

Random/hierarchical spatiotemporal effect. We explored the possibility of a random effect related to the spatial or temporal unit. In spatial terms we included both spatial stratifications (GSAs and FAO Divisions), while, in order to test temporal effects, we divided our 156-year range in the following time bins:

- pre-war (1860 – 1913), WWI (1914-1918), inter-war (1919 – 1938), WWII (1939 – 1945), post-war (1946-2016);
- pre-war (1860 – 1913), war (1914 – 1945), post-war (1946 – 2016);
- pre-war (1860 – 1945), post-war (1946 – 2016);
- pre-industrial fishery (1860 – 1959), post-industrial fishery (1960 – 2016).

Hence, we discriminated our models in two different groups:

- M1 → models considering only fixed effects: GSA (or FAO Division) + temporal effect
- M2 → models gathering fixed and random effects.

M2 models were computed using both GAMMs (Generalized Additive Mixed-Effect Models) and LMEMs (Linear Mixed-Effect Models). Eventually, we combined all possible temporal and spatial effects for both model's classes. No significant differences were detected between time bins for M1 models, while none of the models converged, even after a high number of iterations, in M2 models.

Number of knots for the smooth function. In both models (FAO and GSA Model) we started estimating the number of knots for the GAM's smooth function via REML (Restricted Maximum Likelihood), testing our choice through the gam.check function (Wood, 2017). In this procedure we allocated the same number of knots to each sector's smooth function. Hence, including a factorial variable in the model and asking to the algorithm to estimate a different spline in each sector, some artifacts may be introduced when only few records are available for a specific sector. To validate our patterns, we estimated parallelly single-sector models and compared the trajectories of the two modelling approaches. As expected, the abundance trend locally estimated coincided with the general model in 6 out of 8 sectors (Fig. 7). Only Divisions 2.1 (Adriatic) and 4.1 (Marmara Sea) returned different trajectories with more smoothed curves. However, it is important to underline that the two approaches gave back very similar results if considering the curves' tendencies and the magnitude of the decline inferred (Fig. 8).

Tuna traps exclusion. We found in our analysis that tuna traps surely represented a strong source of mortality for Mediterranean white sharks. Consequently, their dismantling in the second half of the 20th century could constitute a source of bias for our trend analysis. To test for this, we fitted the same model (FAO Model) to our data excluding, this time, all catches coming from tuna traps. No strong differences were detected between the two models in most of the sectors (Fig. 9) but the Balearic (1.1). This is expected because more than a half of records in that particular sector comes from tuna traps.

Figures and Tables

Length - Length					
Unknown Length	**Known Length**	**a**	**b**	**Formula**	**Reference**
PCR	TOT	7.975	1.245	TOT = a + b PRC	Compagno, 1984
TL	PRC	-0.095	0.855	PCR = a + b TL	Mollet & Caillet, 1996
TL	FOR	-5.744	0.944	TL = a + b FOR	Kohler *et al.*, 1996

Tab. 1 Methods used to convert length values in Total Length

Country	**Regional Data Source**	**National Data Source**

Albania	INSTAT; worldbank; populstat.info	populstat.info
Algeria	worldbank; populstat.info	populstat.info
Bosnia and Herzegovina	worldbank; populstat.info	populstat.info
Croatia	eurostat; populstat.info	eurostat; populstat.info
Cyprus	eurostat; populstat.info	
Egypt	worldbank; populstat.info	populstat.info
France	INED; populstat.info	INED; populstat.info
Gibraltar	Gibraltar Government	
Greece	eurostat; populstat.info	eurostat; populstat.info
Israel	citypopulation.de; populstat.info	populstat.info
Italy	ISTAT	
Lebanon	worldbank; populstat.info	populstat.info
Libya	populstat.info	populstat.info
Malta	eurostat; populstat.info	
Monaco	eurostat; populstat.info	
Montenegro	worldbank	worldbank
Morocco	populstat.info	worldbank
Palestina	populstat.info; ONU (for Gaza Strip)	
Slovenia	eurostat; populstat.info	eurostat; populstat.info
Spain	INE; populstat.info	
Syria	citypopulation.de; populstat.info	populstat.info
Tunisia	INS; populstat.info	INS; populstat.info
Turkey	eurostat; worldbank; populstat.info	eurostat; populstat.info

Tab. 2 Table reporting both national and regional population census data sources for each Mediterranean country.

Code	**C**	**D**	**N**	**TU**	**SU**	**R^2 or FD**	**LL**	**AIC**	**Theta**	**R**
GSA Model	GAM	NB	4239	1 year	GSAs	35.6		3216.6	0.445	normality
ZINB-1C	Zero-inflated GLM	NB	4239	1 year	GSAs		-1589	3240.7		non-normality
GLM_2	GLM	NB	4239	1 year	GSAs	34.10		3236.7	0.418	non-normality
ZIP-1C	Zero-inflated GLM	Poisson	4239	1 year	GSAs		-1663	3386.5		non-normality
GLM_1	GLM	Poisson	4239	1 year	GSAs	29.82		3529.5		non-normality
FAO Model	GAM	NB	1256	1 year	Divisions	36.8		2083.4	1.327	normality
ZINB-N1A	Zero-inflated GLM	NB	1256	1 year	Divisions		-1086	2210.2	1.574	non-normality
GLM_3	GLM	NB	1256	1 year	Divisions	20.47		2232.6	0.756	non-normality

Tab. 3 Model fit statistics of the best models used to estimate the abundance trends. Code = model's identifier; C = model's class; D = statistical distribution; N = number of observations; TU = temporal unit; SU = spatial unit; R^2 or FD = adjusted R-square or fitted deviance; LL = log-likelihood; Theta = dispersion parameter; R = residuals analysis.

