August 2023

A common workflow to inform MFSD indicators for marine mammals in the Bay of Biscay & Iberian coast subregion

CetAMBICion

Coordinated Cetacean Assessment,
Monitoring and Management Strategy
in the Bay of Biscay and Iberian Coast sub-region

WP 2 - Task 2.1

CetAMBICion Deliverables 2.2a & 2.2b

Version of August 2023

Drafted by:

In the framework of the CetAMBICion project:

Coordinated Cetacean Assessment, Monitoring and Management Strategy in the Bay of Biscay and Iberian Coast sub-region (CetAMBICion).

The CetAMBICion project, coordinated by the Spanish National Research Council (CSIC) and which includes 15 partners from Spain, France and Portugal, aims to strengthen collaboration and scientific work between the three countries to estimate and reduce cetacean bycatch in the subregion "Bay of Biscay and Iberian Coast", in close collaboration with the fishing industry. Until 2023, the project will work to improve scientific knowledge on population abundance, incidental bycatch and on mitigation measures of the latter.

The project is part of the European Commission's DG ENV/MSFD 2020 (Marine Strategy Framework Directive) call and the objectives are aligned with the Habitats Directive and the Common Fisheries Policy too.

Document Control Sheet

Project	CetAMBICion
Title	Coordinated Cetacean Assessment, Monitoring and Management strategy in the Bay of Biscay and Iberian Coast subregion
Reference	GA No. 110661/2020/839610/SUB/ENV.C2
Coordinator	CSIC
WP	WP2
WP Title	Proposal of coordinated subregional assessment, GES determination and monitoring strategy for cetaceans
Document Type	Deliverable
Document number	CetAMBICion D2.2a
Document Name	A common workflow to inform MFSD indicators for marine mammals in the Bay of Biscay & Iberian coast subregion
Date prepared	2022-11-07
Date revised	2023-08-01
Pages	27
Leader partner	LRUniv/ADERA/AZTI
Participants partners	DGRM; ICNF; IPMA; CHMAR, SEMA; IEO; CSIC; OFB
Authors	Plard Floriane, Authier Matthieu
Reviewers	Teresa Moura (IPMA), Marina Sequeira (ICFN), Ana Mafalda Correia & Cláudia Rodriguez (CIIMAR), Amaia Astarloa Diaz & Javier Franco (AZTI), Andreia Pereira (DGRM), Ana Iñigo (FundacionBiodiversidad), Ruth Fernandez (Advisory Board)

Executive summary

To facilitate the assessment of MFSD indicators for cetacean species under Descriptor 1 and the abundance (D1C2) and distribution (D1C4) criteria, a common workflow among the three European Union (EU) Member States (MS) with waters belonging to the Bay of Biscay & Iberian coast subregion (namely Portugal, Spain, and France) has been developed. The aim of this workflow is to increase the comparability of indicators obtained by the three MS. This workflow allows the collation and common analyses of all data gathered in the subregion to estimate marine mammal species abundance and predict distribution maps. The objectives of this task were threefold. First, a new statistical method: distance sampling including fusion effects, has been developed to analyse together data collected in different surveys by the different MS. This method allows getting estimates with greater precision from distance sampling models. Second, numerical tools to use this workflow and reproduce analyses have been created in the form of the R package AMBldsm (available here). It includes an analytical pipeline to enable data collation and indicator production through a set of friendly-user functions to solve this complex task. Finally, a Shiny application has been developed to visualize marine mammal species distribution maps and abundances (available here).

Recommendations

- Use the AMBIdsm R package to improve comparability of indicator estimates among MS;
- Use mainly summer predictions of marine mammal distribution and abundance. Spring, Winter and Autumn predictions are less robust as they are informed by fewer data;
- Improve geographically coherent sampling of the subregion with surveys also targeting offshore areas;
- Improve temporally coherent sampling of the subregion with surveys in all seasons.

INDEX

Acronyms and Abbreviations

AZTI: Center of scientific research on marine ecosystems based in the Spanish Basque country (https://www.azti.es/).

CODA: Cetacean Offshore Distribution and Abundance, a large-scale ship survey to estimate the abundance and investigate the habitat use of cetacean species in European Atlantic waters beyond the continental shelf that took place in summer 2007.

DS: Distance Sampling.

DSM: Density Surface Model.

ES: Spain.

ESW: effective strip half-width.

EU: European Union.

FR: France.

g(0) : detection probability on the transect line.

GAM: Generalized Additive Model.

GES: Good Environmental Status.

ICES: International Council for the Exploration of the Sea (https://www.ices.dk/Pages/default.aspx).

Ifremer: 'Institut Français de Recherche pour l'Exploitation de la Mer' (https://wwz.ifremer.fr/).

IEO: Spanish Institute of Oceanography (http://www.ieo.es/es/).

IPMA: Portuguese Institute of Marine and Atmospheric Sciences (Instituto Português do Mar e da Atmosfera, https://www.ipma.pt/pt/index.html).

MSFD: Marine Strategy Framework Directive.

ObSERVE: Irish survey of megafauna.

OSPAR: Oslo-Paris convention.

PT: Portugal.

