**Final Report of the Pelagos Agreement-funded project**

# Assessment of species abundance, distribution and habitats in the Pelagos Sanctuary, with a priority given to the Cuvier's beaked whale, the fin whale, the sperm whale and the bottlenose dolphin

June 2025

2023 Call for Technical and Scientific Consultancy of the Pelagos Agreement



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# 2023 CALL FOR TECHNICAL AND SCIENTIFIC CONSULTANCY

# OF THE PELAGOS AGREEMENT

Final Report
July 2025

*General info:*

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|---|---|
| Project title | Assessment of species abundance, distribution and habitats in the Pelagos Sanctuary, with a priority given to the Cuvier's beaked whale, the fin whale, the sperm whale and the bottlenose dolphin |
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| Contract n° | 2023-06 |
| Citation: | Floriane Plard, 2025. Assessment of species abundance, distribution and habitats in the Pelagos Sanctuary, with a priority given to the Cuvier's beaked whale, the fin whale, the sperm whale and the bottlenose dolphin. Pelagos Agreement-funded project |

Activity financed by the Pelagos Agreement in the framework of the
Management Plan 2022 -2027 - Programme of Work 2024-2025

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# Introduction

Within the main objectives of the Pelagos Sanctuary to implement the action «Coexistence between marine mammals and use of the seas» of the management Plan and relevant Action Plan 2022-2027, the aim of call 1 is to estimate cetacean abundances and distributions within the Pelagos Sanctuary. These estimates will provide information to help assess the status of marine mammal populations in the Pelagos Sanctuary, creating an initial status of the cetacean populations and identifying areas of high densities within the Pelagos Sanctuary. The priority has been given to four species, particularly sensitive to human activities: the bottlenose dolphin living close to the coast and to human activities, the fin whale impacted by collision with boats, and the sperm whale and the Cuvier's beaked whale.

Abundance and density distribution are key population parameters. Abundance informs about the status of a species in a region, and maps of population densities allow targeting the preferential areas of presence (Wade 1998, Hammonds et al. 2021a, Waggitt et al. 2020). Using these population characteristics grants making informed decisions about population management and conservation, accounting for threat and risk that might influence the distribution of populations (Freeman 2008, Pace et al. 2015, Jewell et al. 2012).

Population abundance and maps of densities are particularly challenging to estimate in cetaceans (Field et al. 2005, Hammond et al. 2021b, McPherson & Myers 2009). Among several reasons, the natural seasonal and annual extensive movements of these species make their distribution particularly variable among seasons and years. Moreover, the data required to estimate cetacean densities are particularly costly to collect, making them often spatially and temporally sparse and few in quantity. Usually, cetacean abundances in one region are derived from a distance sampling survey covering the region homogeneously along ship or aerial transects (Buckland et al. 1993). While often informative, a given survey reflects the abundance of the population at the time the survey was done. In addition, the low densities of some cetacean species and/or the low probability to detect animals, make the results of only one survey quite uncertain (Hammond et al. 2013; 2021a, Laran et al. 2017, Waggitt et al. 2020).

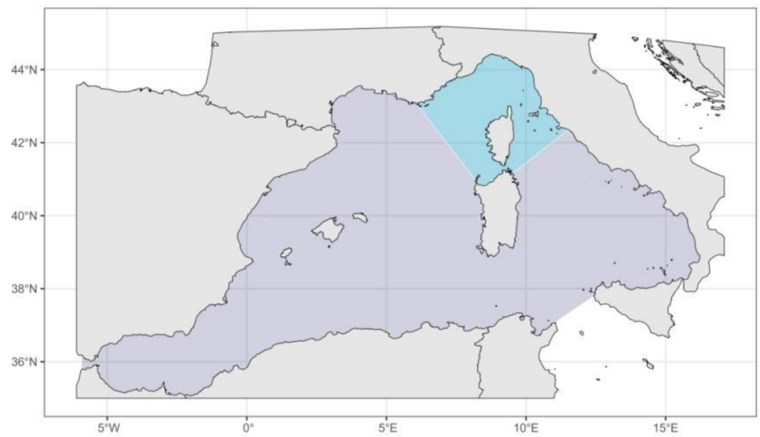



**Figure 1**: Study area including the MFSD Western Mediterranean region (dark blue) and the Pelagos Sanctuary (cyan).

The aim of this project was to gather multiple aerial and boat cetacean surveys from different areas and to combine them to get more robust estimates of cetacean abundance and densities within the Pelagos Sanctuary. Combining multiple surveys from different areas has several advantages. It increases the precision of the estimates by gathering more detection data. It also attenuates the temporal bias as different surveys are collected at different times of the year, reflecting the variable distribution of species in different seasons. It makes the relationships between environmental variables and cetacean densities more robust. Thus, we chose to extend the studied region of the Pelagos Sanctuary to the Western Mediterranean region (Figure 1) of the The Marine Strategy Framework Directive (MFSD) to increase the number of data gathered and obtain more robust estimates of cetacean densities and abundances.

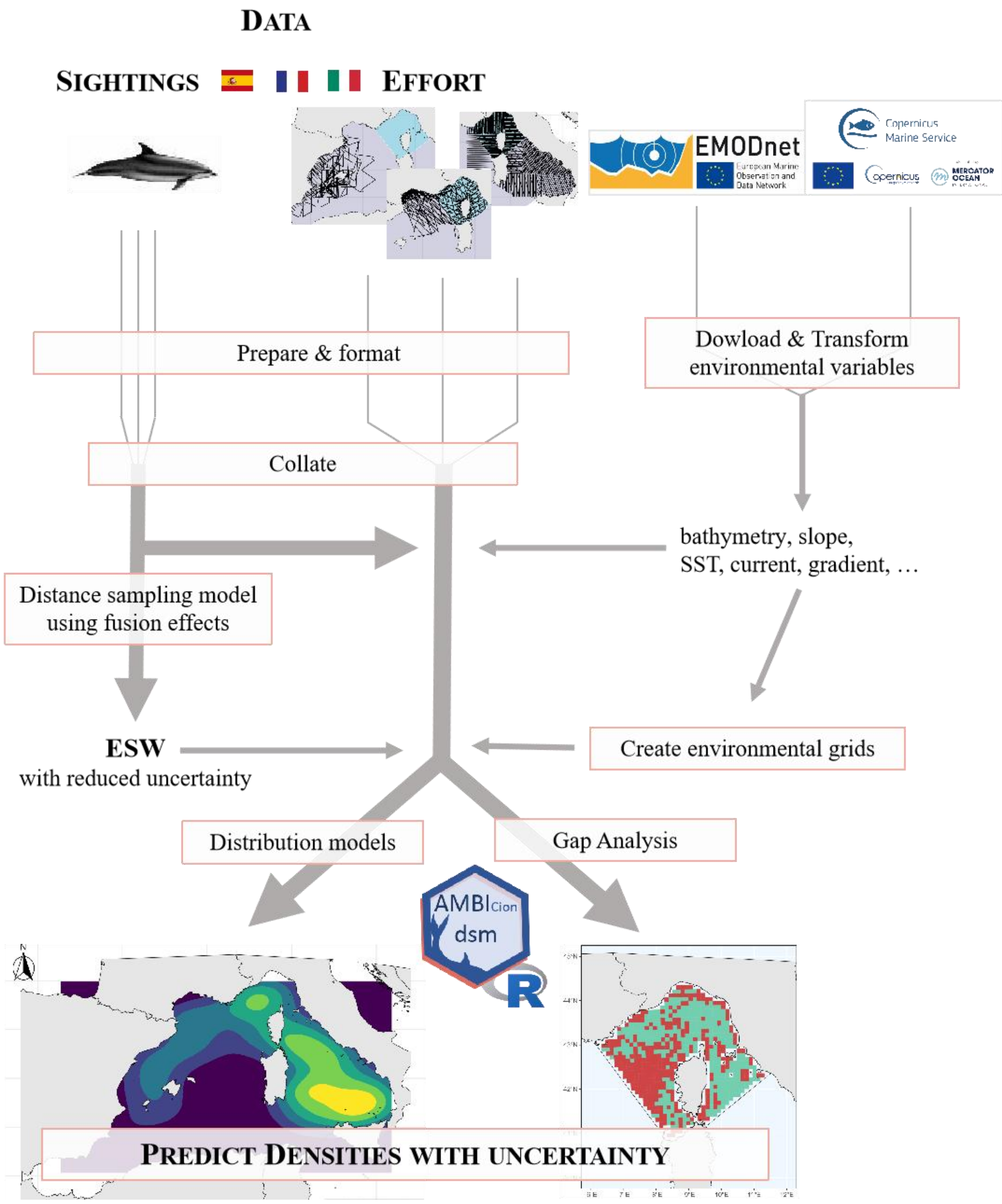



**Figure 2**: Graphical presentation of the method and tasks that have been realized in this call. Adapted from Plard et al. 2024.

The different steps and tasks of this project to estimate cetacean abundance and densities from the gathered data were outlined in Figure 2. After formatting and collating the different dataset, this project estimated detection probabilities for each species and survey. Then, based on the relationships between marine environmental variables and cetacean densities along survey transects, model-based cetacean densities were predicted within the Pelagos Sanctuary. The uncertainty associated with each prediction is reported in the form of maps of coefficients of variation. Moreover, a gap analysis was performed to inform about the extrapolation areas of the predicted densities.

# 1/ Data Call

The Pelagos Secretariat has sent a formal data request to the coordinators of the MFSD reports in Italy, Spain and France. The three countries have kindly agreed to collaborate. Data collected with a distance sampling protocol have been requested only. The three countries have provided the data on effort and sightings from distance sampling surveys they have collected within the Western Mediterranean region (Table 1).

**Table 1**: Summary of surveys collected by the Permanent Secretariat of the Pelagos Agreement.

| | SurveyID | Platform | Season | Effort (km) | Years | In Sanctuary |
|---|---|---|---|---|---|---|
| EU | ASI | Plane | spring | 8459,4 | 2018 | Yes |
| | | Plane | summer | 14815,6 | 2018 | Yes |
| FR | MOOSE | Ship | spring | 2443,1 | 2019, 2021 | Yes |
| | | Ship | summer | 141,3 | 2021 | No |
| | PELMED | Ship | spring | 576,7 | 2018, 2019, 2021 | No |
| | | Ship | summer | 5574,3 | 2017-2021 | Yes |
| | SAMM | Plane | fall | 6074,3 | 2011 | Yes |
| | | Plane | spring | 11120,2 | 2012 | Yes |
| | | Plane | summer | 7515,8 | 2012 | Yes |
| | | Plane | winter | 19302,8 | 2019, 2012 | Yes |
| IT | Pelagos | Plane | winter | 8542,4 | 2009 | Yes |
| | | Plane | summer | 8849,4 | 2009 | Yes |
| | PelaTir_2020 | Plane | fall | 18148,5 | 2020 | Yes |
| | | Plane | summer | 941,1 | 2020 | No |
| | ISPRA23A | Plane | fall | 6963,3 | 2023 | Yes |
| | | Plane | summer | 2763,9 | 2023 | No |
| | ISPRA23S | Plane | spring | 3098,6 | 2023 | No |
| | | Plane | summer | 7967,2 | 2023 | Yes |
| | PelaTir_2010 | Plane | spring | 11218,9 | 2010 | Yes |
| | | Plane | summer | 3855,7 | 2010 | Yes |
| | TurtruAU | Plane | fall | 7844,0 | 2023 | Yes |

| | | | | | | |
|---|---|---|---|---|---|---|
| SP | DMESAL | Plane | summer | 2051,3 | 2023 | No |
| | DMLEBA | Plane | summer | 5324,8 | 2023 | No |
| | ICCAT | Plane | spring | 65396,1 | 2015, 2017-2019, 2021-2022 | No |
| | | Plane | summer | 2749,5 | | No |
| | MEDIAS | Ship | summer | 2552,6 | 2022-2023 | No |

Thus, all effort data collected share a common protocol for recording sightings which is the distance sampling protocol (Buckland et al. 1993). At each observation, the distance from the animal to the observer as well as the angle between the animal and the transect line are collected. This information is used to derive the perpendicular distances from the sightings to the transect line to be able to estimate detection probabilities. The detection probability, often decreasing with distance from the transect line, is estimated using a distance sampling model. This method allows estimating corrected animal densities, accounting for imperfect detection of sightings on the transect. Thus, this protocol guarantees robust estimates of densities along effort data.

## A/ Italy

The surveys provided by Italy (Figure 3) covered the East part of the Western Mediterranean region, covering the Pelagos Sanctuary in recent and old years. They total 80193.2 km of effort. These aerial surveys included the ISPRA surveys conducted in summer and fall 2023, the PelaTir surveys conducted in 2010 and 2020, and the oldest survey collected so far; the Pelagos survey conducted in winter and summer 2009. An aerial costal survey collected in fall 2023: TrutruAU has been added in this second step of the analysis to target detections of coastal species such as the bottlenose dolphin.

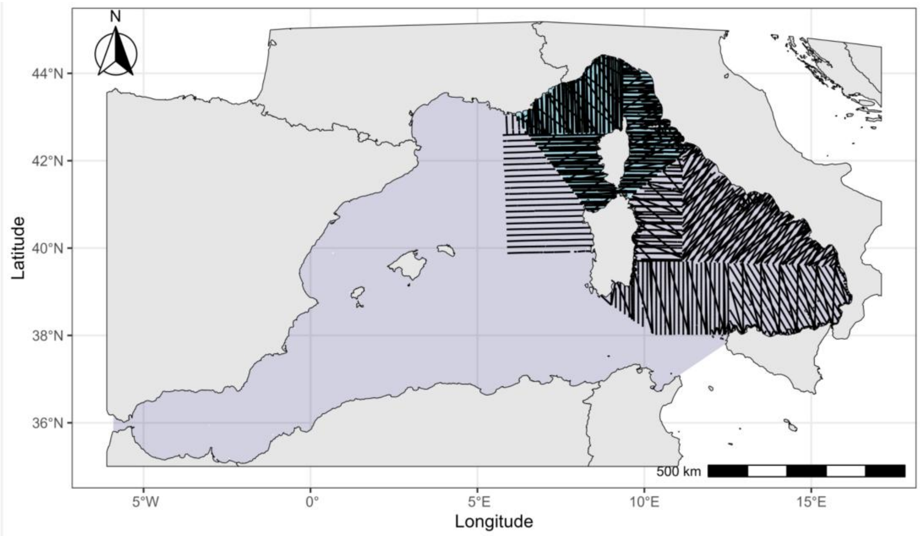



**Figure 3**: Transects of aerial surveys shared by Italy.

*Data suppliers:* Data maintained and hosted by ISPRA (Istituto Superiore per la Protezione e la Ricerca Ambientale) and funded by the Italian Ministero dell'ambiente e della tutela del territorio e del mare.