Code	Fitted Deviance	N° of Knots (GCV)	Smooth Term P-value
FAO Model	36.8	10	
- Sector 1.1		10	0.01022
- Sector 1.2		10	0.07214
- Sector 1.3		10	0.00113
- Sector 2.1		10	0.00134
- Sector 2.2		10	4.25e-05
- Sector 3.1		10	0.02946
- Sector 3.2		10	0.44554
- Sector 4.1		10	1.03e-05
Single-sector 1.1	7.29	10	0.106
Single-sector 1.2	3.57	10	0.075
Single-sector 1.3	18.80	10	4.82e-05
Single-sector 2.1	3.86	10	0.0185
Single-sector 2.2	32.0	10	7e-08
Single-sector 3.1	7.92	10	0.0408
Single-sector 3.2	12.6	10	0.438
Single-sector 4.1	31.4	10	0.00031

Tab. 4 FAO Model and Single-sector models in details.

Model Type	Mean Value of RMSE
GAM with Obs. Effort as offset term	0.599
GAM with a spline on the Obs. Effort	0.640

Tab. 5 Mean value of RMSEs for the two tested models calculated after 150 resampling procedure.

Taxonomic Group	Trophic Category	Family	Species	TOT	YOY	JUV	SUB	ADL
Bird	Bird	Laridae	Unidentified seagull	3				1
Bird	Bird	Unidentified bird	Unidentified bird	1			1	
Bird	Bird	Diomedeidae	Unidentified albatross	1				1
Chondrichthyans	Batoids	Unidentified family	Unidentified ray	2				2
Chondrichthyans	Other sharks	Alopiidae	*Alopias vulpinus*	2			1	1
Chondrichthyans	Other sharks	Carcharhinidae	*Prionace glauca*	1				1
Chondrichthyans	Other sharks	Lamnidae	*Isurus oxyrinchus*	1				1
Empty	Empty	Empty	Empty	3			1	2
Inedible object	Inedible object	Inedible object	Inedible object	20	2	1	2	13
Marine mammal	Mysticetes	Balaenopteridae	*Balaenoptera physalus*	2				1
Marine mammal	Mysticetes	Physeteridae	*Physeter macrocephalus*	2				
Marine mammal	Mysticetes	Unidentified family	Unidentified Mysticete	2				
Marine mammal	Odontocetes	Delphinidae	*Delphinus delphis*	1				1

Marine mammal	Odontocets	Delphinidae	*Stenella coeruleoalba*	7			1	2
Marine mammal	Odontocets	Delphinidae	*Tursiops truncatus*	5			2	1
Marine mammal	Odontocets	Delphinidae	*Grampus griseus*	1				
Marine mammal	Pinnipeds	Phocidae	*Monachus monachus*	2				2
Marine mammal	Odontocets	Phocoenidae	*Phocoena phocoena*	2			1	1
Marine mammal	Odontocetes	Unidentified family	Unidentified Odontocete	28			1	23
Mollusca	Mollusc	Unidentified mollusc	Unidentified mollusc	1			1	
Mollusca	Mollusc	Unidentified squid	Unidentified squid	1				1
Reptile	Chelonians	Cheloniidae	*Chelonia mydas*	1				1
Reptile	Chelonians	Cheloniidae	*Caretta caretta*	5			1	2
Reptile	Chelonians	Cheloniidae	Unidentified turtle	6				4
Teleost	Teleost	Belonidae	*Belone belone*	1		1		
Teleost	Teleost	Clupeidae	*Sardina pilchardus*	1				1
Teleost	Teleost	Lophiidae	*Lophius spp.*	1		1		
Teleost	Teleost	Merlucciidae	*Merluccius merluccius*	1		1		
Teleost	Teleost	Molidae	*Mola mola*	1				1
Teleost	Teleost	Scombridae	*Thunnus spp.*	19				17
Teleost	Teleost	Scombridae	*Thunnus thynnus*	3				3
Teleost	Teleost	Scombridae	*Sarda sarda*	3			1	2
Teleost	Teleost	Scombridae	*Auxis rochei*	1				1
Teleost	Teleost	Scombridae	*Thunnus alalunga*	1			1	
Teleost	Teleost	Scorpaenidae	*Scorpaena spp.*	1				1
Teleost	Teleost	Sparidae	*Dentex dentex*	1				1
Teleost	Teleost	Unidentified family	Unidentified teleost	8	1			6
Teleost	Teleost	Xiphiidae	*Xiphias gladius*	6			1	4
Terrestrial mammal	Terrestrial mammal	Bovidae	*Ovis aries*	1				1
Terrestrial mammal	Terrestrial mammal	Bovidae	*Capra hircus*	3				3
Terrestrial mammal	Terrestrial mammal	Bovidae	*Bos taurus*	1				1
Terrestrial mammal	Terrestrial mammal	Canidae	*Canis lupus familiaris*	2			1	1
Terrestrial mammal	Terrestrial mammal	Equidae	*Equus caballus*	1				
Terrestrial mammal	Terrestrial mammal	Felidae	*Felis silvestris catus*	1			1	
Terrestrial mammal	Terrestrial mammal	Hominidae	*Homo sapiens*	18			2	10
Terrestrial mammal	Terrestrial mammal	Suidae	*Sus scrofa domesticus*	1				1