SCANS: Small Cetaceans in the European Atlantic and North Sea, large-scale ship and aerial survey to study the distribution and abundance of cetaceans in European Atlantic waters that takes place in summer.

SDM: Species Distribution Model.

WP: Work package of the CetAMBICion project.

List of Contents

Tables

Figures

1. Introduction

The aim of the work Package 2 of Cetambicion is to coordinate subregional assessments, Good Environmental Status (GES) determination and a monitoring strategy for cetaceans in the MSFD subregion “Bay of Biscay and Iberian Coast”. The determination of GES depends on the definition of indicators and of suitable methods to measure them. Estimates of these indicators are then compared to threshold values to assess the GES of each species. The list of species and definition of indicators were agreed in task 2.2, while the threshold values will be discussed in task 2.3. The general objective of task 2.1 is to combine the data collected by the three countries to estimate the abundance and distribution of cetacean species in their national waters and to develop a suitable methodological framework to analyse collated data together and to provide estimates of key indicators under Descriptor 1 abundance (D1C2) and distribution (D1C4).

Deliverable 2.1 detailed how data extracted from ship- and plane-based surveys, using a distance sampling protocol for recording cetacean sightings, were collated. A total of 242,646 km of dedicated and ecosystemic/multidisciplinary survey effort accomplished between 2005 and 2021 were compiled for WP2: corresponding to an approximate tally of 57,200 common dolphins; 7,300 bottlenose dolphins; 6,300 striped dolphins; 3,500 long-finned pilot whales; 1,400 fin whales; 500 harbour porpoises; 350 Risso's dolphins, 100 Cuvier's beaked whales; 100 sperm whales and 100 minke whales.

A coherent methodological framework is needed to analyse these heterogeneous datasets. The present deliverable presents the methodological framework that was developed in Task 2.1 to provide estimates of key indicators under Descriptor 1 abundance (D1C2) and distribution (D1C4). The challenge was to create an efficient and reproducible methodology able to regroup and analyse heterogenous data. The three following objectives have been achieved and are detailed in the three next sections:

- The development of a new statistical model to enhance data collation and estimate effective strip half-width (ESW) with reduced uncertainty in distance sampling models
- The creation of practical, reproducible and efficient tools to apply this methodological framework
- The creation of an application to visualize predicted abundances and density maps of cetacean species in the Bay of Biscay and the Iberian coast subregion

2. A new statistical model to make the most of heterogeneous data in distance sampling models

Bias and precision of statistical estimates such as abundance depend both on the quality of the input data and the statistical models used to analyse it. The first step to getting unbiased and precise estimates is to collect data using robust design protocols such as distance sampling (DS; Buckland et al. 2004) where the probability to detect an individual can be estimated in relation to the distance of detection and environmental conditions during observation (Buckland et al. 2004). The second step to getting unbiased and precise estimates, is to use a statistical model able to account for the variability of the data. Using a collated dataset has the advantage to increase the information available to estimate abundance but has the disadvantage to potentially increase heterogeneity within data. A very simple example illustrating the bias induced by heterogeneity within data is if two surveys carried out in poor and good environmental conditions are combined, the statistical model must be able to correct abundance estimates in relation to low and high detection probabilities instead of estimating abundance as the average between the number of detections made during the two surveys.

To make the most of this heterogeneous dataset, a new methodology was developed in Task 2.1 to be able to analyse distance sampling data combining detections from different species and surveys, in one model. In summary, statistical fusion effects were included in distance sampling models. 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.

By analysing together all available information while correcting for species and surveys heterogeneity in detection probabilities, this new model allows for higher precision in estimates of densities in the areas monitored by the surveys.