## B/ France

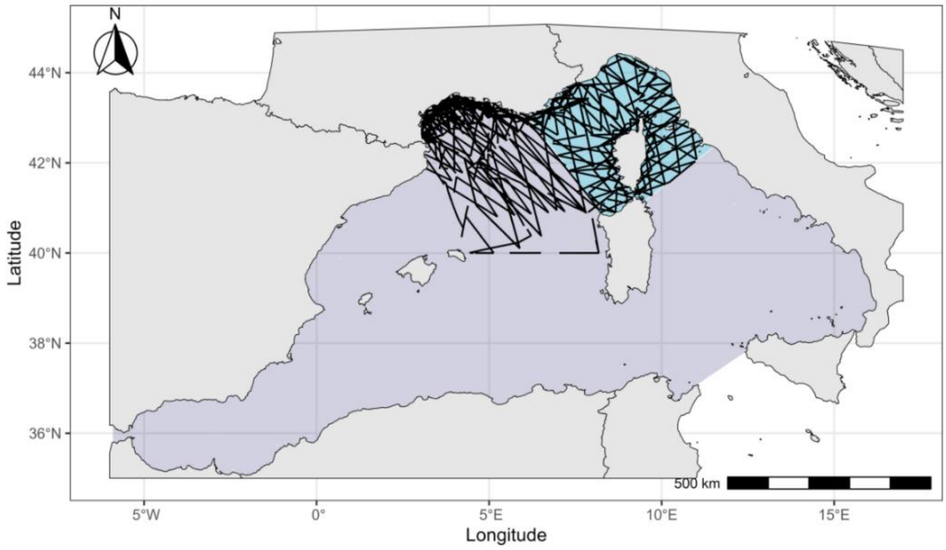



**Figure 4**: Transects of surveys shared by France.

The surveys provided by France (Figure 4) include two ship surveys MOOSE and PELMED conducted from 2017 to 2021 and the aerial large survey SAMM conducted in 2012 and 2019. They cover mainly the Gulf of Lion and the Pelagos Sanctuary. They total 52748 km of effort.

*Data suppliers:* Data hosted and maintained by the Observatoire Pelagis (UAR3462 La Rochelle Université, CNRS). Supported by the French ministry in charge of the environment, the Office Français de la Biodiversité (formely the Agence Française de la Biodiversité and Agence des Aires Marines Protégées) and Ifremer.

## C/ Spain

The surveys provided by Spain (Figure 5) cover the West part of the Western Mediterranean region covering the coast and waters of Spain. The gathered survey data total 78074 km of effort. Spain surveys included a recent ship survey MEDIA conducted in 2022 and 2023 along the coasts of Spain. Two aerial surveys DMESAL and DMLEBA have also been collected in 2023 in the Spain waters. A third aerial survey ICCAT from 2015 to 2022 flying over the Balearic islands originally aimed to collect information about tuna species, but also collected data on marine megafauna.

*Data suppliers:*

DMESAL-DMLEBA: Data maintained by the IEO, owned by MITECO. Funded through Next Generation EU recovery.

ICCAT: This work has been carried out under the ICCAT Atlantic-Wide Research Programme for Bluefin Tuna (GBYP), which is funded by the European Union, several ICCAT CPCs, the ICCAT Secretariat, and other entities (see https://www.iccat.int/gbyp/en/overview.asp). The content of this paper does not necessarily reflect ICCAT's point of view or that of any of the other sponsors, who carry no responsibility. In addition, it does not indicate the Commission's future policy in this area.

MEDIAS: Data collected and maintained by the IEO. Co-financed by the EU through the European Maritime Fund, Fisheries and Aquaculture (FEMPA), within the National Program for the Collection, Management and Use of Data on the Fisheries Sector and the Support for Scientific Advice (PNDB).

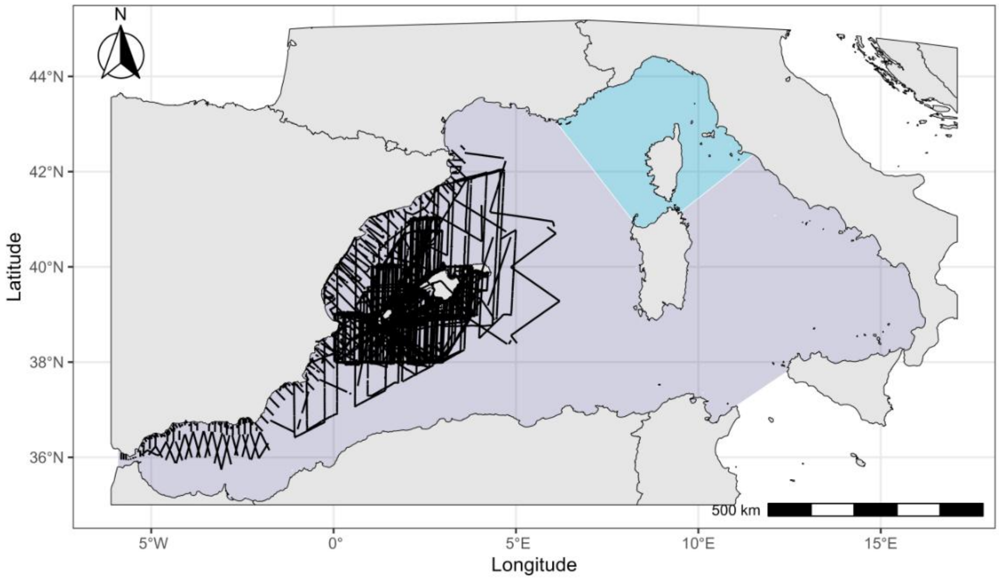



**Figure 5**: Transects of surveys shared by Spain.

## D/ European data

The ASI European survey was also added to this dataset as this plane survey covered most of the Western Mediterranean, and the Pelagos Sanctuary especially in 2018 with 23275km of effort.

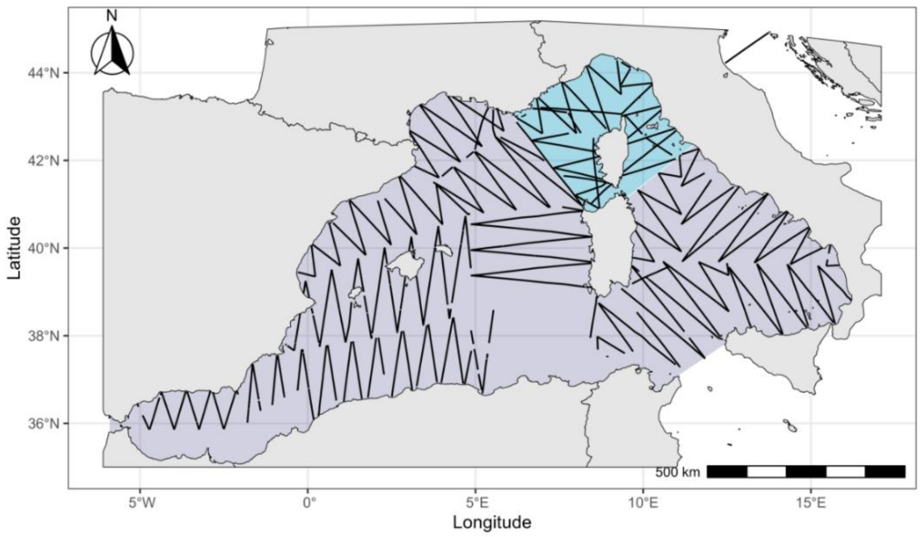



**Figure 6**: Transects of surveys shared by ASI.

*Data suppliers:* Data maintained and funded by ACCOBAMS

## 2/ Data Preparation

A first important step to collate data from different surveys is to homogenize and format all data in the same way so they can be used together. In this step, effort data of each survey have been checked to include effort collected when at least one observer was present. Effort over land, during circle backs and unstandardised effort were excluded. Boat and plane speed, and plane elevation greatly influence detection probability. Effort data were kept if the speed was between 8 and 16 knots for boats and between 50 and 150 knots for planes. Plane elevation was limited from 150 to 400 meters.

In a second step, efforts were linearised to avoid increasing the actual covered and sampled area. Effort data were then cut into segments of about 10 km, the conditions of observation including the number of observers, the elevation of observation, the sea state and the subjective conditions remaining similar along each segment. After this preparation, all effort data were collated.

The sightings data were also checked and prepared. Data were included if information about species name, group size, spatial location, date and time of the sighting, perpendicular distance, and observation side were available. Using this information, each sighting was linked to the effort segment it was observed on, in order to gather the condition of observation of each sighting that may influence the detection probability.

A first filter was applied on species name and the following species were retained: fin whale *Balaenoptera physalus*, common dolphin *delphinus delphis*, risso's dolphin *Grampus griseus*, long-finned pilot whale *Globicephala melas*, sperm whale *Physeter macrocephalus*, striped dolphin *Stenella coeruleoalba*, bottlenose dolphin *Tursiops truncatus,* Cuvier's beaked whale *Ziphius cavirostris*, and sightings of unidentified ziphius species, large whales, small and medium cetaceans.

### A/ Bottlenose Dolphin

495 sightings of individuals or groups of bottlenose dolphins (Figure 7) were available in the collated and prepared dataset. Many of these sightings have occurred in the Gulf of Lion and in the Pelagos Sanctuary.

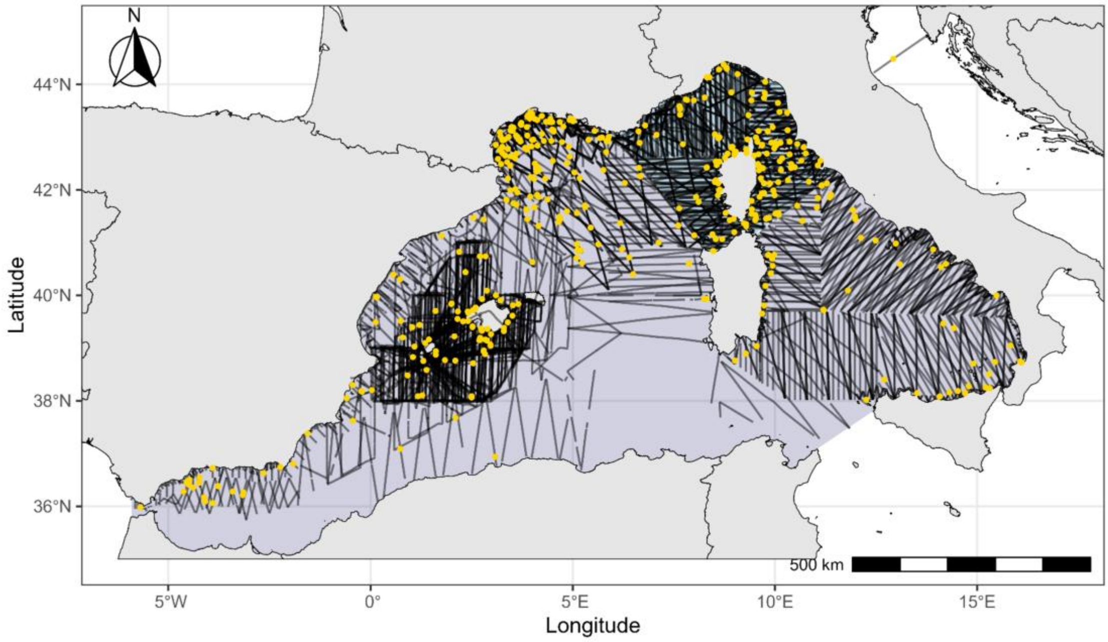



**Figure 7:** Spatial distribution of the sightings of Bottlenose dolphins on gathered effort.

## B/ Sperm whale

110 sightings of individuals or groups of sperm whales (Figure 8) were available in the current collated and prepared dataset. A lot of them occurred in the Canaries Islands and some in the Pelagos Sanctuary.

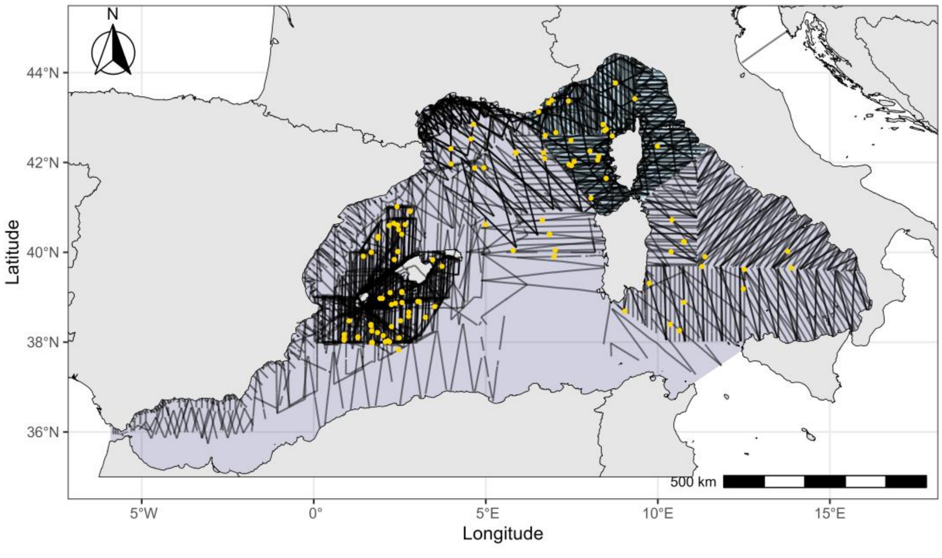



**Figure 8:** Spatial distribution of the sightings of Sperm whales on gathered effort.

## C/ Fin whale

283 sightings of individuals or groups of fin whales (Figure 9) were available in the current collated and prepared dataset. Most of these sightings were observed in the Gulf of Lion and in the Pelagos Sanctuary.