Tab. 6 Stomach content analysis data

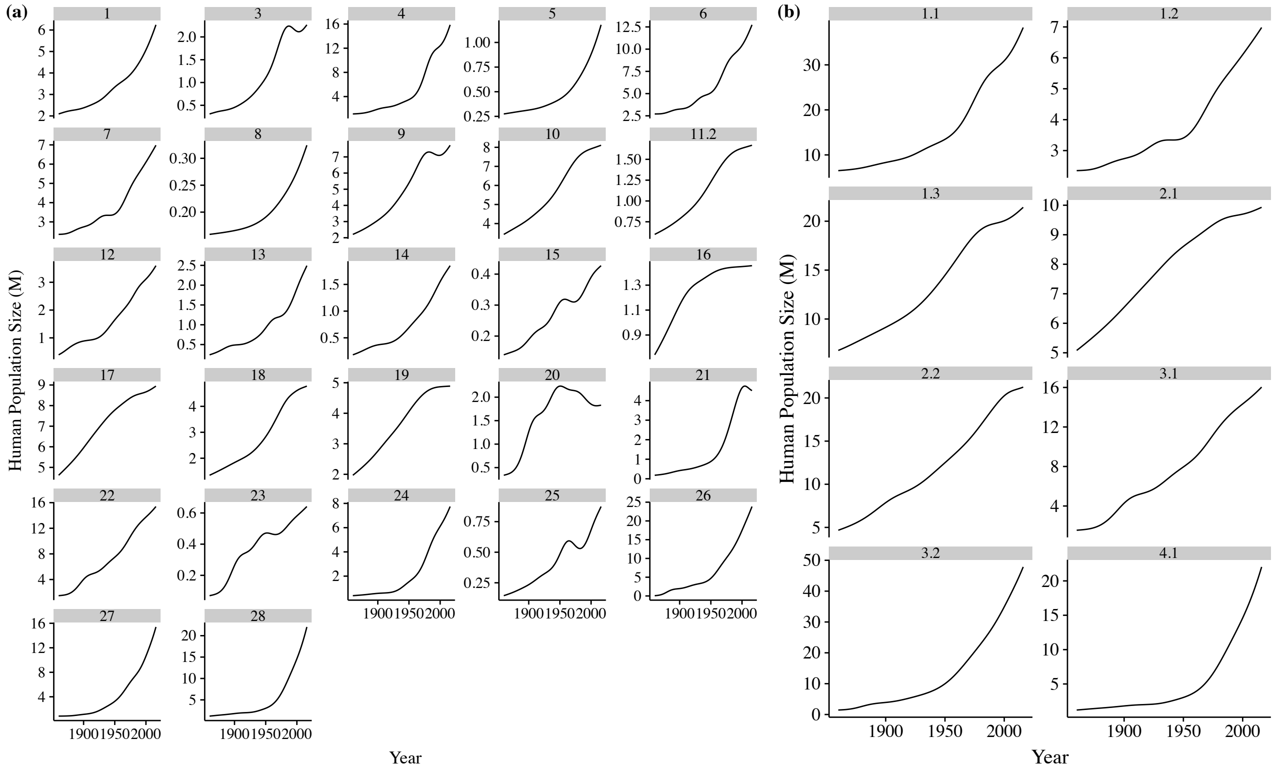


Fig. 1 Human population size trajectories both for GSAs (a) and FAO Divisions (b).