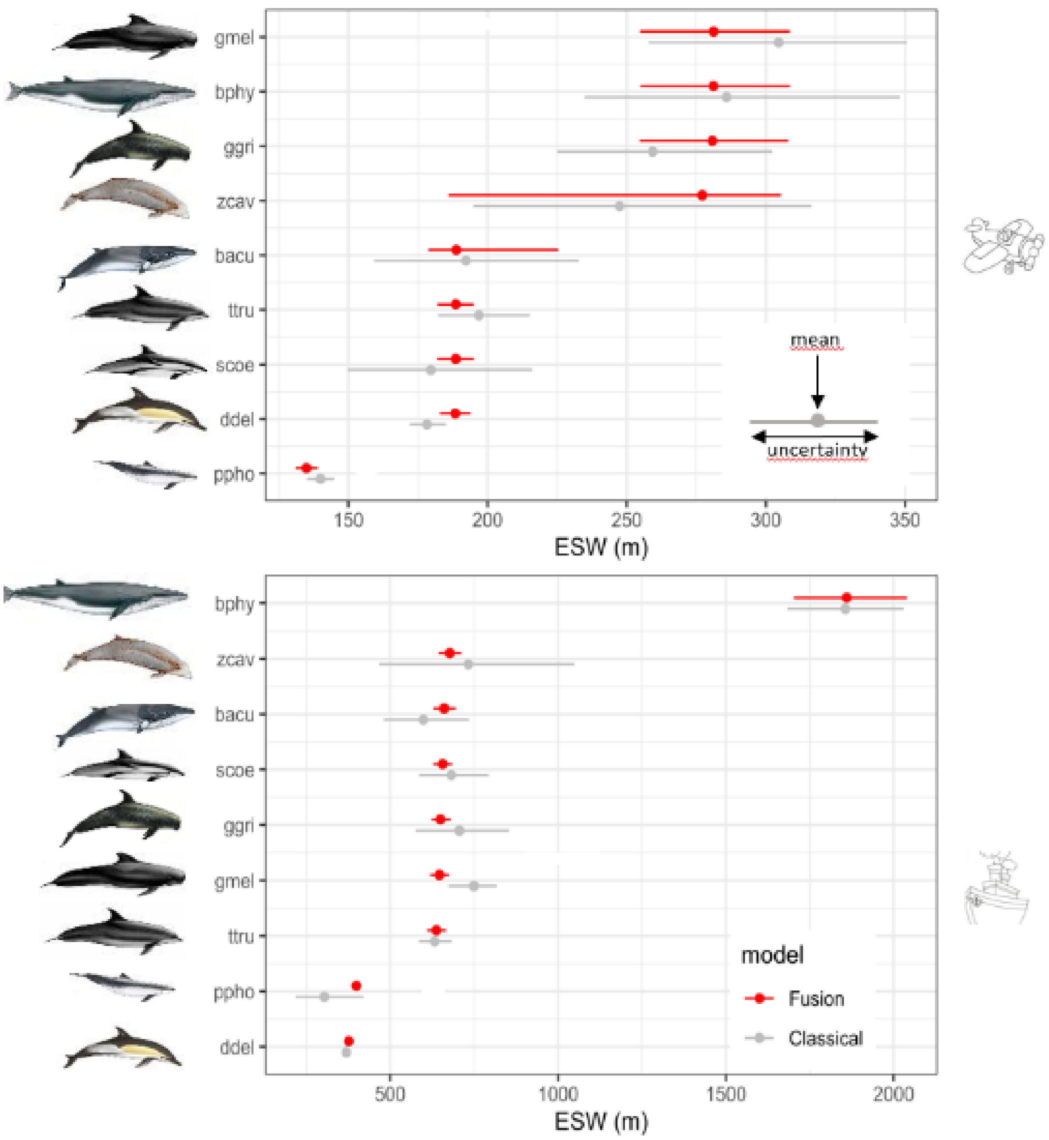

Figure 1: Representation of the reduced uncertainty in Effective strip half width (ESW) estimated from DS models using fusion vs. classical statistical effects. Classical statistical effects are defined as simple categorical effects (also sometimes called factor effects) of species and surveys. Local densities are then deduced from the number of detected animals and ESW. Mean and uncertainty (95% credible interval) in ESW are shown with dot and line respectively. Top panel: plane surveys; bottom panel: ship surveys.

A simulation analysis was performed to demonstrate the performance of this new DS model including the fusion effect compared to models classically used until now: DS models including factor or random effects. This analysis showed that DS models using fusion effects had a greatly reduced uncertainty in all cases and a lower bias than alternative models. We applied this method to the data collated from the three partner countries under task 2.1 (Figure 1). Results showed a reduced uncertainty in ESW estimated from models using fusion effects when compared to classical DS model (Figure 1).

Densities and ESW estimated with this new model can be used to estimate abundance and build density maps both via Density Surface Models (DSM) or species distribution models (SDM). A scientific publication is currently being revised for the journal *Marine Mammal Science*. This contribution will be useful for future analysis of large collated datasets. To make the methodology more user-friendly, we have added a group of functions to the R package (AMBIdsm, Table 1) that can be used to build and run this new model.

3. An R package for practical, reproducible and efficient use of the common methodological framework

To enhance the comparability and reproducibility of complex analyses, we set up a common framework. We wrote efficient R functions that implement a common methodology to estimate abundance and density maps in the R package: AMBIdsm. The main functionalities of the package that correspond to the different parts of the methodology are presented below (Table 1 & Figure 2).

a- Format data

Data collected by the different partners are heterogeneous and saved in different formats. A first step is to homogenize datasets, such that they become comparable: with identical variable names and codes. The second step is to check that there are no remaining errors. Several quality assurance functions were created to check sightings and effort data. The third step is to linearize the effort data (which is a correction of the data for small deviation of the platform from the transect) and split bouts of homogenous effort ("legs") into smaller segments for DSM or SDM. The practical difficulties with large spatial data lie in the computer memory requirements for data wrangling and fitting statistical models. We developed a collection of efficient and fast functions to help in these tasks.

b- Prepare grids with environmental data (a.k.a. prediction grids)

Distribution of species is predicted from a model that uses environmental data (see deliverable 2.1a). Statistical relationships between densities and environmental variables are learnt from data and used to predict densities in areas that have not been surveyed. To do so, data on environmental variables that potentially influence cetacean distribution and habitat need to be fetched. A collection of functions using the European program Copernicus and EMODnet were developed to download raw static (e.g. bathymetry) and dynamic (e.g. mean monthly sea surface temperature, primary productivity) covariates. Raw variables were also used to derive additional variables such as sea floor slope or gradient in sea surface temperature. These variables were then used to prepare both prediction grids and effort data (Figure 2).