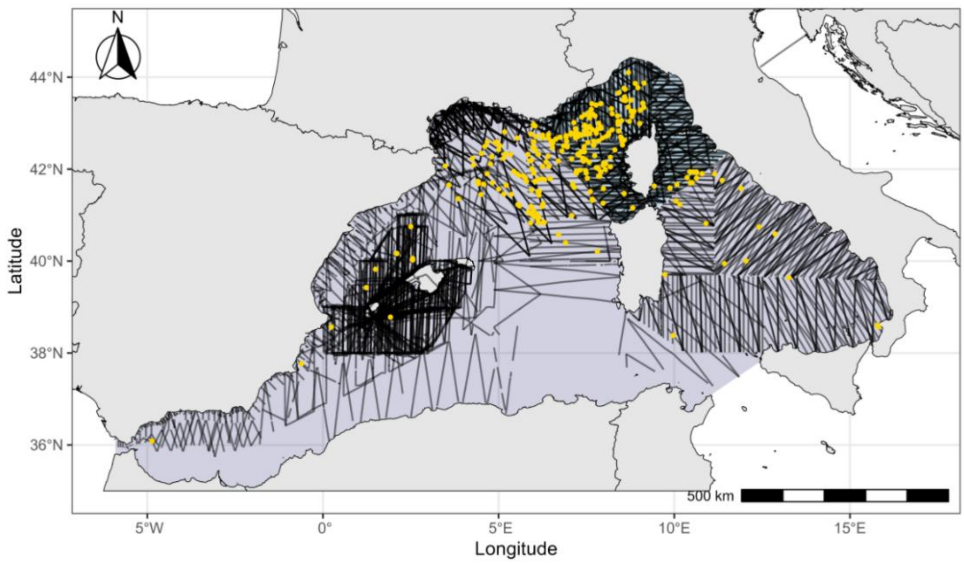



**Figure 9:** Spatial distribution of the sightings of Fin whales on gathered effort.

## D/ Cuvier's beaked whale

48 sightings of individuals or groups of Cuvier's beaked whales (Figure 10) and 6 sightings of unidentified ziphius species were available in the current collated and prepared dataset. I grouped both types of sightings to increase the number of data points to analyze the densities of Cuvier's beaked whale in the Western Mediterranean region as the sightings are widespread in the region.

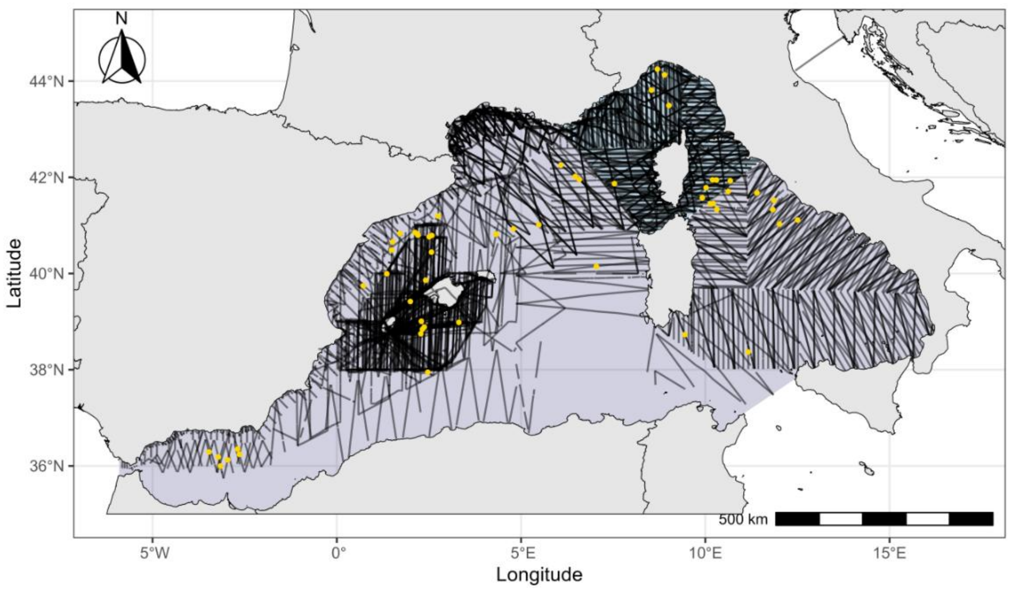



**Figure 10:** Spatial distribution of the sightings of Cuvier's beaked whales on gathered effort.

## E/ Other species

Among other species available, one observation of rough-toothed dolphin (*Steno bredanensis*) has been removed. 62 sightings of long-finned pilot whales, 162 sightings of Risso's dolphins, 42 sightings of common dolphin and 2372 sightings of striped dolphins (Figure 11 for this last species) were kept in the current collated and prepared dataset. They were used to improve the estimates of detection probability in the distance sampling model (see below).

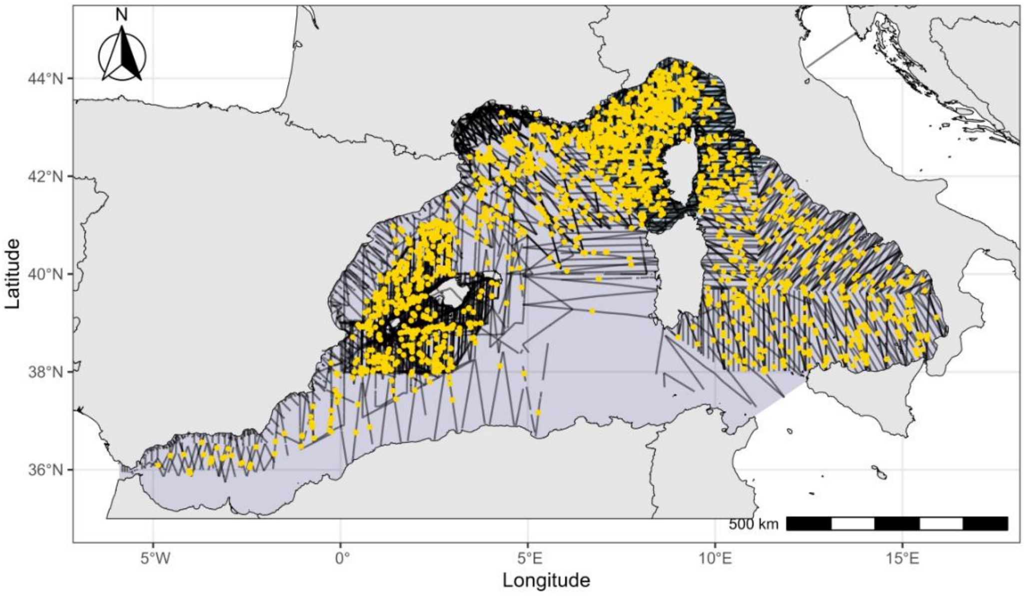



**Figure 11**: Spatial distribution of the sightings of Striped dolphin on gathered effort.

## 3/ Environmental Variables

The densities of cetacean species in the Pelagos Sanctuary were predicted from density surface models (Buckland et al. 2015, Miller et al. 2013) and marine environmental variables characterizing the area using relationships between environmental variables and cetacean densities estimated along the effort data. These models do not directly reflect the habitat of cetacean populations or their true distribution, but reflect maps where cetaceans are expected to occur.

Marine environmental variables have been used in previous studies to predict the density and distribution of marine mammals (Astarloa et al. 2021, Virgili et al. 2019, Waggitt et al. 2020). The two main challenges we face with cetacean species are their wide distribution and large movements making their distribution highly dynamic among and within years. Their distributions result from complex interactions of ecological processes including oceanographic and biological components (Croll et al. 1998, Barlow et al. 2020). Food availability plays a major role for their distribution (Benoit-Bird & Au, 2003; Hastie et al., 2004; Frederiksen et al., 2006). Unfortunately, robust data on the dynamics distribution of most prey of cetaceans were not available within the whole studied region, preventing us from directly using prey data to predict cetacean densities (Guisan & Zimmermann, 2000).

**Table 2**: Marine environmental covariables downloaded to predict densities of cetacean species. The static variable bathymetry was downloaded from the website of EMODnet (https://emodnet.ec. europa.eu/en/bathymetry). Other static variables: slope, aspect and roughness of the sea floor were derived from the variable bathymetry using the function terrain of the package terra (Hijmans et al. 2022) in the statistical software R. The dynamic variables: sea surface temperature, net primary productivity and marine currents were downloaded at a monthly temporal coverage from 2001 to 2023 from the website of Copernicus Marine Service (https://data.marine.copernicus. eu/products). Monthly temporal scale was chosen as the trade-off to minimize the amount of data download and to maximize potential predicted scale. Sea surface temperature gradient was derived from the sea surface temperature using the function DetecFronts of the package grec (Wencheng 2024) in the statistical software R.

| Environmental variable | | Original scale | Justification | Source |
|---|---|---|---|---|
| Static | Bathymetry (m) | 1/16 arc minute | Deep and shallow column waters influence the presence of variable preys (e.g. squids or fish species) | EMODnet |
| | Slope (rad) | | Associated with currents, high slopes induce enhanced primary production or prey aggregation | |
| | Aspect (rad) | | Describe currents and prominent structures such as canyons, seamounts or mountain chains, used as proxies for predator hotspots and useful in locations where access to biological data is limited | |
| | Roughness (m) | | Describe micro-irregularities in space, revealing heterogenous sea floor potentially enhancing diverse habitats and fish assemblages | |
| Dynamic | Sea surface temperature (SST) mean (°C) | 0.083 degree | Variability of SST over time and space influences directly prey and cetacean distributions | Copernicus |
| | Sea surface temperature gradient (°C/m) | | Horizontal gradients of SST reveal front locations, mixing of water and is associated with enhanced primary | |
| | Eddy kinetic Energy (EKE ; m/s) | | High EKE are linked to the development of eddies, upwelling of nutrients and enhanced primary production, which induce prey aggregation | |
| | Net primary productivity (NPPV ; mg.m-3.day-1) | 0.25 degree | Net primary production is a proxy of zooplankton distribution, feeding cetacean preys | |

Nevertheless, prey distribution can be correlated to oceanographic and physiographic environmental variables easier to collect at large spatial scale and with higher robustness (Forney 2020). These oceanographic variables are thus relevant to predict cetacean densities (Redfern et al., 2006, Forney 2020). A candidate set of static and dynamic variables has been selected based on their use in previous models of cetacean densities and their accessibility at large spatial scale. They are summarized in table 2.

Environmental variables were used to prepare prediction grids covering the Pelagos Sanctuary area and the Western Mediterranean MFSD region. Grids of 10km² resolution were prepared to be consistent with prepared segments of effort that have been cut every 10km. Environmental variables were also associated with the centroid of each segment of effort to perform the gap analysis and the density surface models.

The environmental variables included in prediction grids used to predict animal densities were averaged over the studied period and for each season considered: winter and summer from 2009 to 2023. Some environmental variables (sea surface temperature gradient and EKE), were missing but not randomly, they were missing often near the coast. These missing points were estimated using the package missMDA in R (Josse & Husson 2016) from a combination of linear relationships among all environmental variables. In this second step, we also used these linear relationships to predict missing data in the cells including the coast line to include them specifically in maps of predictions.

## 4/ Gap Analysis

The intermediate report concluded that the distribution of data over years was highly heterogeneous and no data were available before 2009 (Figure 12), and it was not possible to develop models on different temporal periods. Thus, in the analyses presented here, data from all years were pooled for each species.

Even after excluding among year variability, some of the predictions can be made in areas poorly informed by available data. To inform decision makers and stakeholders about the limits and uncertainty of the results, a gap analysis was performed. This gap analysis highlights temporal periods and spatial areas where predictions of cetacean densities will be highly uncertain because informed by few data.

### A/ Descriptive information

A first summary of the collated effort data revealed an unbalanced coverage of months (Figure 12). Most of the data was collected in Summer. To account for the biological phenology of species for which distribution might change with season, two seasons were considered for the analysis of cetacean distribution, abundance and densities: the summer season included the months from May to September and the winter season including the months from October to February. No data were collected in March and April.

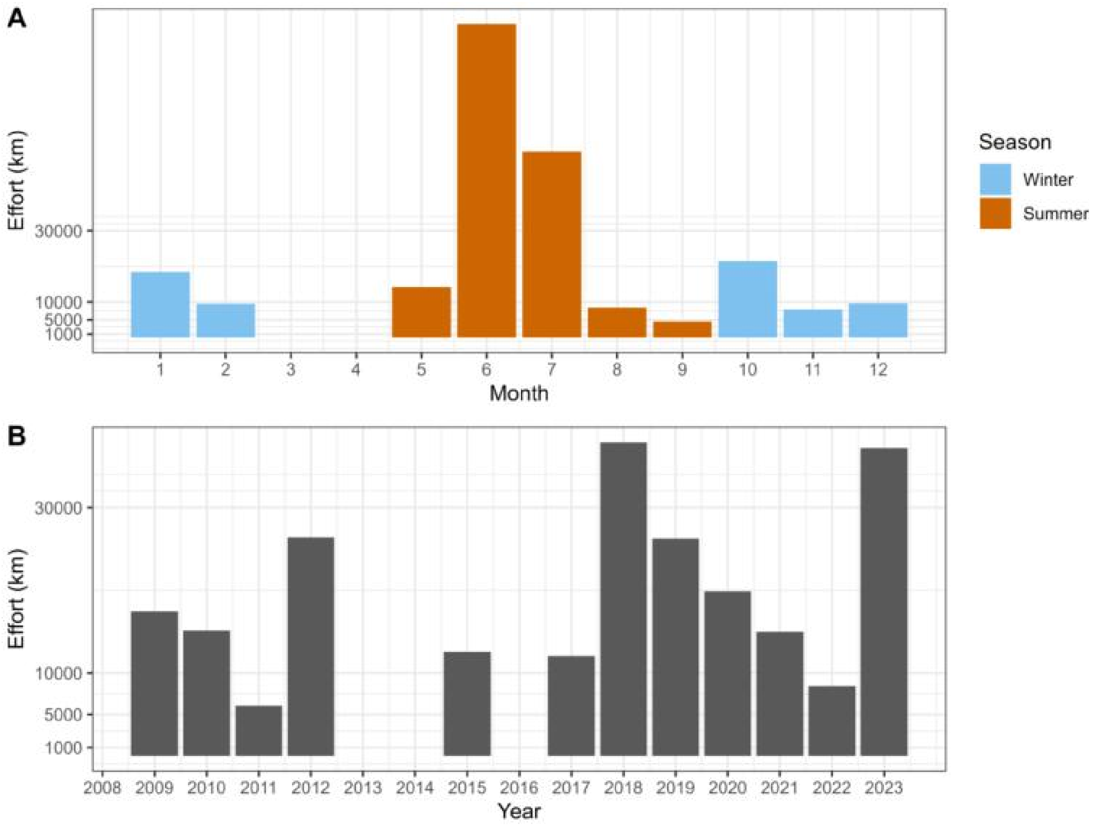



**Figure 12**: Number of kilometers of effort gathered per month (A) and per year (B), all surveys included.

In figure 13, the number of available kilometers of effort is shown according to the season of data collection on a logarithmic scale. This figure reveals very little data for purple, blue to dark green colours. Grey areas were not covered by any survey. From this raw analysis, we can see that the Pelagos Sanctuary was relatively well covered in the winter and summer seasons compared to other areas of the Western Mediterranean.