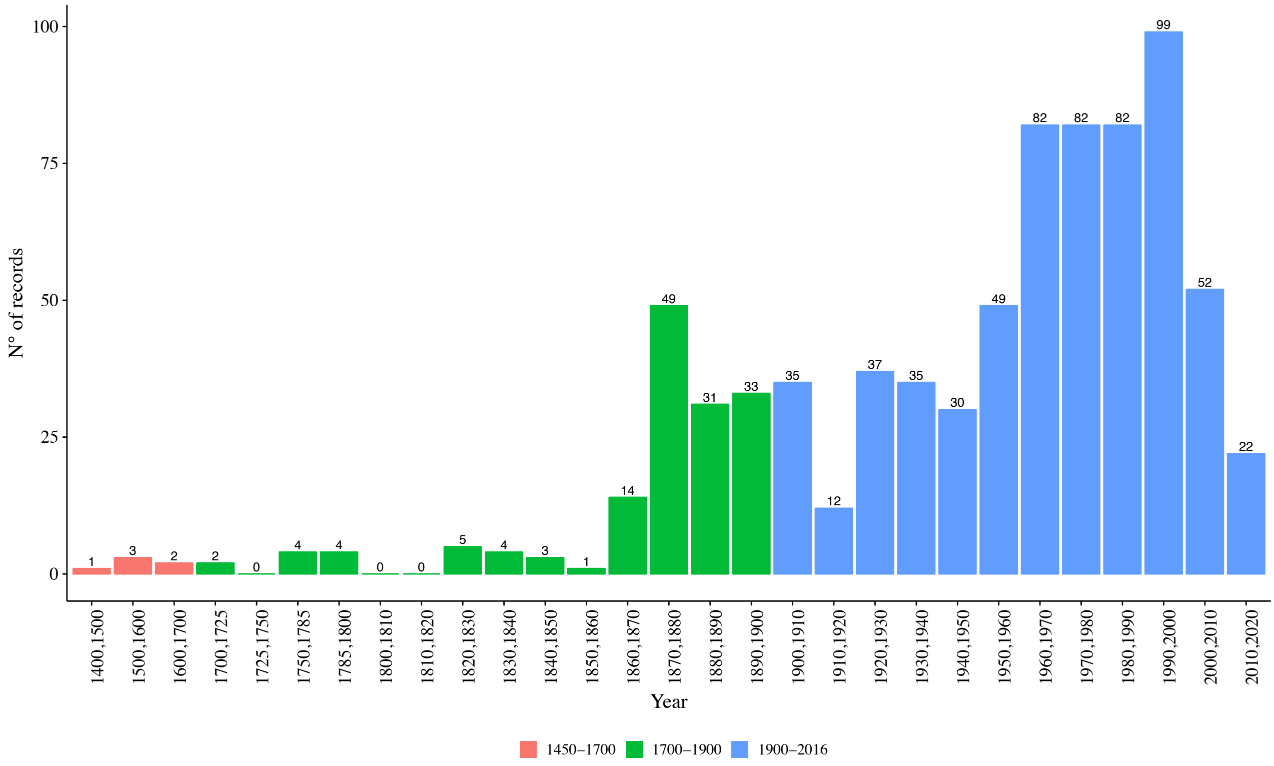
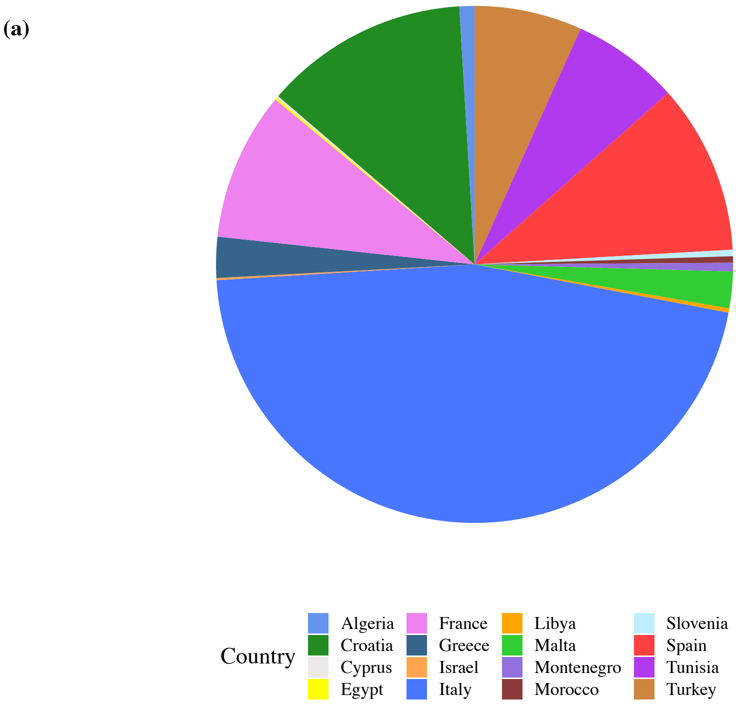


Fig. 2 Sightings temporal distribution. Colors correspond to macro-temporal periods. The specific number of recorded sightings is reported over each bar.



(b)

Country	Frequency	Percentage
Algeria	7	0.94
Croatia	95	12.79
Cyprus	1	0.13
Egypt	1	0.13
France	69	9.29
Greece	19	2.56
Israel	1	0.13
Italy	342	46.03
Libya	2	0.27
Malta	17	2.29
Montenegro	4	0.54
Morocco	3	0.40
Slovenia	3	0.40
Spain	79	10.63
Tunisia	50	6.73
Turkey	50	6.73

Fig. 3 (a) Pie chart reporting the sightings distribution in function of Mediterranean countries. (b) Table reporting the number of specimens recorded in each country and the relative percentage.