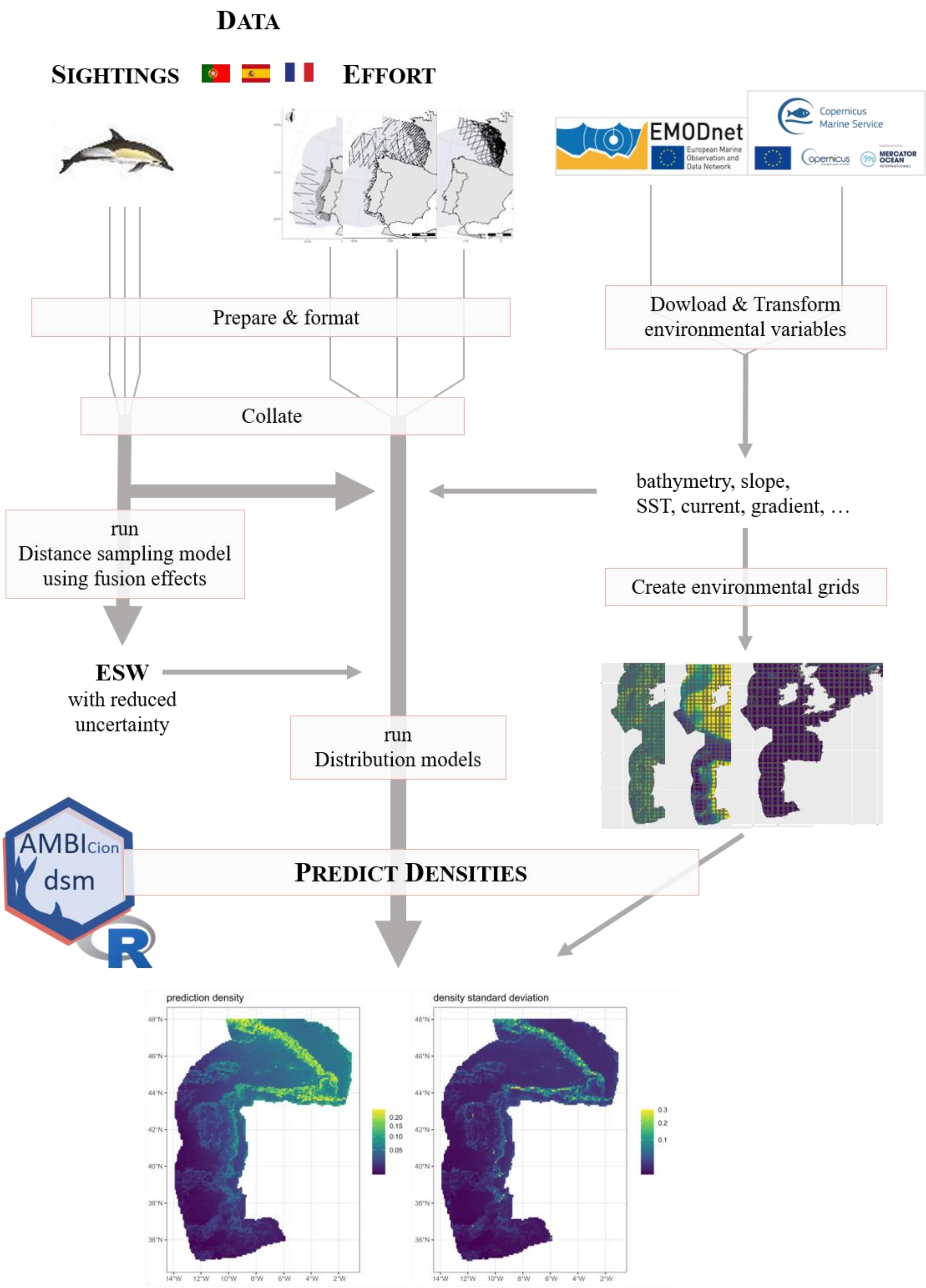

Figure 2: Framework of the common methodology developed in Task 2.1. The R package AMBIdsm has been created to run the different parts of this common methodology in a practical, reproducible and efficient way.

Table 1: Main functions of the package AMBIdsm and their usage.

PREPARE EFFORT AND SIGHTINGS DATA	
function	usage
eff_check_columns	Check format and columns of effort data
eff_check_leg	Check length and comments of the different legs
eff_linearize	Linearize legs to get correct leg length
eff_segment	Divide legs into smaller segments that will be used in distribution models
sight_check_columns	Check format and columns of sightings data
sight_bindSegID	Add segment IDs and observation conditions to sightings data
ENVIRONMENTAL DATA	
function	usage
env_loadsta	Download static environmental variables from EMODnet
env_loaddyn	Download dynamic environmental variables from Copernicus
env_toraster	Prepare and derive dynamic environmental variables
env_grid	Create prediction grids
env_bind	Add environmental variables to effort data
DISTANCE SAMPLING MODELS	
function	usage
esw_run_all	Run distance sampling models using fusion effects
esw_plot	Visualize fit and results from a model
esw_predict	Predict esw on effort data
SPECIES DISTRIBUTION MODELS	
function	usage
eff_bindObs	Add animal count to effort data
dsm_run_all	Run distribution surface models
dsm_plot	Visualize fit and results from a model
dsm_extrapol	Determine extrapolation points/areas
dsm_predict	Get prediction maps and abundance