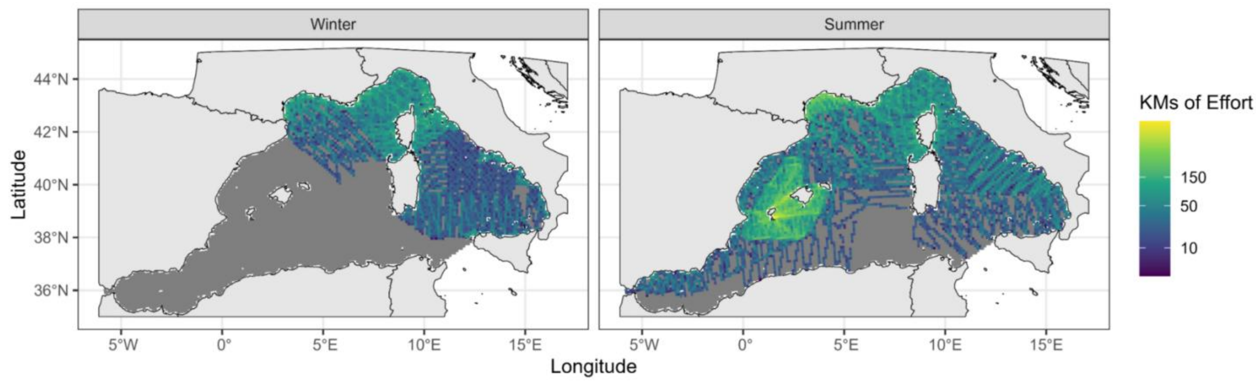



**Figure 12** : Spatial coverage of the number of kilometers of effort gathered per season.

## B/ Analysis

To be able to understand how all data from the Western Mediterranean region can inform prediction in the Pelagos Sanctuary, a gap analysis was performed. The gap analysis assumes that the Western Mediterranean region is a complex ecosystem that can be characterized by marine environmental variables (Tew Kai et al. 2020), the same ones as we described in the previous section. These environmental variables define an environmental space that shares similar or variable latitude, longitude, sea floor topography, current, surface temperature or primary production values in each season. We included latitude and longitude because the predictions of density surface models are often highly influenced by the spatial component including longitude and latitude. This environmental space can thus be studied with geometric tools including distance and hulls to realize a gap analysis. It will reveal spatial areas where predictions will be extrapolated (i.e. not informed by data but extrapolated from the model only) and areas where predictions will be interpolated from data (i.e. well informed by data) (Authier et al. 2017; Bouchet et al. 2019).

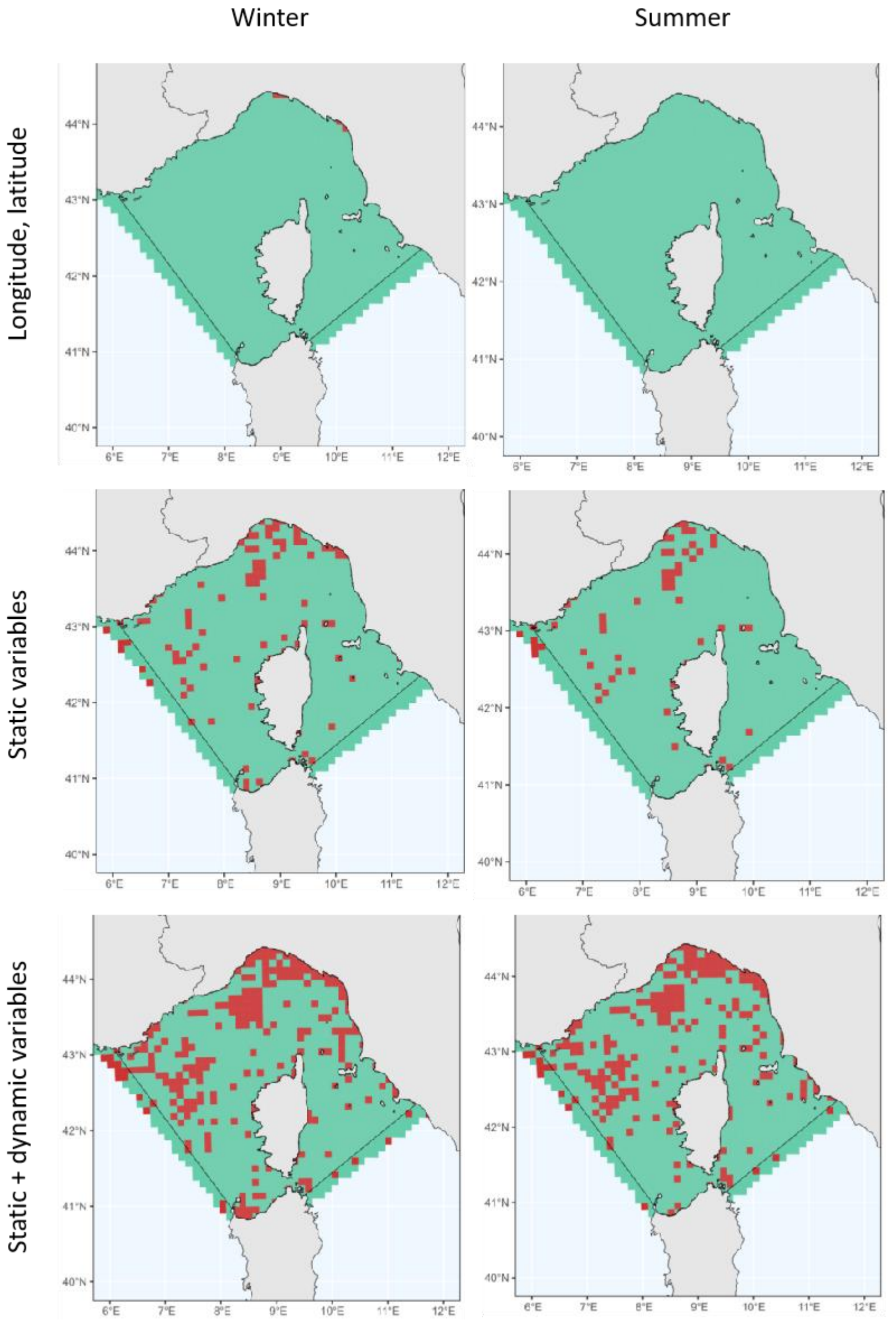
The first step of this gap analysis is thus to study how the available data covered this environmental space. An environmental space must be seen as a space of N-dimension where each dimension is a marine environmental variable. If we consider only two environmental variables such as latitude and longitude, a simple polygon including all data points can be created from the observed values of both variables at the centroid of each effort segment. The second step is to build the environmental space of the predicted area. Then, this analysis will reveal the gaps between the predicted and data-based environmental spaces and will allow us to map these gaps as extrapolations on the predicted maps. Three extrapolation analyses were performed with different environmental variables considered: 1/including only latitude and longitude, 2/ including static variables and 3/ including all (static and dynamic) environmental variables

A first result of this gap analysis informs about the extrapolated or interpolated value of each prediction point. The prediction points are the centroids of the cells forming the predicted maps (the different cells are visible on figure 14). I analysed if each prediction point was included or not within the data-based N-dimension environmental space. If a predicted point is included within this data-based environmental space, the associated prediction is considered as an interpolation (green cells) while if the point is outside of the data-based environmental space, it is considered as an extrapolation (red cells, Figure 14).

## C/ Results

The extrapolation analysis (Figure 14) shows that the Pelagos Sanctuary was broadly covered by data in winter and summer (first line of Figure 14). However, some small areas were not sampled (second line of Figure 14). Combinations of seasonal average of dynamic variables were different from the value of these variables during sampling periods in some areas (third line of Figure 14). Indeed, seasonal averages cover 6 months while data surveys often span less than a month in the season. Thus results might not reflect average seasonal densities but may be biased towards months when surveys were performed: June/July for the Summer season and October for the Winter season. Results for the Western Mediterranean are presented in Annexe A, Figures A1 and A2. In summer, the south of the Western Mediterranean was not covered. In winter, the south and West parts of the Western

Mediterranean were not sampled.




**<u>Figure 13</u>**: Gap Analysis: Interpolated (green) and Extrapolated (red) predictions per season. Three gap analyses have been performed: 1/ including only longitude/latitude, 2/ including static variables only, 3/ including static and dynamic variables.

The nearby analysis (Figure 15) reveals the same main patterns as the extrapolation analysis with more details. It shows that if we combine all years, most data in winter were collected in the Western part of the Pelagos Sanctuary. In summer, A large part of the data was collected around the Balearic Islands by the ICCAT survey. Thus, this analysis informs also about the potential weight of the different surveys included.

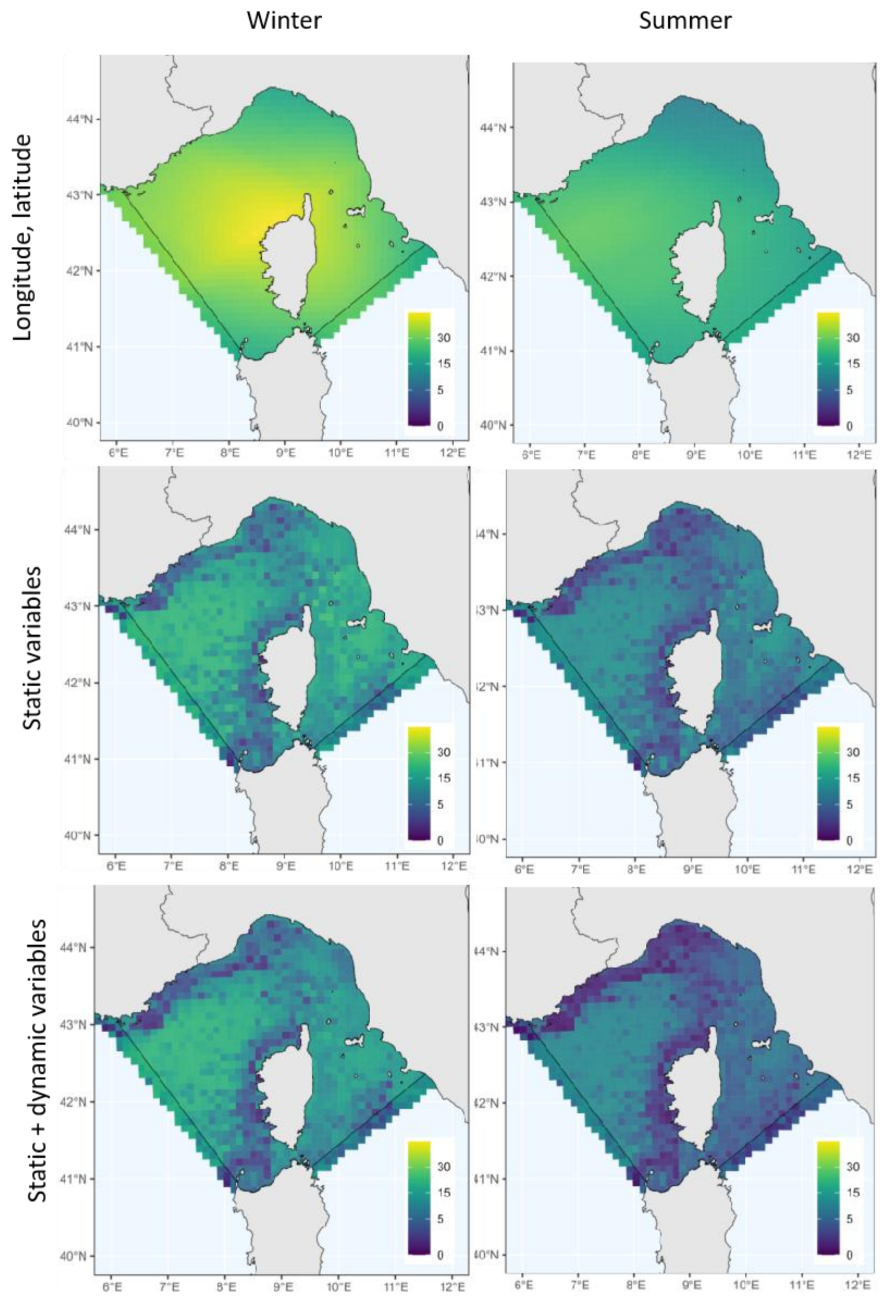



**Figure 14**: Gap Analysis: Percentage of data informing the prediction in each cell of the prediction grid per season. Three gap analyses have been performed: 1/ including only longitude/latitude, 2/ including static variables only, 3/ including static and dynamic variables.

## 5/ Corrected cetacean densities along effort data

A/ Analysis

Some animals remain undetected along transects. The probability of detection often varies with species and environmental conditions including the survey platform of observation, the meteorological conditions and the marine conditions during the survey. The probability to detect an individual or group of individuals often decreases with increasing distance to the transect line (Miller et al. 2017). Distance sampling models are commonly used to estimate the probability of detection for a given species in a given survey (Buckland et al. 2001, Buckland et al. 2015). The declining detection probability is modelled by a decreasing function, often a half-normal or a hazard rate function (Buckland et al. 2015). This function is fitted to the observed number of detections according to observed perpendicular distances to the transect line (Figure 15). Distance sampling models aim to estimate the area actually covered by the survey. To do this, they estimate the effective strip half width (ESW), the distance at which as many animals are seen beyond it as are missed up to it, to deduce the effective area sampled during the line transect survey (Buckland et al. 2001). This value accounts for the missing individuals and is used to derive corrected animal densities.

This analysis gives robust results for common species with many detections but results are more uncertain for rare species (Buckland et al. 2015, Miller et al. 2017, Figure 15). To increase the accuracy and precision of estimated ESW, I used a new methodology (Plard et al. 2024) based on pooling information from multiple species and surveys. Pooling observations with expected similar detection functions is a statistical technique to increase precision (Marques et al. 2007). However when pooling multiple survey and species, one must also account for the heterogeneity in detection probabilities among survey and species (see pooling robustness, Buckland et al. 2015, Rexstad et al. 2023) as pooling species or survey with heterogeneous detection functions would result in biased ESW. Sighting data from multiple surveys and species shared common information about the influence of the increasing distance from the transect line and the environmental conditions on the probability to detect individuals. In this new methodology, this information will be used to increase precision in ESW using fusion effects (Malsiner-Walli et al. 2018, Plard et al. 2024). Fusion effects are state of the art statistical methods that allow the clustering of homogeneous categories of one variable automatically (Malsiner-Walli et al. 2018, Miller and Harrison 2018, Hu et al. 2022). Implemented in distance sampling models, this new method allows grouping surveys and/or species with homogeneous detection probabilities automatically while keeping apart heterogeneous ones. This methodology has been tested using simulation analyses and showed that in all cases, results using fusion effects were as or more precise and accurate than common distance sampling models (Plard et al. 2024).