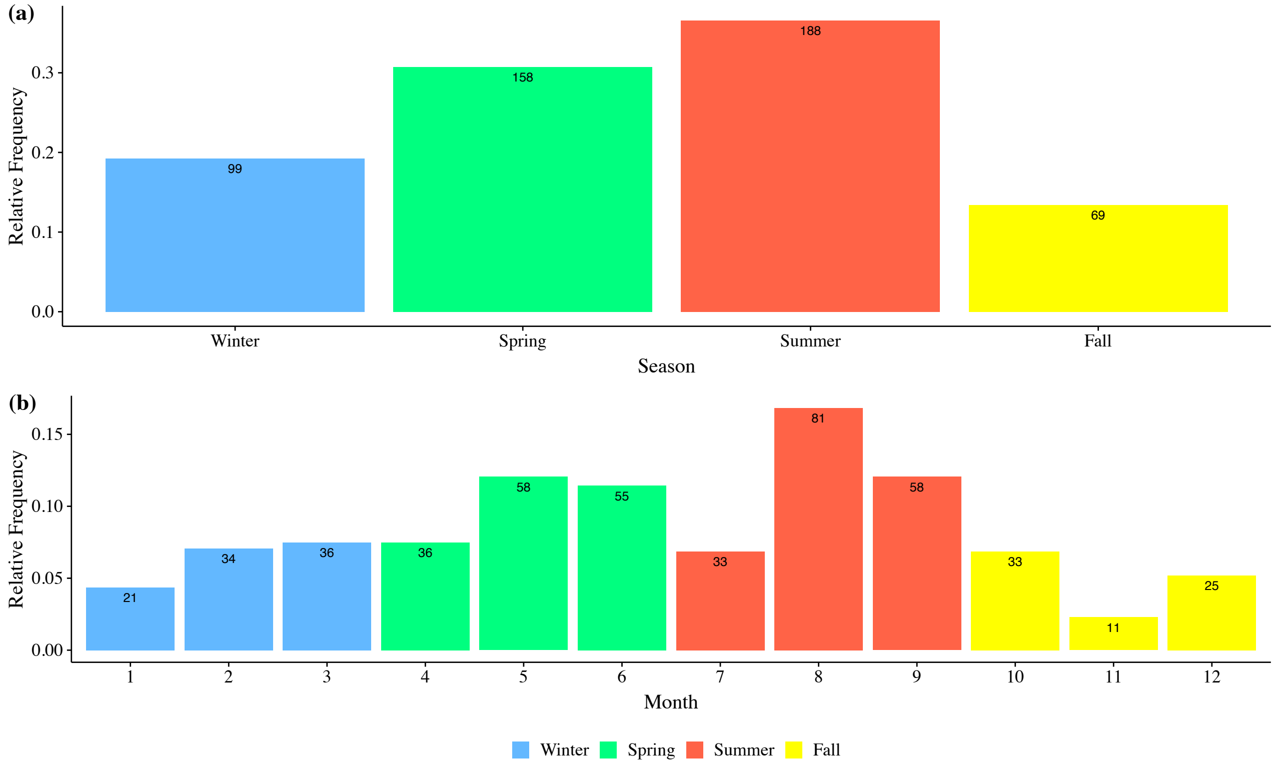
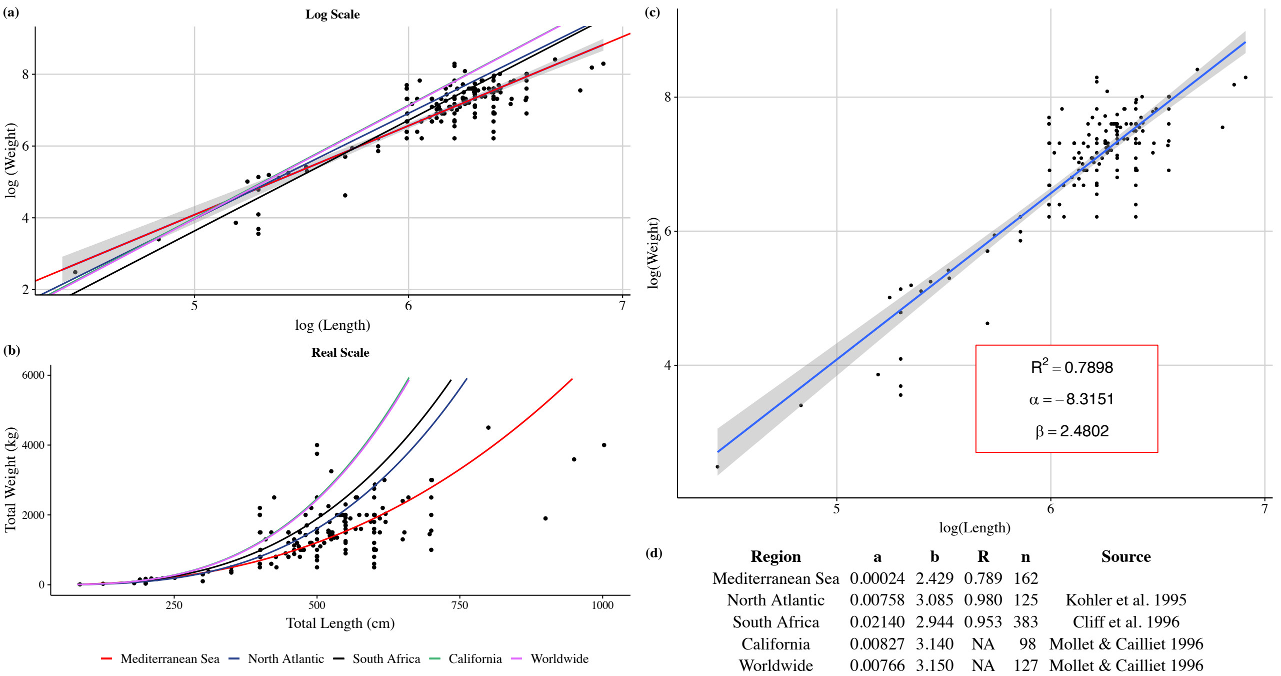


Fig. 4 Seasonal (a) and monthly (b) distribution of the shark sightings. The precise number of specimens recorded is reported over each bar. Colors match with seasons in both panels.