c- Run DS models

The aim of DS models is to estimate densities in the area covered by the surveys. Detection functions are fit to the distribution of perpendicular distances to the transect line to estimate ESW. ESW represents the distance from the line transect where all animals would have been observed. Multiplied by the length of each transect segment, estimated ESW allow to derive the effective area sampled and to deduce animal densities around each segment of transects. A collection of functions allowing to run DS models using classical and fusion effects were written and included in the R package AMBIdsm, to estimate ESW in a Bayesian framework with the package nimble (de Valpine et al. 2017).

d- Run DSM/SDM, estimate abundance and predict density maps

Finally, a collection of functions has been implemented to perform species distribution analysis. Multiple models that include as predictors all possible combinations of selected environmental variables are run. For each species and each season, models were fit on data from the different years and included combinations of 1 to 3 environmental variables among bathymetry, sea floor slope, sea floor aspect, sea surface temperature, gradient in sea surface temperature, eddy kinetic energy, and net primary productivity. For dynamic variables, month was used as the temporal resolution. Then, depending on their fit, the 5 best models were selected using the leave-one-out information criterion and averaged using associated weights (Yao et al. 2018) to predict abundance and density maps. A function has also been created to check the fit of the models with appropriate diagnostics including rootogram, QQplot and plot of predicted against observed values.

All these functions have been encapsulated into the R package AMBIdsm available here. Documentation of the package, of each function as well as tutorials are available with the package. This documented package allows making easy and reproducible future analysis of abundance and distribution using multiple DS datasets. This package also contributes to the visibility of the project as it is public and can be used to fit DSM/SDM and estimate abundance for cetacean species in the future.

4. A shiny application to visualize the maps produced

Using the AMBIdsm package and the collated dataset collected from the three countries and European programs, we have predicted abundance and produced the density maps of 9 cetacean species in the Bay of Biscay and Iberian coast subregion in the four seasons (when the data were available). In table 2, abundance estimates for Summer and Winter are presented. It is important to note that these predictions are model-based and include extrapolations based on environmental variables for areas that had not been surveyed (see deliverable 2.1). Values must be interpreted carefully in relation to their uncertainty given by their standard error and confidence interval. The R package also allows to estimate of the level of extrapolation the different areas of the prediction grids. On the shiny app, when the level of extrapolation is too high (i.e. when the quantity of sampled data that informs predictions is too low, the threshold being chosen by the user), no predicted values are shown on the maps.

A gap analysis has been reported in deliverable 2.1. This analysis revealed that data are missing for winter months for a complete assessment of cetacean distribution and abundance in the Bay of Biscay and Iberian coast. The DSM performed here confirmed this result and also showed that abundance and density maps estimated in all seasons have large confidence intervals in a large area of the subregion (see the ShinyApp). As demonstrated by the spatial gap analysis, predicted density maps also highlighted high uncertainties due to extrapolation in non-surveyed offshore areas, and particularly areas offshore Portugal.

A shiny application was developed to visualize predicted abundances and distribution maps (Figure 3) obtained from the analysis of the collated dataset from the three countries and European programs. This application can be freely consulted on the web (available here). Different areas can be selected in the maps such that each country can select its assessment area.