Using this methodology, I analyzed separately boat and aerial surveys to account for the heterogeneous detection probabilities of these two types of surveys. The distributions of perpendicular distances including or not «attracted dolphins» were similar, so all detections were used for this analysis. Attracted individuals concerned only bottlenose dolphin that are seen close to the boat in most cases. 1km was used as truncation distance for aerial data. For boat surveys, few cetaceans were detected, so the following species were analysed only: bottlenose dolphin, striped dolphin, common dolphin, fin whale and sperm whales were grouped with undetermined large whales to get an ESW for sperm whale from boat surveys. All observations were included with a maximum of 3 km for sperm whales, 2,5 km for fin whales and 1km for other species.

Because this call aims to predict the densities of rare species (sperm whale, Cuvier's beaked whale and fin whale), all data collected in Beaufort lower than 6 were used and Beaufort was added as an explanatory variable in the based model to account for variable probability detections in variable marine conditions. I also tested the effect of subjective conditions as a continuous variable from 1 to 4 to account for the effect of bad environmental conditions on detection probabilities. Thus, 2 based models have been created. The first one included the variable beaufort in interaction with species and survey ID. The second one included subjective conditions in interaction with species and survey ID. Beaufort and subjective conditions have not been included in the same model as these two variables are highly correlated. Survey ID and species have been included as fusion effects. All models from the based models to the simplest model including only the additive effect of survey ID and species have been tested and compared by wAIC (Watanabe 2013). The simplest model within a delta-wAIC of 2 from the model with the lowest wAIC has been selected to respect the rule of parsimony. Both hazard rate and half normal detection functions have been tested.

## B/ Results

### -- *Boat surveys*

Regarding the low number of detections from boat surveys, the models including hazard rate functions did not converge. Models including beaufort as an additive variable did not converge either. Thus, the models presented here are the model including a half normal probability detection function and subjective conditions as a variable accounting for heterogeneity in marine conditions. The selected model to describe the probability of detection from boat vessels included an additive effect of subjective conditions in addition to the effect of species and survey ID (Table 3).

**Table 3:** Comparison of models of detection functions for boat surveys. Models using half normal probability detection functions are shown. k gives the number of parameters.

| | Half Normal | |
|---|---|---|
| **Model** | **k** | **wAIC** |
| G(Species):Subjective + Subjective:G(SurveyID) | 18 | 150 |
| G(Species) +Subjective:G(SurveyID) | 13 | 150 |
| G(Species) + G(SurveyID) + Subjective | 10 | 151 |
| G(SurveyID) + G(Species):Subjective | 14 | 151 |
| G(Species) + G(SurveyID) | 9 | 154 |

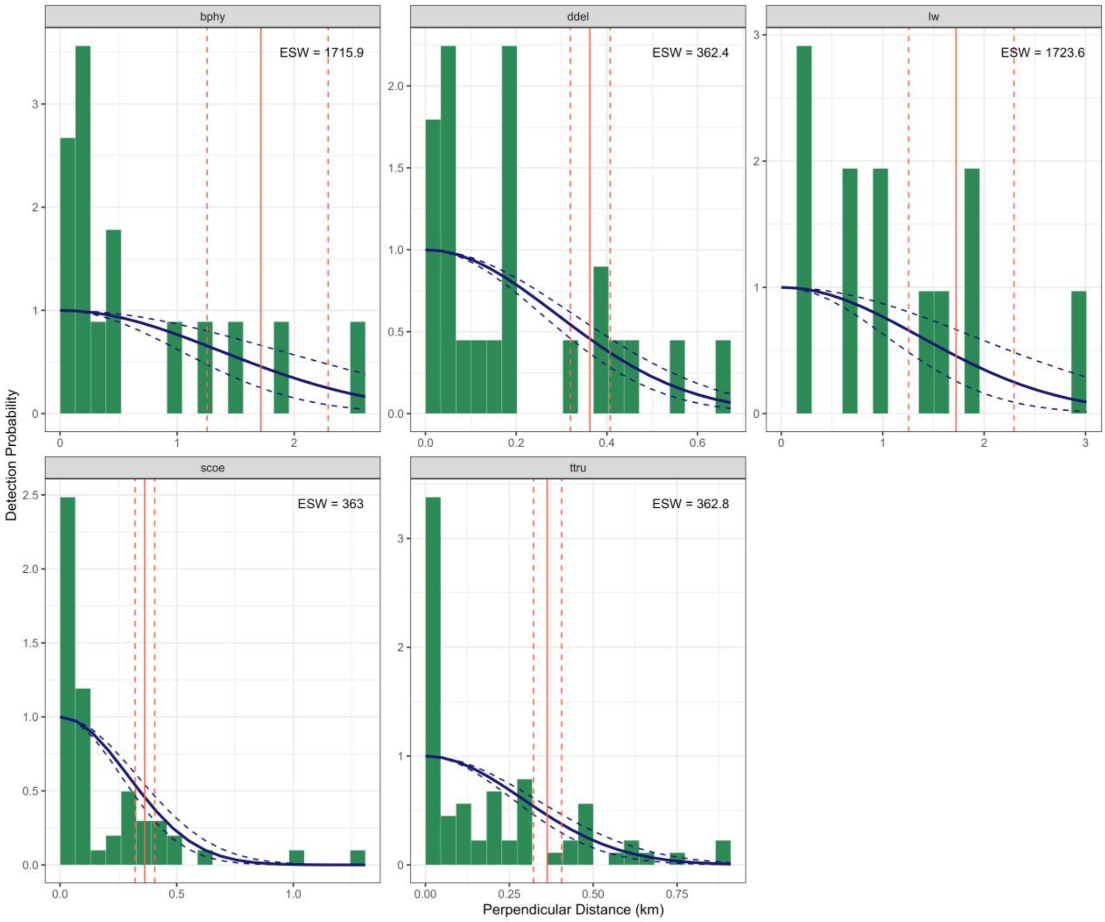



**Figure 15**: Fit of detection functions of the selected model for boat surveys using a half normal detection function (dark blue) on histograms of the number of sightings per km to the transect line on five species: the fin whale (bphy), the common dolphin (ddel), large whales (lw including sperm whale), the striped dolphin (scoe), and the bottlenose dolphin (ttru). Red lines show the estimated ESW. Dotted lines show uncertainty (95% credible intervals) around the mean (plain line) for ESWs and for detection functions.

All surveys have been merged into one unique group by the fusion effect showing no detectable heterogeneity among boat surveys. Species have been split into 2 different groups: the large whales including fin whale, undetermined large whale and sperm whale with an ESW of a bit more than 1700 m and a group of dolphins including common dolphin, striped dolphin and bottlenose dolphin with an ESW of 362 m (see Figure 16 for the value for each species and credible intervals) in average conditions. The subjective conditions showed a negative effect on the probability of detection, the distance decreasing as the conditions deteriorate (Figure 17, Table A1). The selected model showed good convergence (Figure A3) but the fit to the data for the different species were heterogeneous with poor fit for large whales, fin whales and common dolphin.

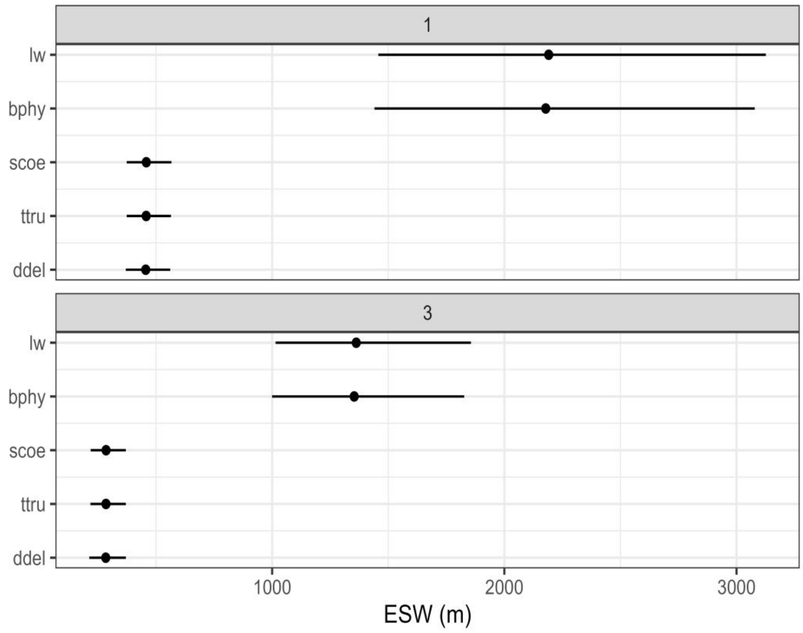



**Figure 16**: ESW of the 5 species estimated from the selected distance sampling model on boat surveys using fusion effect for species and Survey ID, and an additive effect of subjective conditions. The two plots show predictions for ESW at Subjective condition 1 (Good, top) and 3 (Low, bottom). Each line represent a species: the fin whale (bphy), the common dolphin (ddel), large whales (lw including sperm whale), the striped dolphin (scoe), and the bottlenose dolphin (ttru). Mean ESW are represented by the points and credible intervals at 95% are shown by the horizontal lines.

### --*Aerial Surveys*

**Table 4:** Comparison of models of detection functions for aerial surveys. k gives the number of parameters.

| | Hazard rate | | Half Normal | |
|---|---|---|---|---|
| **Model** | **k** | **wAIC** | **k** | **wAIC** |
| G(Species) + Beaufort:G(SurveyID) | 33 | 19822 | 32 | -260 |
| G(Species) + G(SurveyID) + Beaufort | 22 | 19825 | 21 | -258 |
| G(Species):Beaufort + Beaufort:G(SurveyID) | 41 | 19805 | 40 | -243 |
| G(SurveyID) + G(Species):Beaufort | 29 | 19815 | 28 | -242 |
| G(Species) + Subjective:G(SurveyID) | 33 | 20531 | 32 | -239 |
| G(Species) + G(SurveyID) | 21 | 19833 | 20 | -229 |
| G(Species) + G(SurveyID) + Subjective | 22 | 19825 | 21 | -227 |
| G(Species):Subjective + Subjective:G(SurveyID) | 41 | 19846 | 40 | -226 |
| G(SurveyID) + G(Species):Subjective | 29 | 19838 | 28 | -215 |

The selected model (the simplest model with the lowest wAIC within a Delta wAIC of 2 from the lowest wAIC) was the same from models including a hazard rate or a half-normal detection function from aerial vessels. It included an additive effect of beaufort in addition to the effect of species and survey ID (Second model, Table 4). I selected the model using a half normal detection function as the fits were better but results from the model using a hazard rate function are displayed in Figure A5.

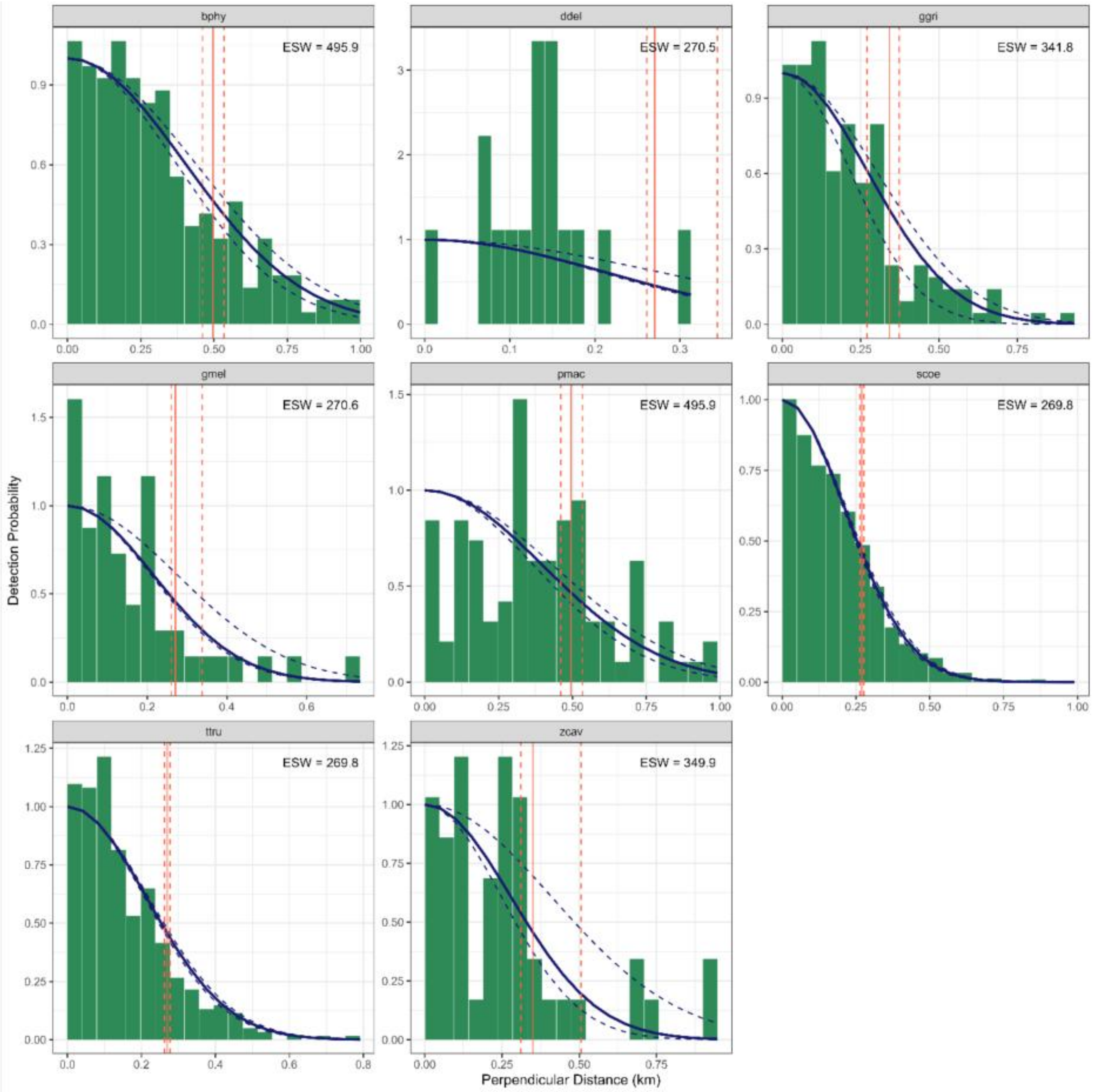



**Figure 17**: Fit of detection functions of the selected model for aerial surveys using a half normal detection function (dark blue) on histograms of the number of sightings per km to the transect line on the eight species: the fin whale (bphy), the common dolphin (ddel), the Risso's dolphin (ggri), the long-finned pilot whale (gmel), the sperm whale (pmac), the striped dolphin (scoe), the bottlenose dolphin (ttru), and the Cuvier's beaked whale (zcav). Red lines show the estimated ESW. Dotted lines show uncertainty (95% credible intervals) around the mean (plain line) for ESWs and for detection functions.