Region	a	b	R	n	Source
Mediterranean Sea	0.00024	2.429	0.789	162	
North Atlantic	0.00758	3.085	0.980	125	Kohler et al. 1995
South Africa	0.02140	2.944	0.953	383	Cliff et al. 1996
California	0.00827	3.140	NA	98	Mollet & Cailliet 1996
Worldwide	0.00766	3.150	NA	127	Mollet & Cailliet 1996

Fig. 5 Length-Weight Relationship in log scale (a) and natural scale (b) for Mediterranean white sharks (c) and other white shark populations (a-b) distributed worldwide. (d) Table reporting intercept, a, slope, b, R², number of specimens sampled, n, and source of each regression line.

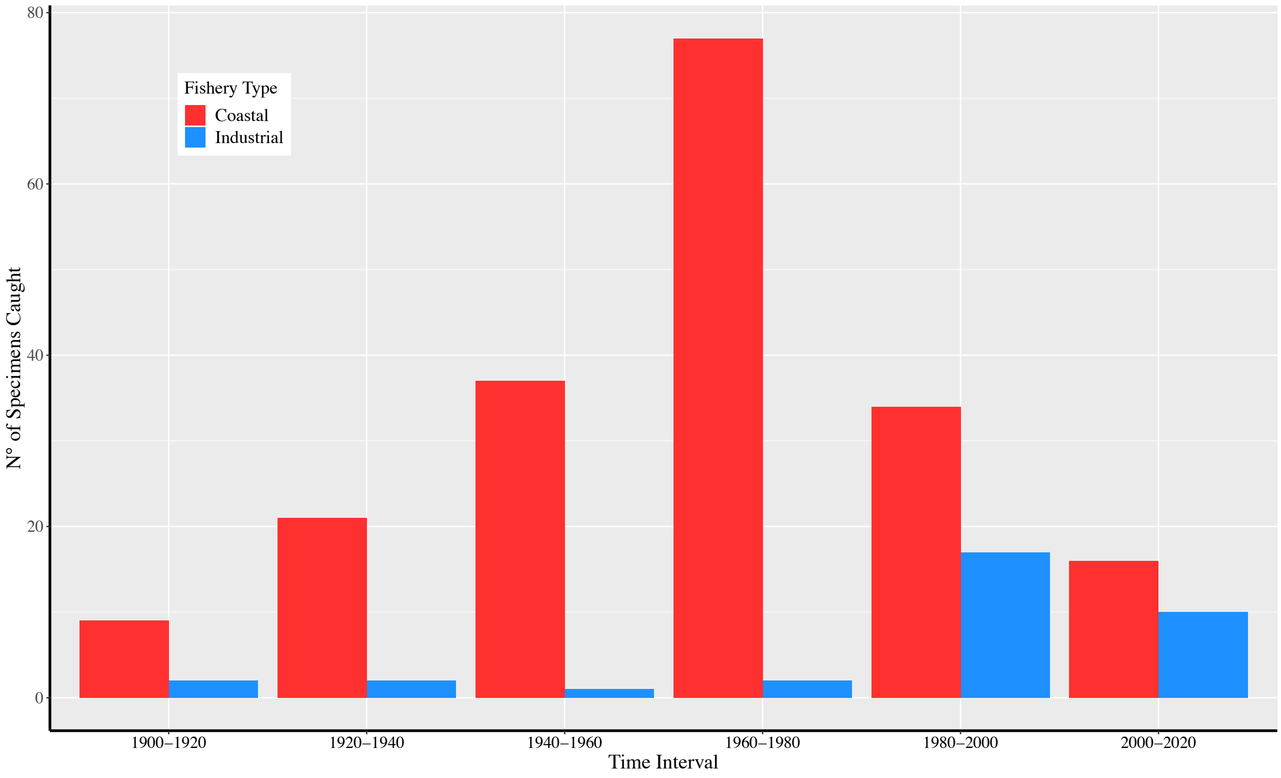


Fig. 6 White shark catches produced by coastal and industrial fishery in the period 1900-2016. Fishing gears have been categorized in the following way: Industrial – Trawl, Purse Seine and Longline; Coastal – Gillnets, Harpoon, Tuna Trap, Line, Others.