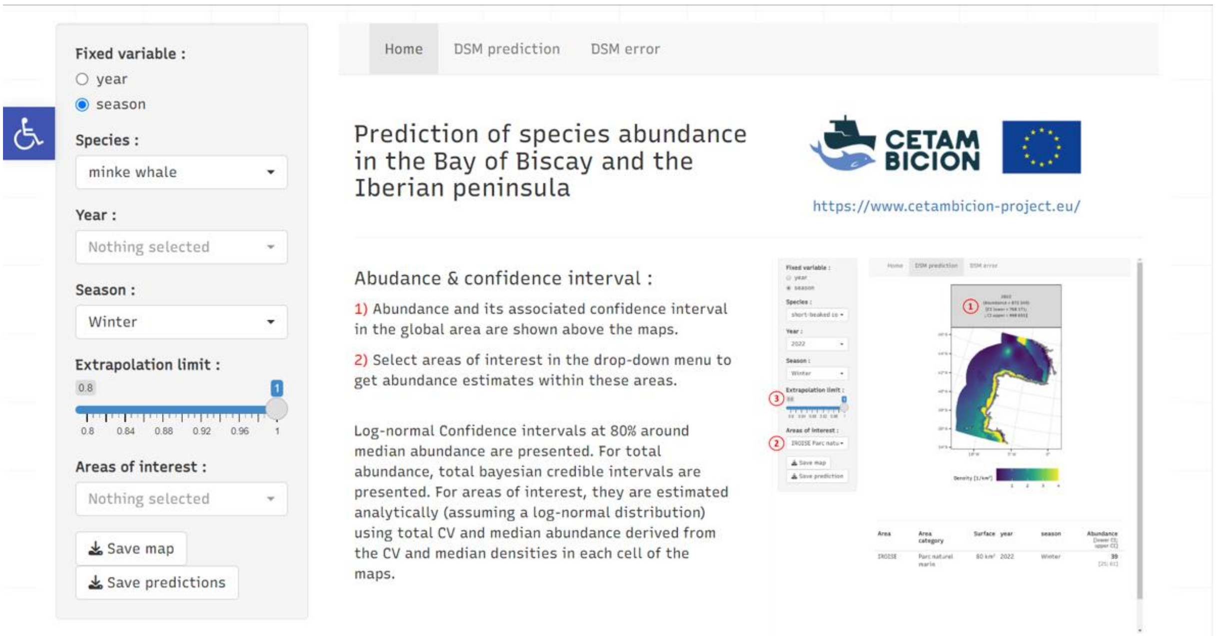

Figure 3: Screen-shot of the shiny application available online to visualize maps and abundance of cetacean species in the Bay of Biscay and Iberian Coast. Example shown for Minke whale.

To make the comparison of our results with previously estimated density maps easier, we built a map for each of the years when European survey campaigns were conducted: 2005 (SCANS II), 2007 (CODA), 2016 (SCANS III) and 2022 (SCANS IV). Note that no data from SCANS IV or from 2022 have been used to fit the models so maps built for 2022 are fully predictive. The maps produced in this project are qualitatively similar to maps produced in the previous European surveys. Temporal variability was accounted for in the model in two ways. First, annual dynamics of environmental variables have been included in the model so predictions in different years depend on the dynamic of these environmental variables. Second, a linear temporal trend on abundance was tested within the Bay of Biscay and Iberian coast for each season and species. Results showed that linear temporal trends were not significant for all species. The absence of a significant trend can reflect a true absence of a decline (or increase) as well as a lack of data in older years compared to recent years to detect a decline (or increase) or a non-linear decline not captured in the model.

Table 2: Predicted median abundance (total number of individuals) and their confidence interval at 80% of cetacean species in the Bay of Biscay and Iberian Coast subregion in Summer and Winter seasons. These numbers are model-based predictions and include geographic and environmental extrapolations (especially in winter). Note for example the large uncertainties for instance in the winter predicted abundance of harbour porpoises.

	Summer			Winter		
	Mean	IC_10%	IC_90%	Mean	IC_10%	IC_90%
Minke whale	328	176	476	851	51	2299
Fin whale	11499	10285	12630	1341	177	3079
Common dolphin	799266	714065	879617	973578	351073	1546745
Risso’s dolphin	9253	2732	17765	11549	4065	18825
Long-finned pilot whale	19362	13901	24680	35201	9584	61613
Harbour porpoise	8193	6960	9356	314395	6639	778606
Striped dolphin	207261	90605	326102	889691	127523	1403769
Bottlenose dolphin	29595	22408	35588	112376	20629	311100
Beaked whales	16102	7502	25650	234188	3270	577646

5. Conclusion

Both technical and fundamental methodological developments have allowed the common and efficient analysis of DS data collected by the three MS to get improved predictions of abundance and distribution maps of cetacean species in the Bay of Biscay and the Iberian coast subregion. The results of this analysis showed that density maps are robust (against extrapolation) for most species in summer but that data are still lacking in spring, winter and autumn months as well as in areas offshore of Portugal.

The common methodological framework that was developed under Task 2.1 can be reused in future assessments by each country because of the creation of a user friendly and efficient R package. This will allow the different countries to have comparable and homogenised results. Both the documented R package and the scientific article to be published in an international journal will guarantee the visibility and utility of this work beyond the project. We hope it will encourage others to use this methodology to favour the use of a common methodology among European Countries. The R package can already be accommodated with new species and areas such as the Mediterranean Sea.

6. References

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

Hu, G., H.-C. Yang, Y. Xue, and D. K. Dey. 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

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

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

de Valpine, P., D. Turek, C. Paciorek, C. Anderson-Bergman, D. Temple Lang, and R. Bodik. 2017. Programming with models: writing statistical algorithms for general model structures with NIMBLE. Journal of Computational and Graphical Statistics, 26:403–413

Yao, Y., Vehtari, A., Simpson, D. and Gelman, A. (2018) 'Using stacking to average Bayesian predictive distributions (with discussion)', Bayesian Analysis, 13(3), pp. 917–1003. doi: 10.1214/17-BA1091.

7. Acknowledgements

We are indebted to all data providers and all the participants involved in the data collection. We thank Phil Hammond (University of Saint Andrews) and Anita Gilles (TiHO, Hannover) for providing the SCANS and CODA data, Laurena Leacy for the ObSERVE data. We thank all partners of the CetAMBICion project for feedback and critical comments. We thank the Advisory Board, in particular Ruth Fernandez a for critical and helpful review of the present report.