Surveys have been merged into three groups: SAMM and DMESAL with the lowest ESW; the second group included ASI, ISPRA 2023 fall and summer, PelaTir 2020, DMLEBA, and Pelagos 2009 winter; the last group with the largest ESW included ICCAT, PelaTir 2010, and Pelagos 2009 summer (Figure 19). Species have also been split into 3 different groups: the large whales including fin whale, and sperm whale with an ESW of 496 m; the second group including Risso's dolphin, and Cuvier's beaked whale with an ESW of about 345 m and the last group including other dolphins and long-finned pilot whale with an ESW of 270 m (see Figures 18 & 19 for the value for each species and credible intervals) in average conditions of Beaufort and survey. The Beaufort showed a negative effect on the probability of detection, the distance decreasing as the marine conditions deteriorated (Figure 19, Table A2). The selected model showed good convergence (Figure A4) and good fit to the raw data.

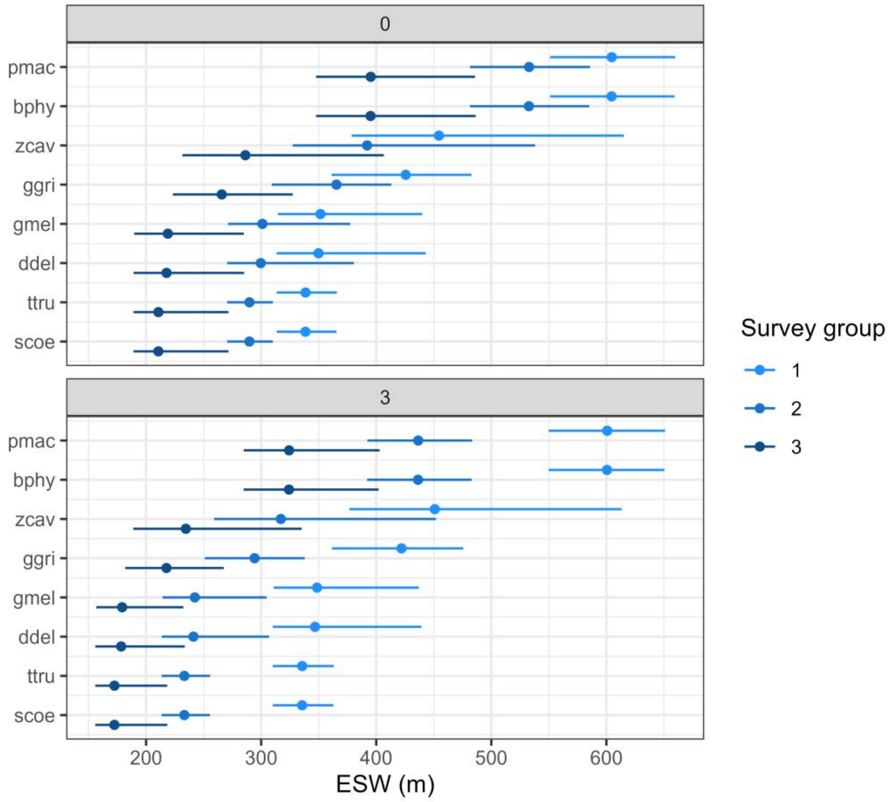



**Figure 18**: ESW of the 8 species estimated from the selected distance sampling model on aerial surveys using fusion effect for species and Survey ID, and an additive effect of Beaufort. The two plots show predictions for ESW at Beaufort 0 (top) and 3 (bottom). Each line represents a species: the fin whale (bphy), the common dolphin (ddel), the Risso's dolphin (ggri), the long-finned pilot whale (gmel), the sperm whale (pmac), the striped dolphin (scoe), the bottlenose dolphin (ttru), and the Cuvier's beaked whale (zcav). The three colors represent predictions for the three groups of surveys. Mean ESW are represented by the points and credible intervals at 95% are shown by the horizontal lines.

## 6/ Abundance and density maps

### A/ Analysis

The results of the distance sampling models allowed to derive the corrected densities of cetaceans on each segment of the effort data from the number of detected animals and ESW. Because distance sampling models assume perfect detection on the transect line, estimated animal densities should theoretically be further corrected by bias availability (Marsh & Sinclair 1989, Buckland et al. 2004, Barlow 2015) before using them to estimate abundance and density maps. The most common reason why cetacean individuals are not available to be detected is them being submerged when diving. This availability bias is particularly important in species such as sperm whale, fin whale and Cuvier's Beaked whale. Bias availability has not been estimated from the gathered survey data used in this analysis. Thus, previous estimates of bias availability have been collected from the literature (Virgili et al. 2019, Sigournay et al. 2020, Okamura et al. 2012, Laran et al. 2017) and similar surveys using robust protocol (SCANS IV, Gilles et al. 2023, SCANS III Hammond et al. 2021). These estimates were used to correct animal densities. Because these values are highly uncertain but have a great impact on abundance predictions, models have been done both on animal densities corrected and uncorrected by bias availability. Values used for bias availability are gathered in Annexe A, Table A3.

Density surface models were used (DSM, Elith, J. & Leathwick 2009, Buckland et al. 2015, Miller et al. 2013) to estimate the relationship between cetacean densities and environmental variables (listed in table 2). Aerial data were used for all species but boat data only for striped dolphin, bottlenose dolphin, and fin whale as the number of detections from boat surveys were too low for other species. Because complex relationships were expected between environmental variables and cetacean densities (see environmental variables part), additive generalized linear models (GAMs) were used as they are able to account for highly flexible relationships (Wood 2006). For each species, a set of models including all combinations of three (or less) selected environmental variables was run. This combination included a maximum of three covariates to avoid excessive complexity of models and difficulty in their interpretation (Mannocci et al., 2014). This combination excluded correlated covariates. The correlation between slope and roughness was very high (0.98). Thus, the variable roughness was deleted from the selected environmental static variables.

Each DSM model also included a spatial smooth entered as an interactive field between latitude and longitude. A barrier spatial model (Bakka et al. 2019) including the physical borders of Corsica, Sardinia and the Balearic Islands has also been tested using knots forming a mesh over the predicted areas. However some knots poorly informed by the data predicted implausible values. Season (Winter vs. Summer) has been included in interaction with the spatial smooth. The consequence of this modelisation is that predictions for the two seasons can be largely independent. The maximum number of knots allowed for each smooth (spatial and environmental variables) was 6 to avoid high complexity in the model.

The five best fitting models were selected using the Leave-one-out Information Criterion (LOOIC) developed by Vehtari et al. (2017, 2020). To avoid losing any important effect and getting results reflecting a model choice only, the five best selected models were averaged using a stacking method (Yao et al. 2018). This method combines and weights the predictions of different models to get averaged predictions. Median densities of each species in the Pelagos sanctuary and the Western Mediterranean were predicted using these five staged best models from the environmental covariates describing the areas. To reflect the uncertainty in predictions, coefficients of variation of animal densities and extrapolated predictions are reported. Coefficients of variation were estimated for each predicted cell as the median absolute deviation divided by the median density from the DSM model. For each model, extrapolated predictions were highlighted (white cells in predicted maps) using the specific environmental variables selected in the five best models. The analysis is similar as the one explained in the part 4/Gap Analysis.

Abundance were predicted from the staged five best selected models using densities uncorrected by bias availability. It was estimated as the weighted (over the five best models) sum of the median densities in each cell by the area (10km x 10km) of the cell. 80% confidence intervals of the abundance were estimated using the matrix of variance covariance of estimated parameters from the staged five best selected models.

## B/ Results

### -- *Fin whale*

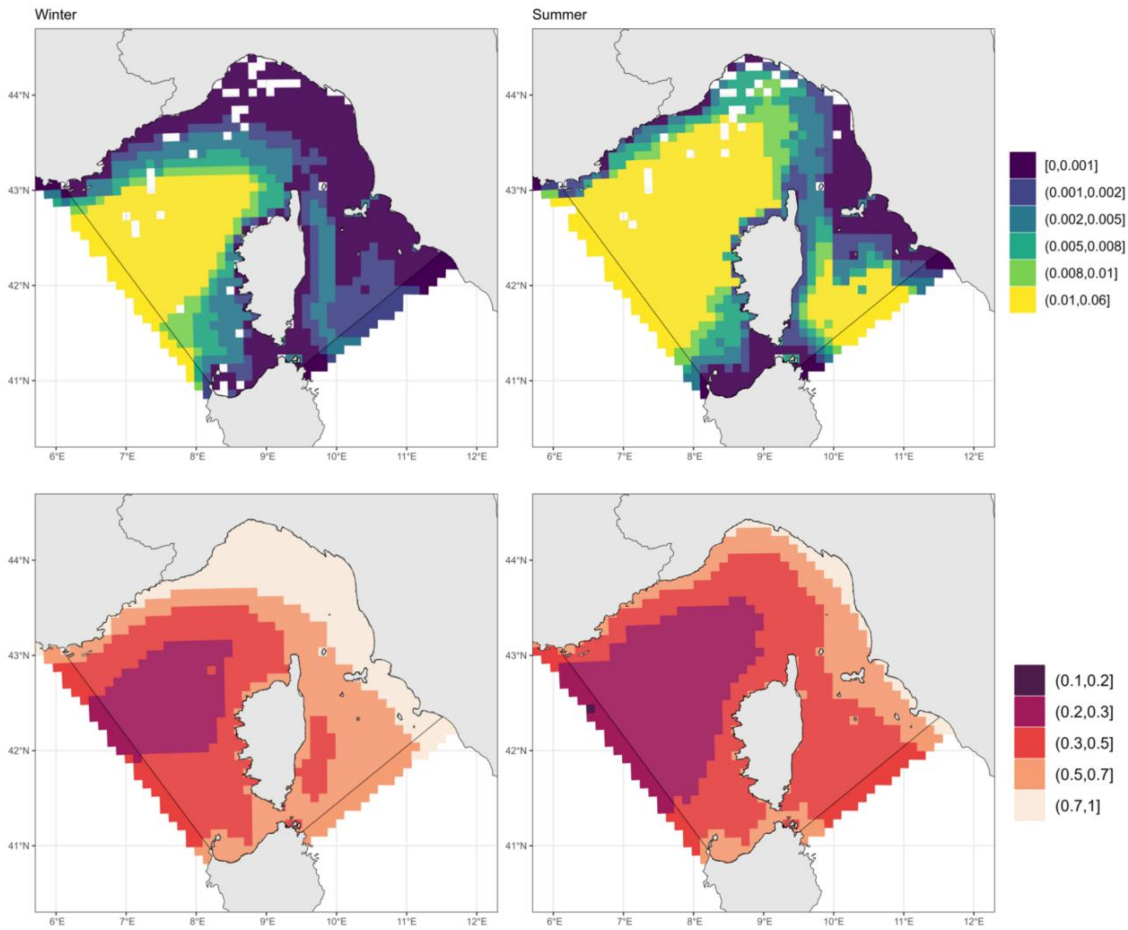
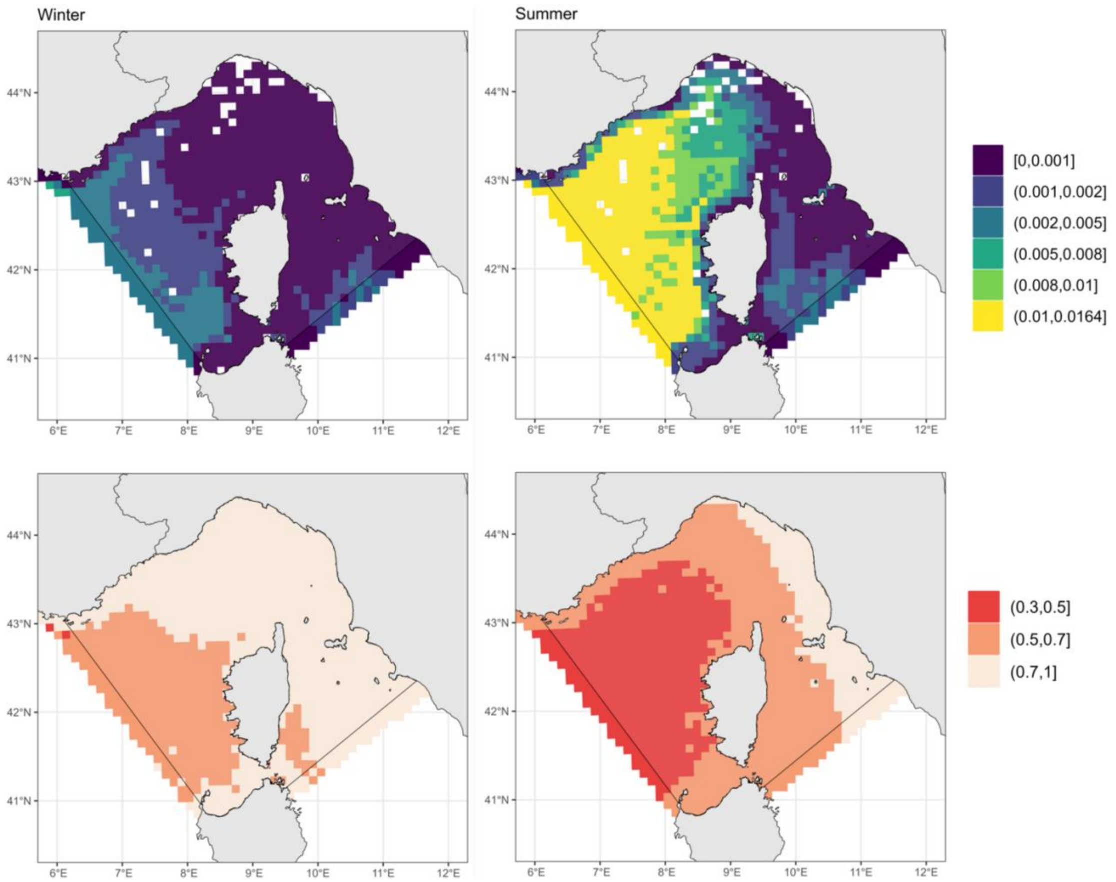



**Figure 19**: Predicted densities (top) and coefficients of variation (bottom) of the fin whale (*Balaenoptera physalus*) in the Pelagos Sanctuary in winter (left) and summer (right). Predictions of the model using densities corrected by g0 (bias availability) are shown. Densities are the number of individuals per km². Areas left in white are extrapolated areas.