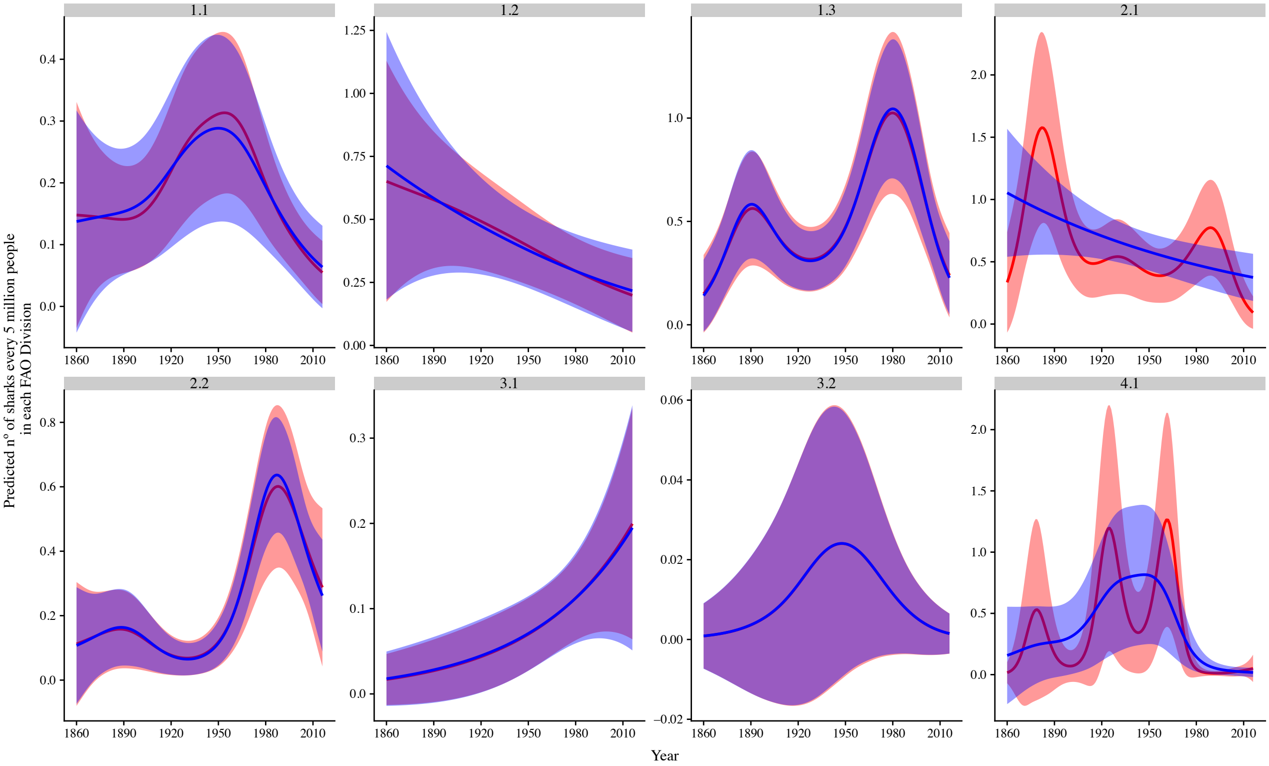


Fig. 7 Single-sector models (blue) and FAO Model (red) trajectories comparison in each FAO Division.

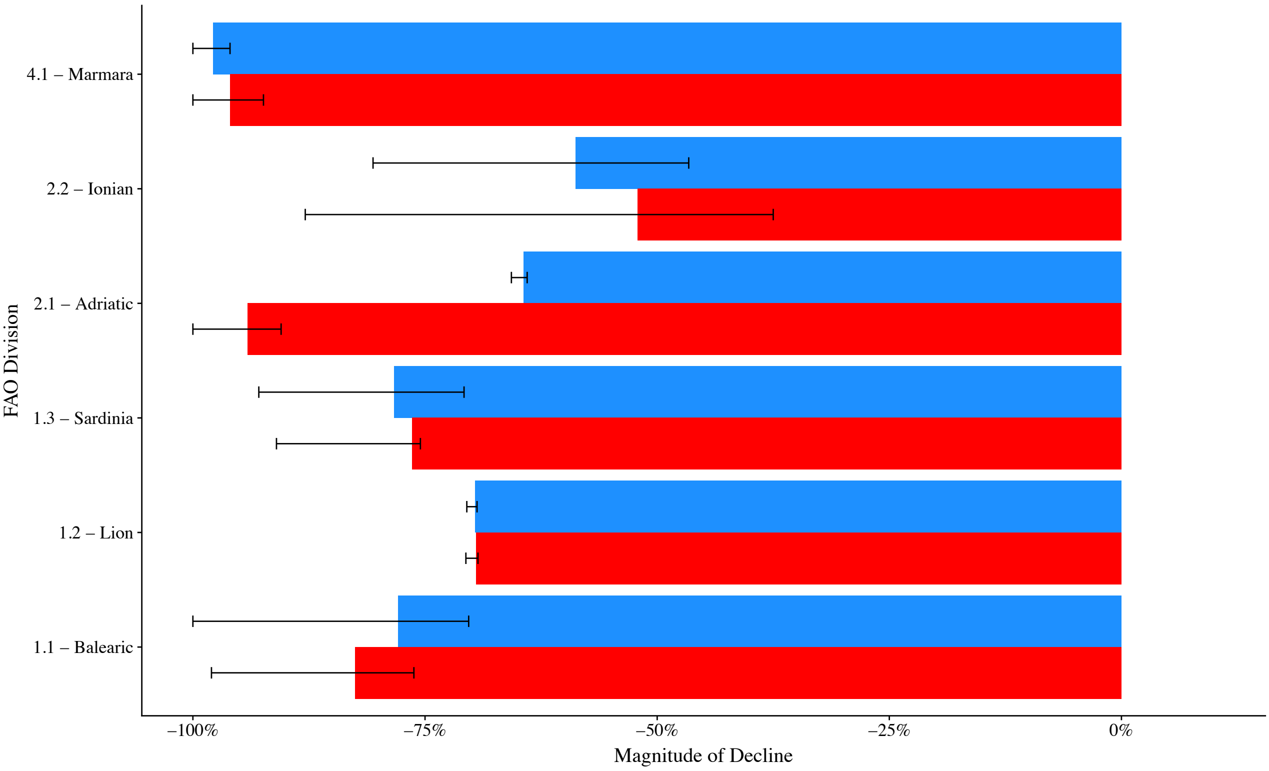


Fig. 8 Comparison between the Single-sector models (blue) and the FAO Model(red) in terms of magnitude of decline.