8. Appendix 0

Hexagonal ('hex') sticker of the AMBIdsm package

Appendix 1: Table of covariates and model fit summary statistics

species	season	model	Bathy	Slope	Aspect	SST	SSTgrad	EKE	NPPV	stacking_weights	AIC	looic
minke whale	Winter	1	1	0	1	0	0	0	0	0,00	187,98	197,25
minke whale	Winter	2	0	0	1	0	0	1	0	0,00	187,98	198,52
minke whale	Winter	3	0	0	1	0	0	1	1	0,00	187,98	198,80
minke whale	Winter	4	0	0	1	1	1	0	0	1,00	187,98	199,01
minke whale	Winter	5	0	0	0	0	0	1	1	0,00	187,97	199,19
minke whale	Summer	1	1	0	0	1	0	1	0	0,83	2211,52	2210,19
minke whale	Summer	2	0	0	1	1	0	1	0	0,00	2213,48	2212,14
minke whale	Summer	3	1	0	1	1	0	0	0	0,00	2214,47	2212,89
minke whale	Summer	4	1	0	0	1	0	0	1	0,03	2217,02	2213,49
minke whale	Summer	5	0	0	1	1	0	0	1	0,14	2217,30	2214,07
minke whale	Spring	1	1	0	0	1	0	1	0	0,35	1079,36	1075,60
minke whale	Spring	2	0	0	0	1	1	1	0	0,00	1081,16	1077,30
minke whale	Spring	3	0	0	0	1	0	1	0	0,63	1081,16	1077,64
minke whale	Spring	4	0	0	1	1	0	1	0	0,00	1081,17	1077,77
minke whale	Spring	5	0	0	0	1	0	1	1	0,02	1081,16	1077,89
minke whale	Autumn	1	1	0	0	1	1	0	1	0,00	630,01	630,30
minke whale	Autumn	2	1	0	0	1	0	0	1	0,08	630,01	630,43
minke whale	Autumn	3	1	0	0	1	1	1	0	0,92	630,79	630,48
minke whale	Autumn	4	1	0	1	0	0	0	1	0,00	630,01	630,60
minke whale	Autumn	5	1	0	0	1	1	0	0	0,00	630,79	630,90
fin whale	Winter	1	0	0	0	0	0	1	1	0,00	124,72	248,61
fin whale	Winter	2	0	0	0	0	0	0	1	0,00	124,72	249,43
fin whale	Winter	3	0	0	0	1	1	0	1	1,00	124,72	263,38
fin whale	Winter	4	0	1	0	0	0	0	1	0,00	126,51	264,67
fin whale	Winter	5	0	1	0	0	0	1	1	0,00	126,51	289,47
fin whale	Summer	1	1	0	1	1	0	0	0	0,72	3229,14	3342,42
fin whale	Summer	2	1	0	0	0	0	1	0	0,00	3347,28	3419,94
fin whale	Summer	3	1	0	0	1	1	0	0	0,00	3347,62	3424,87

fin whale	Summer	4	1	0	0	1	1	1	0	0,00	3347,29	3443,62
fin whale	Summer	5	1	0	0	1	0	1	0	0,28	3228,70	3453,01
fin whale	Spring	1	1	0	0	0	0	0	1	0,66	625,45	659,06
fin whale	Spring	2	1	0	0	1	1	0	1	0,34	624,73	660,56
fin whale	Spring	3	1	0	0	1	1	0	0	0,00	625,32	660,97
fin whale	Spring	4	1	0	0	1	0	0	1	0,00	625,45	661,52
fin whale	Spring	5	1	0	0	1	1	1	0	0,00	625,32	661,63
fin whale	Autumn	1	0	0	0	1	1	0	0	0,00	2083,70	2233,85
fin whale	Autumn	2	1	1	0	1	1	0	0	0,15	2067,09	2255,56
fin whale	Autumn	3	1	0	0	1	1	0	0	0,84	2058,95	2263,07
fin whale	Autumn	4	1	0	0	1	1	0	0	0,00	2059,40	2272,49
fin whale	Autumn	5	1	0	0	1	1	1	0	0,00	2054,82	2313,84
common dolphin	Winter	1	1	0	1	0	0	1	0	0,00	5007,78	5077,21
common dolphin	Winter	2	1	0	1	1	1	0	0	0,02	5006,59	5079,73
common dolphin	Winter	3	1	0	0	1	1	1	0	0,58	5006,59	5081,45
common dolphin	Winter	4	1	0	0	0	0	0	0	0,30	5007,77	5081,84
common dolphin	Winter	5	1	0	1	0	0	0	1	0,10	5007,77	5083,22
common dolphin	Summer	1	1	0	0	1	0	0	1	0,54	10409,66	10654,70
common dolphin	Summer	2	1	0	0	1	0	0	0	0,00	10409,66	10672,73
common dolphin	Summer	3	1	0	1	1	1	0	0	0,33	10455,28	10676,21
common dolphin	Summer	4	1	0	0	1	1	0	0	0,02	10465,02	10684,07
common dolphin	Summer	5	1	0	0	1	0	1	0	0,11	10415,02	10684,41
common dolphin	Spring	1	1	0	0	1	1	0	0	0,00	11703,15	11757,81
common dolphin	Spring	2	1	0	0	1	0	0	1	0,69	11703,15	11762,91
common dolphin	Spring	3	1	0	0	0	0	1	1	0,02	11709,76	11765,13
common dolphin	Spring	4	1	0	1	0	0	0	1	0,00	11705,28	11765,77
common dolphin	Spring	5	1	0	0	1	0	0	0	0,29	11703,15	11766,58
common dolphin	Autumn	1	1	0	0	1	0	0	0	0,00	12499,42	12603,79
common dolphin	Autumn	2	1	0	0	1	1	0	0	0,14	12520,85	12604,35
common dolphin	Autumn	3	1	1	0	1	0	0	0	0,77	12517,82	12607,23
common dolphin	Autumn	4	1	0	1	0	0	0	1	0,03	12517,97	12610,50
common dolphin	Autumn	5	1	0	1	1	1	0	0	0,06	12520,85	12612,98