The five best selected models for fin whales included the bathymetry, the slope, the aspect, the SST gradient and the EKE with a main effect of bathymetry (Annexe C: Figure C1 & Table C1). Fin whales were predicted to be mostly present in the deep waters of the Pelagos

Sanctuary in both seasons. In winter, they seem to be more present in the South part of their distribution area (Figure 20, Annexe B: Figure B1). Coefficients of variation are relatively good for summer but higher in winter near the coast (Figure 20). Abundance of fin whales has been estimated at 216 [175:264] in winter and 536 [452:616] in summer in the Pelagos Sanctuary from the models uncorrected by bias availability (Table 5, Table B1). Here and below, confident intervals at 80% are given in square brackets.

### -- *Sperm whale*




**<u>Figure 20</u>**: Predicted densities (top) and coefficients of variation (bottom) of the sperm whale (*Physeter macrocephalus*) in the Pelagos Sanctuary in winter (left) and summer (right). Predictions of the model using densities corrected by g0 (bias availability) are shown. Densities are the number of individuals per km². Areas left in white are extrapolated areas.

The five best selected models for sperm whales included the bathymetry, the SST, the aspect, and the SST gradient with a main effect of bathymetry, SST, and aspect (Figure C2, Table C2). Sperm whales were predicted to be mostly present in the Western part of the Pelagos Sanctuary. They are not present in winter (Figure 21, Figure B2). Coefficients of variation are relatively high in the Eastern part of the Pelagos Sanctuary and very high in winter in general, showing the relatively high uncertainty around these maps (Figure 21). Abundance of sperm whales has been estimated at 16 [6:25] in winter and 92 [48:120] in summer in the Pelagos Sanctuary from the models uncorrected by bias availability (Table 5, Table B1).

### -- *Bottlenose dolphin*

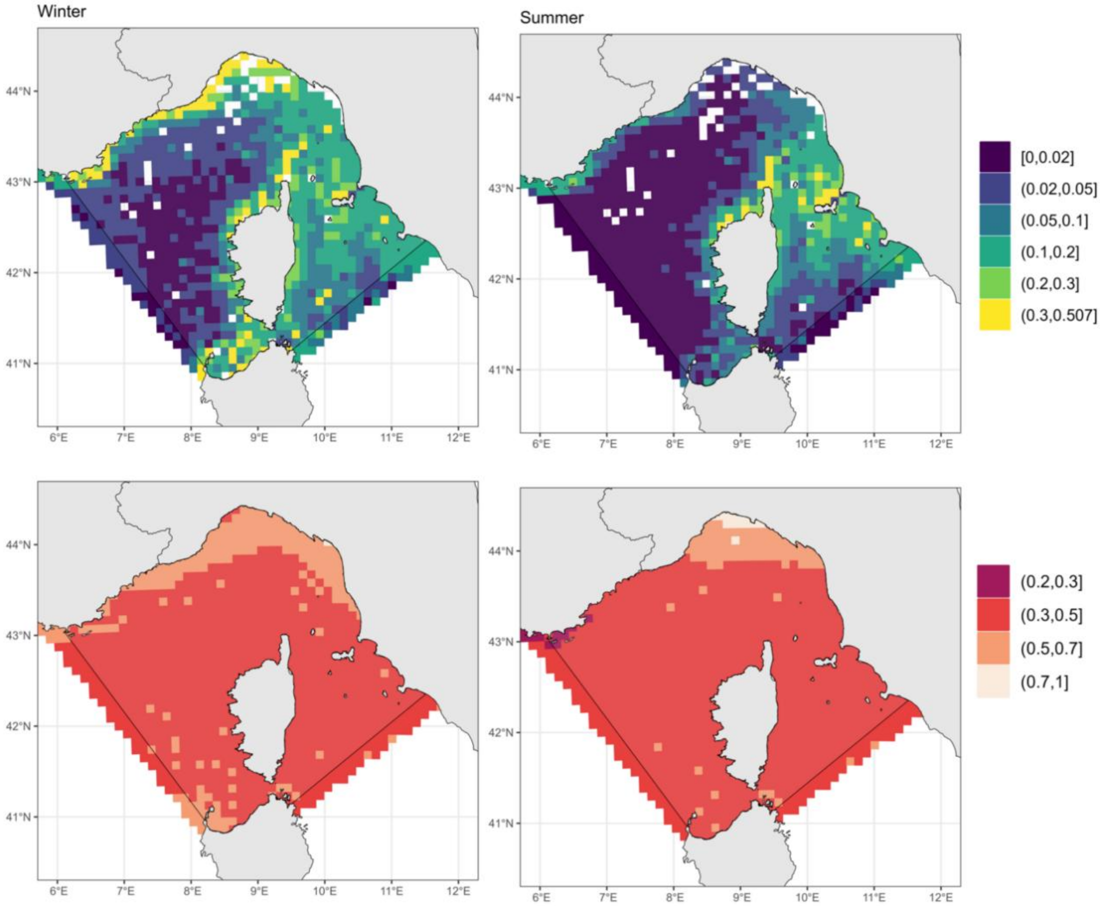



**Figure 21**: Predicted densities (top) and coefficients of variation (bottom) of the Bottlenose dolphin (T*ursiops truncatus*) in the Pelagos Sanctuary in winter (left) and summer (right). Predictions of the model using densities corrected by g0 (bias availability) are shown. Densities are the number of individuals per km². Areas left in white are extrapolated areas.

The five best selected models for bottlenose dolphin included the bathymetry, the slope, the SST gradient, and the EKE with a main effect of bathymetry, and aspect (Figure C3, Table C3). Bottlenose dolphins are often found near the coast. The models predictions revealed a higher density East of Corsica in Summer. In winter, their density increased also on the north coast of Italy, and on the coasts of Monaco and France (Figure 22, Figure B3). Coefficients of variation are relatively low in both seasons, showing the relatively low uncertainty of these maps (Figure 22). Abundance of Bottlenose dolphins has been estimated at 4936 [3499:6127] in winter and 2500 [1789:3135] in summer in the Pelagos Sanctuary from the models uncorrected by bias availability (Table 5, Table B1).

### -- *Cuvier's beaked whale*

The five best selected models for Cuvier's beaked whale included the bathymetry, the SST, the aspect, EKE, and the SST gradient with a main effect of bathymetry and SST (Figure

C4, Table C4). Cuvier's beaked whales were predicted to be rare in the Sanctuary but can be found on the slope and in the Tyrrhenian sea south east of Corsica (Figure 23, Figure B4). Coefficients of variation are high, showing the relatively high uncertainty around these maps in both seasons (Figure 23). Abundance of Cuvier's beaked whales has been estimated at 63 [31:94] in winter and 180 [68:273] in summer in the Pelagos Sanctuary from the models uncorrected by bias availability (Table 5, Table B1).

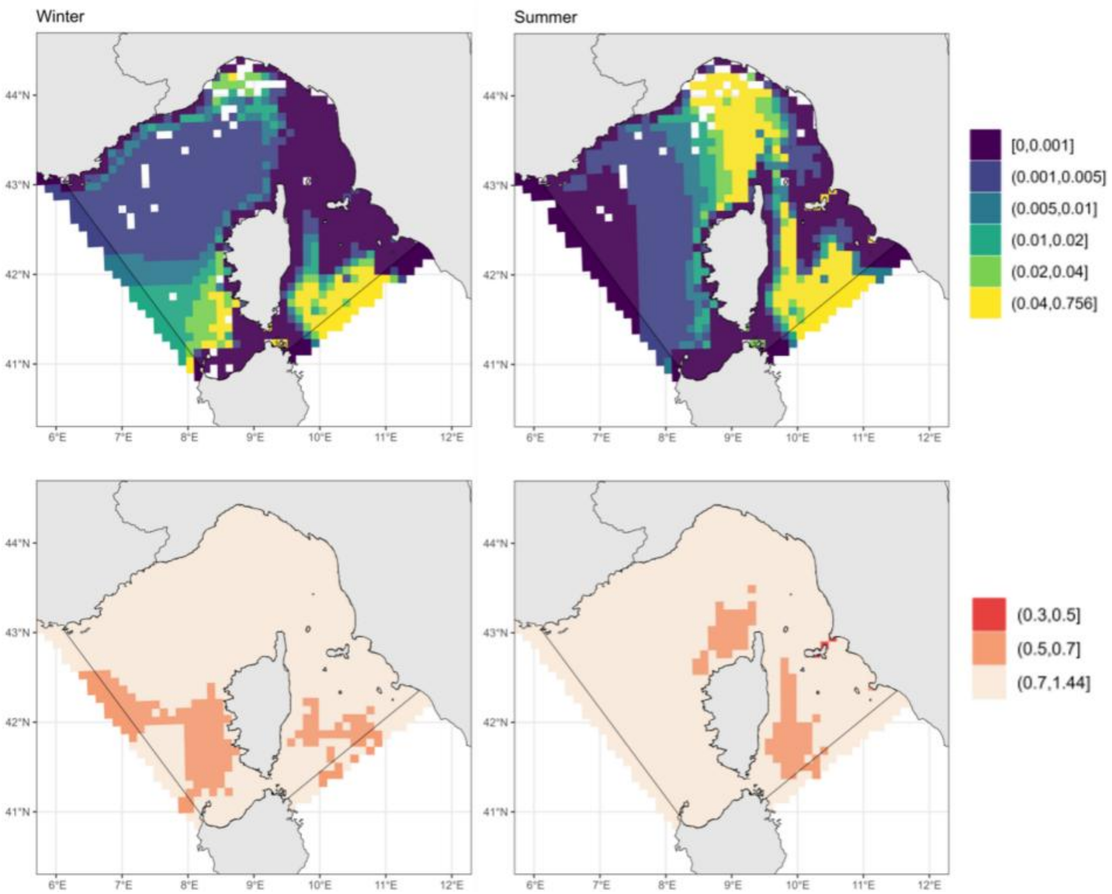



**Figure 22**: Predicted densities (top) and coefficients of variation (bottom) of the Cuvier's beaked whale (*Ziphius cavirostris*) in the Pelagos Sanctuary in winter (left) and summer (right). Predictions of the model using densities corrected by g0 (bias availability) are shown. Densities are the number of individuals per km². Areas left in white are extrapolated areas.

*-- Other species*

The five best selected models for striped dolphins included the bathymetry, the SST, the NPPV, the slope and the SST gradient (Figure C5, Table C5). Striped dolphins were predicted in high numbers year round in the Pelagos Sanctuary. Highest densities are predicted to occur in summer in the West of Corsica (Figure B5-B6). Coefficients of variation are relatively low showing the relatively low uncertainty around these maps (Figure B6). Abundance of striped dolphins has been estimated at 45093 [37155:52180] in winter and 61612 [51839:71834] in summer in the Pelagos Sanctuary (Table B1).

The predicted models for Risso's dolphins and long-finned pilot whales show relatively high uncertainty. They are presented in Figures B7 to B10 and models are shown in Figures C6-C7 and Tables C6-C7 .

**Table 5:** Abundance of cetacean species in the Pelagos Sanctuary estimated using densities uncorrected by g0, the bias availability. 80% confidence intervals are given.

| Species | Season | median | CI-10% | CI-90% | CV |
|---|---|---|---|---|---|
| **Bottlenose dolphin** | Summer | 2500 | 1789 | 3135 | 0,25 |
| **Bottlenose dolphin** | Winter | 4936 | 3499 | 6127 | 0,25 |
| **Cuvier's beaked whale** | Summer | 180 | 68 | 273 | 0,78 |
| **Cuvier's beaked whale** | Winter | 63 | 31 | 94 | 0,56 |
| **Fin whale** | Summer | 536 | 452 | 616 | 0,18 |
| **Fin whale** | Winter | 216 | 175 | 264 | 0,13 |
| **Sperm whale** | Summer | 92 | 48 | 120 | 0,34 |
| **Sperm whale** | Winter | 16 | 6 | 25 | 0,67 |

## 7/ Discussion

The results of this analysis revealed high variation in temporal and spatial coverage of cetaceans densities in the Pelagos Sanctuary. The predictions for two seasons: the summer and the winter have been produced. However more data were available in summer than in winter making summer maps more robust than winter maps. Data have been pooled over years, so variation among-year was not analyzed. While we know populations are dynamics and abundance and densities might change over years, the available data limited this work to produce results that do not vary over time. Nevertheless, these maps are still very useful as they give standardized predictions informed by all available robust datasets of cetaceans densities in the Pelagos Sanctuary and the Western Mediterranean.

The predictions showed variations between seasons for most species and particularly for sperm whales and striped dolphins. No report has used season as a factor in DSM model to predict variation among seasons as it was done here. Usually, variation among seasons are predicted from variation in environmental variables between seasons (Cañadas et al. 2024, Waggitt et al. 2020) but not from different spatial distribution of species. Here, even using a very flexible model for season, the density maps were similar for some species, highlighting the robustness of the results. A model including an interaction between season and environmental variables was also tested but it was not retained as it gave overfitted predictions for most species. An interaction between the spatial smooth and season was preferred so the models were able to reflect true variation in spatial distribution between seasons.

Predicted density maps are similar to maps obtained by the NAVFAC report (Cañadas et al. 2024), especially for fin whales or bottlenose dolphins. However maps of Cuvier's beaked whales and sperm whales differed. These species are less abundant and coefficients of variation show high uncertainties for these maps. The difference between maps can result from an heterogeneity among data used in the different analyses. In the present analysis, the dataset was restricted to data sampled with a distance sampling protocol only and might miss some areas not sampled. Data collected from robust protocols only have been gathered to limit the uncertainty due to data collection and heterogeneity. In the NAVFAC report, opportunistic data were also used and sampling bias or preferential sampling of opportunistic data might not have been corrected for, while it can greatly influence the results (Gelfand et Shirota 2019, Simmonds et al. 2020).