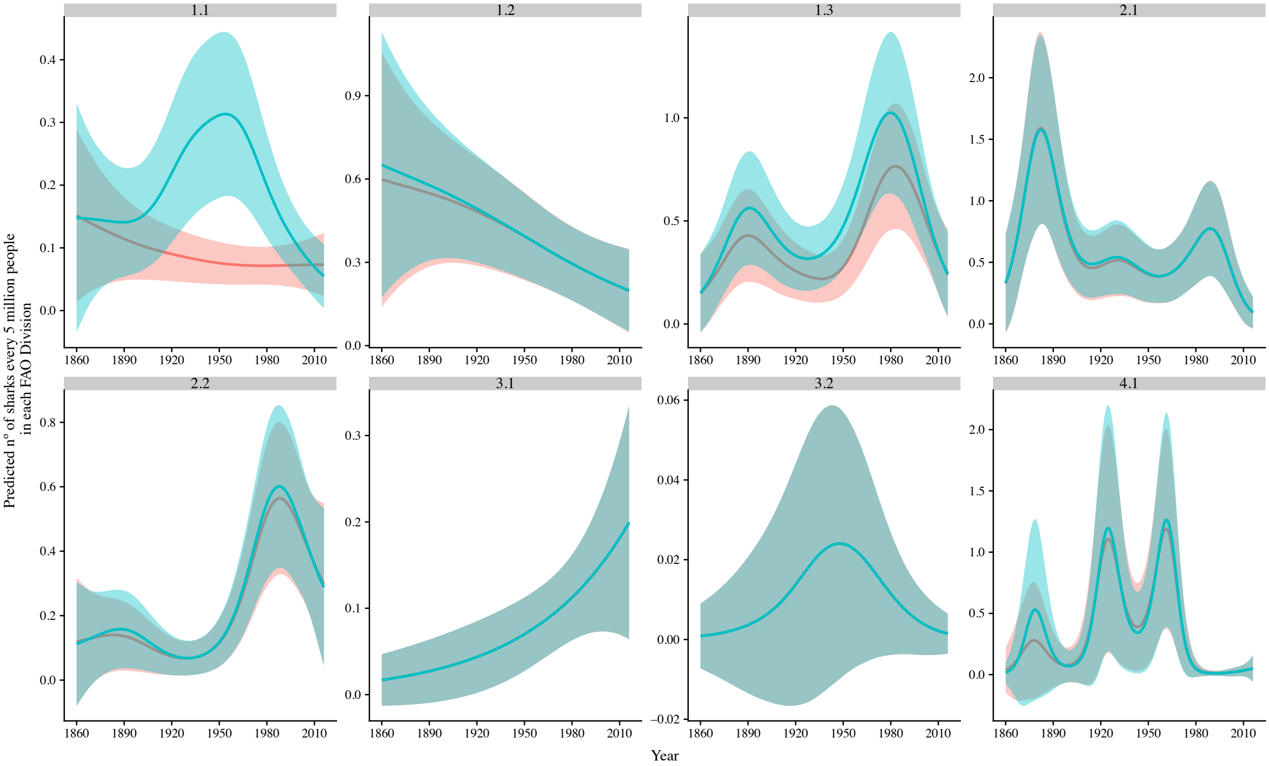


Fig. 9 Comparison between the trajectories predicted by the FAO Model (aquamarine) and trajectories obtained excluding from the analysis all the tuna trap catches (red).

Literature Cited

Baskerville, G. L. (1972). Use of logarithmic regression in the estimation of plant biomass. *Canadian Journal of Forest Research*, 2(1), 49-53.

Ferretti, F., Morey Verd, G., Seret, B., Sulić Šprem, J., Micheli, F. (2016). Falling through the cracks: the fading history of a large iconic predator. *Fish and fisheries*, 17(3), 875-889.

McPherson, J. M. ,& Myers, R. A. (2009). How to infer population trends in sparse data: examples with opportunistic sighting records for great white sharks. *Diversity and Distributions*, 15(5), 880-890.

Serena, F., Barone, M., Mancusi, C., Magnelli, G., Vacchi, M. (2006). The MEDLEM database Application: a tool for storing and sharing the large shark's data collected in the Mediterranean countries. In Basusta, N., Keskin, C., Serena, F., Seret, B. (eds.) *The Proceedings of the Workshop on Mediterranean Cartilaginous Fish with Emphasis on Southern and Eastern Mediterranean* (pp. 118-129). Turkish Marine Research Foundation, Istanbul, Turkey.

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B)*, 73(1), 3-36

Wood, S. N. (2017). *Generalized additive models: an introduction with R*. Chapman and Hall/CRC.

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