For the bottlenose dolphin, the main difference is the presence of this species in large densities around the Balearic islands in the NAVFAC report while the present report predicts medium to low densities of bottlenose dolphins around the Balearic islands. This low density of bottlenose dolphins around the islands can be a true result regarding the very high sample effort from ICCAT in this region or we can also hypothesize that this specific survey did not detect all dolphins as their main goal was to collect tuna detections, which might have biased data collection. The very high densities of sperm whales found around the Balearic islands in summer and around Naples in Winter in the NAVFAC report may, however, look like a bias due to preferential sampling. In the current report, sperm whales were predicted to be found in relatively large densities in a large zone from South of the Balearic Island to Corsica and Sardinia (as also reported by Boisseau et al. 2024). In both reports, Cuvier's beaked whales were predicted near the coast of Gena. In the present report, relatively high densities of this species was found South-West Corsica and in the North of the Tyrrhenian sea.

In the predicted maps, only interpolated areas are shown while extrapolated areas are left blank. Extrapolated areas cover the West and South of the Western Mediterranean in winter. In summer, no data has been collected in the south western Mediterranean. However for the Pelagos Sanctuary, most of the predictions are interpolated from the data. While the fit of distance sampling models were questionable for boat surveys, both boat and aerial surveys have been used to predict the densities of 3 species: striped dolphin, bottlenose dolphin, and fin whale. The predictions did not change much if we included both datasets or only aerial data.

Abundance were reported from models using densities uncorrected by the availability bias. Indeed, as this correcting factor has a very large impact on abundance estimates and because g0 values have not been estimated from the surveys that were included in the analysis, it was decided to show only uncorrected values. This way, anyone can choose a given correcting factor to correct the abundance values and then compare them to other abundance estimates.

# References


Astarloa, A., Glennie, R., Chust, G., García-Baron, I., Boyra, G., Martínez, U., Rubio, A. & Louzao, M. (2021) Niche segregation mechanisms in marine apex predators inhabiting dynamic environments. Diversity and Distributions 27, 799–815

Authier, M., Saraux, C., & Péron, C. (2017). Variable selection and accurate predictions in habitat modelling: A shrinkage approach. Ecography, 40, 549–560.

Bakka, H., Vanhatalo, J., Illian, J. B., Simpson, D., & Rue, H. (2019). Non-stationary Gaussian models with physical barriers. Spatial statistics, 29, 268-288.

Barlow, J. (2015) Inferring trackline detection probabilities, g(0), for cetaceans from apparent densities in different survey conditions. Marine Mammal Science 31, 923–943.

Barlow, D., Bernard, K., Escobar-Flores, P., Palacios, D., Torres, L. (2020) Links in the trophic chain: Modeling functional relationships between in situ oceanography, krill, and blue whale distribution under different oceanographic regimes. Marine Ecology Progress Series, 642, 207–225.

Benoit-Bird, K.J., & Au, W.W.L. (2003). Prey dynamics affect foraging by a pelagic predator (Stenella longirostris) over a range of spatial and temporal scales. Behavioral Ecology and Sociobiology, 53, 364–373.

Boisseau, O., Reid, J., Ryan, C., Moscrop, A., McLanaghan, R., & Panigada, S. (2024). Acoustic estimates of sperm whale abundance in the Mediterranean Sea as part of the ACCOBAMS Survey Initiative. Frontiers in Marine Science, 11, 1164026.

Bouchet, P.J.; Miller, D.L.; Roberts, J.J.; Mannocci, L.; Harris, C.M. & Thomas, L. (2019) From Here and Now to There and Then: Practical Recommendations for Extrapolating Cetacean Density Surface Models to Novel Conditions. University of Saint Andrews

Buckland, S.T.; Anderson, D.R.; Burnham, K.P. & Laake, J.L. (1993) Distance Sampling - Estimating Abundance of Biological Populations. Chapman & Hall, 1st Edition.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L. & Thomas, L. (2001) Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press Oxford.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L. & Thomas, L. (2004) Advanced distance sampling: estimating abundance of biological populations. Oxford University Press Oxford.

Buckland, S.T., Rexstad, E.A., Marques, T.A. & Oedekoven, C.S. (2015) Distance sampling: methods and applications, vol. 431. Springer.

Cañadas, A., Roberts, J. J., Yack, T. M. & Halpin P. N. (2024) Marine species density models for the Mediterranean and Black seas. Naval Facilities Engineering Systems Command Atlantic, for U.S.

Croll, D.A., Tershy, B.R., Hewitt, R. P., Demer, D.A., Fiedler, P.C., Smith, S.E., Armstrong, W., Popp, J. M., Kiekhefer, T., Lopez, V.R., Urban, J., Gendron, D. (1998) An integrated approch to the foraging ecology of marine birds and mammals. Deep-Sea Research Part II: Topical Studies in Oceanography, 45, 1353–1371.

Drouot, V., Gannier, A., & Goold, J. C. (2004). Diving and feeding behaviour of sperm whales (Physeter macrocephalus) in the northwestern Mediterranean Sea. Aquatic mammals, 30(3), 419-426

Elith, J. & Leathwick, J.R. (2009) Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution and Systematics 40, 677–697.

Field, S.A., Tyre, A.J. & Possingham, H.P. (2005) Optimizing allocation of monitoring effort under economic and observational constraints. The Journal of Wildlife Management 69, 473–482.

Frederiksen, M., Edwards, M., Richardson, A.J., Halliday, N.C., & Wanless, S. (2006). From plankton to top predators: Bottom-up control of a marine food web across four trophic levels. Journal of Animal Ecology, 75, 1259–1268.

Freeman, M.M. (2008) Challenges of assessing cetacean population recovery and conservation status. Endangered Species Research 6, 173–184

Forney K.A. (2000) Environmental Models of Cetacean Abundance: Reducing Uncertainty in Population Trends. Conservation Biology, 14, 1271–1286.

Gelfand, A. E., & Shirota, S. (2019). Preferential sampling for presence/absence data and for fusion of presence/absence data with presence-only data. Ecological Monographs, 89(3), e01372.

Gilles A, Authier M,Ramirez-Martinez NC, Araújo H,Blanchard A, Carlström J, ..., Hammond PS (2023) Estimates of cetacean abundance in European Atlantic waters in summer 2022 from the SCANS-IV aerial and shipboard surveys

Guisan, A., & Zimmermann, N.E. (2000). Predictive habitat distribution models in ecology. Ecological Modelling, 135, 147–186.

Hammond, P.S., Macleod, K., Berggren, P., Borchers, D.L., Burt, L., Cañadas, A., Desportes, G., Donovan, G.P., Gilles, A., Gillespie, D. et al. (2013) Cetacean abundance and distribution in European Atlantic shelf waters to inform conservation and management. Biological Conservation 164, 107–122.

Hammond, P.S.; Lacey, C.; Gilles, A.; Viquerat, S.; Börjesson, P.; Herr, H.; MacLeod, K.; Ridoux, V.; Santos, M.B.; Scheidat, M.; Teilmann, J.; Vingada, J. & Øien, N. (2021a) Estimates of Cetacean Abundance in European Atlantic Waters in Summer 2016 from the SCANS-III Aerial and Shipboard Surveys. Sea Mammal Research Unit, University of Saint Andrews, UK.

Hammond, P.S., Francis, T.B., Heinemann, D., Long, K.J., Moore, J.E., Punt, A.E., Reeves, R.R., Sepúlveda, M., Sigurðsson, G.M., Siple, M.C. et al. (2021b) Estimating the abundance of marine mammal populations. Frontiers in Marine Science 8, 1316.

Hastie, G.D., Wilson, B., Wilson, L.J., Parsons, K.M., & Thompson, P.M. (2004). Functional mechanisms underlying cetacean distribution patterns: Hotspots for bottlenose dolphins are linked to foraging. Marine Biology, 144, 397–403

Hijmans, R. J., Bivand, R., Forner, K., Ooms, J., Pebesma, E., & Sumner, M. D. (2022). Package 'terra'. *Maintainer: Vienna, Austria*.

Hu, G., Yang, H.C., Xue, Y. & Dey, D.K. (2022) Zero-inflated poisson model with clustered regression coefficients: Application to heterogeneity learning of field goal attempts of professional basketball players. Canadian Journal of Statistics, *51*, 157-172

Jewell, R., Thomas, L., Harris, C.M., Kaschner, K., Wiff, R., Hammond, P.S. & Quick, N.J. (2012) Global analysis of cetacean line-transect surveys: detecting trends in cetacean density. Marine Ecology Progress Series 453, 227–240.

Josse J, Husson F (2016). "missMDA: A Package for Handling Missing Values in Multivariate Data Analysis." Journal of Statistical Software, 70(1), 1–31.

Laran, S., Authier, M., Blanck, A., Doremus, G., Falchetto, H., Monestiez, P., Pettex, E., Stephan, E., Van Canneyt, O. & Ridoux, V. (2017) Seasonal distribution and 42 960 abundance of cetaceans within French waters-Part II: The Bay of Biscay and the English Channel. Deep Sea Research Part II: Topical Studies in Oceanography 141, 31–40

Malsiner-Walli, G., Pauger, D. & Wagner, H. (2018) Effect fusion using model-based clustering. Statistical Modelling 18, 175–196.

Mannocci, L., Catalogna, M., Dorémus, G., Laran, S., Lehodey, P., Massart, W., ... & Ridoux, V. (2014). Predicting cetacean and seabird habitats across a productivity gradient in the South Pacific gyre. Progress in Oceanography, 120, 383-398.

Marques, T.A., Thomas, L., Fancy, S.G. & Buckland, S.T. (2007) Improving estimates of bird density using multiple-covariate distance sampling. The Auk 124, 1229–1243.

Marsh, H. & Sinclair, D.F. (1989) Correcting for visibility bias in strip transect aerial surveys of aquatic fauna. The Journal of Wildlife Management 53, 1017–1024

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, 880–890

Miller, D.L., Burt, M.L., Rexstad, E.A. & Thomas, L. (2013) Spatial models for distance sampling data: recent developments and future directions. Methods in Ecology and Evolution 4, 1001–1010.

Miller, D.L., Rexstad, E., Thomas, L., Marshall, L. & Laake, J.L. (2017) Distance sampling in r. BioRxiv p. 063891.

Miller, J.W. & Harrison, M.T. (2018) Mixture models with a prior on the number of components. Journal of the American Statistical Association 113, 340–356.

Moore, J. E., & Barlow, J. P. (2013). Declining abundance of beaked whales (Family Ziphiidae) in the California current large marine ecosystem. PLoS One, 8(1), e52770.

Okamura, H., Minamikawa, S., Skaug, H. J., & Kishiro, T. (2012). Abundance estimation of long-diving animals using line transect methods. Biometrics, 68, 504-513.

Pace, D., Tizzi, R. & Mussi, B. (2015) Cetaceans value and conservation in the Mediterranean Sea. Journal of Biodiversity & Endangered Species 2015, 1-24.

Plard, F., Araújo, H., Astarloa, A., Louzao, M., Saavedra, C., Bonales, J.A.V., ... & Authier, M. (2024). Using fusion effects to decrease uncertainty in distance sampling models when collating data from different surveys. Marine Mammal Science.

Redfern, J. V., Ferguson, M., Becker, E. A., Hyrenbach, K. D., Good, C., Barlow, J., Kaschner, K., … & Werner, F. (2006) Techniques for Cetacean–Habitat Modelling. Marine Ecology Progress Series, 310, 271-295

Rexstad, E., Buckland, S., Marshall, L. & Borchers, D. (2023) Pooling robustness in distance sampling: Avoiding bias when there is unmodelled heterogeneity. Ecology and Evolution 13, e9684

Sigourney, D. B., Chavez-Rosales, S., Conn, P. B., Garrison, L., Josephson, E., & Palka, D. (2020). Developing and assessing a density surface model in a Bayesian hierarchical framework with a focus on uncertainty: insights from simulations and an application to fin whales (Balaenoptera physalus). PeerJ, 8, e8226.

Sigourney, D. B., DeAngelis, A., Cholewiak, D., & Palka, D. (2023). Combining passive acoustic data from a towed hydrophone array with visual line transect data to estimate abundance and availability bias of sperm whales (Physeter macrocephalus). PeerJ, 11, e15850

Simmonds, E. G., Jarvis, S. G., Henrys, P. A., Isaac, N. J., & O'Hara, R. B. (2020). Is more data always better? A simulation study of benefits and limitations of integrated distribution models. Ecography, 43(10), 1413-1422

Tew-Kai E, Quilfen V, Cachera M, Boutet M (2020) Dynamic Coastal-Shelf Seascapes to Support Marine Policies Using Operational Coastal Oceanography: The French Example. Journal of Marine Science and Engineering, 8, 585.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Statistics and computing, 27, 1413-1432.

Vehtari A, Gabry J, Magnusson M, Yao Y, Bürkner P, Paananen T, Gelman A (2020). “loo: Efficient leave-one-out cross-validation and WAIC for Bayesian models.” In R package version 2.4.1, .

Virgili, A., Authier, M., Boisseau, O., Cañadas, A., Claridge, D., Cole, T., Corkeron, P., Dorémus, G., David, L., Di-Méglio, N., Dunn, C., Dunn, T. E., García-Barón, I., Laran, S., Lauriano, G., Lewis, M., Louzao, M., Mannocci, L., Martínez-Cedeira, J., … Ridoux, V. (2019). Combining multiple visual surveys to model the habitat of deep-diving cetaceans at the basin scale: Large-scale modelling of deep-diving cetacean habitats. Global Ecology and Biogeography, 28, 300–314.

Wade, P. R. (1998) Calculating Limits To the Total Allowable Human-Caused Mortality of Cetaceans and Pinnipeds. Marine Mammal Science, 14, 1-37

Waggitt, J.J., Evans, P.G., Andrade, J., Banks, A.N., Boisseau, O., Bolton, M., ... & Hiddink, J.G. (2020). Distribution maps of cetacean and seabird populations in the North-East Atlantic. Journal of Applied Ecology, 57, 253-269.

Watanabe, S. (2013). A widely applicable Bayesian information criterion. The Journal of Machine Learning Research, 14(1), 867-897.

Wencheng L.M. (2024) Package Gradient-Based Recognition of Spatial Patterns in Environmental Data Version 1.6.0.

Wood, S. N. (2017). Generalized additive models: an introduction with R. chapman and hall/CRC.

Yao Y., Vehtari A., Simpson D. & Gelman A., 2018. Using Stacking to Average Bayesian Predictive Distributions (with Discussion) Bayesian Analysis, 13: 917-100.