Risso's dolphin	Winter	1	0	0	1	1	1	0	1	0,39	354,54	351,67
Risso's dolphin	Winter	2	0	1	1	0	0	0	1	0,00	355,60	352,91
Risso's dolphin	Winter	3	1	1	0	0	0	0	1	0,00	355,59	353,12
Risso's dolphin	Winter	4	0	1	0	1	1	0	1	0,00	356,54	353,29
Risso's dolphin	Winter	5	0	0	1	1	0	0	1	0,61	354,54	353,33
Risso's dolphin	Summer	1	0	0	1	1	0	1	0	0,00	1100,65	1206,12
Risso's dolphin	Summer	2	1	0	1	0	0	0	0	0,53	1100,65	1209,12
Risso's dolphin	Summer	3	0	0	1	0	0	0	1	0,00	1100,65	1209,57
Risso's dolphin	Summer	4	1	0	1	0	0	1	0	0,33	1100,65	1210,33
Risso's dolphin	Summer	5	1	0	1	0	0	0	1	0,13	1100,65	1210,41
Risso's dolphin	Spring	1	0	0	0	0	0	1	1	0,00	949,98	1081,30
Risso's dolphin	Spring	2	1	0	0	1	1	1	0	0,22	949,98	1090,43
Risso's dolphin	Spring	3	1	0	0	0	0	0	1	0,00	950,44	1095,54
Risso's dolphin	Spring	4	0	0	0	1	1	0	0	0,00	950,44	1097,99
Risso's dolphin	Spring	5	0	0	0	0	0	0	1	0,78	950,44	1098,77
Risso's dolphin	Autumn	1	0	0	0	0	0	1	1	0,00	484,65	513,48
Risso's dolphin	Autumn	2	0	0	1	0	0	0	0	0,00	484,65	514,05
Risso's dolphin	Autumn	3	1	0	0	1	0	0	1	0,00	484,46	514,34
Risso's dolphin	Autumn	4	0	0	0	1	0	0	0	1,00	484,65	516,08
Risso's dolphin	Autumn	5	0	0	0	0	0	0	0	0,00	484,65	516,33
long-finned pilot whale	Winter	1	1	1	0	0	0	0	1	0,09	412,83	438,87
long-finned pilot whale	Winter	2	0	1	0	0	0	1	1	0,90	412,83	439,54
long-finned pilot whale	Winter	3	0	1	0	0	0	0	1	0,00	412,83	442,64
long-finned pilot whale	Winter	4	1	0	1	0	0	0	1	0,00	416,89	443,18
long-finned pilot whale	Winter	5	0	1	1	0	0	0	1	0,00	412,83	443,52
long-finned pilot whale	Summer	1	1	0	1	0	0	1	0	0,30	1924,34	2010,84
long-finned pilot whale	Summer	2	1	0	0	1	1	0	0	0,08	1924,88	2014,36
long-finned pilot whale	Summer	3	1	0	0	1	1	0	0	0,00	1924,88	2015,97
long-finned pilot whale	Summer	4	1	0	0	1	0	1	0	0,00	1924,88	2016,42
long-finned pilot whale	Summer	5	1	0	0	0	0	0	0	0,62	1924,88	2017,33
long-finned pilot whale	Spring	1	1	0	0	0	0	0	1	0,28	3369,89	3499,96
long-finned pilot whale	Spring	2	1	0	0	1	0	0	1	0,21	3357,52	3501,72

long-finned pilot whale	Spring	3	1	0	0	1	1	0	1	0,20	3368,05	3502,09
long-finned pilot whale	Spring	4	1	0	1	0	0	0	1	0,00	3368,07	3505,21
long-finned pilot whale	Spring	5	1	0	0	0	0	1	0	0,31	3371,76	3505,80
long-finned pilot whale	Autumn	1	0	1	1	1	0	0	0	0,47	1511,77	1633,88
long-finned pilot whale	Autumn	2	1	0	0	0	0	0	1	0,38	1483,63	1634,98
long-finned pilot whale	Autumn	3	1	0	0	1	0	0	1	0,00	1480,53	1638,34
long-finned pilot whale	Autumn	4	0	1	0	1	0	0	0	0,09	1511,64	1638,45
long-finned pilot whale	Autumn	5	0	1	0	1	0	1	0	0,06	1511,77	1639,01
harbour porpoise	Winter	1	1	0	0	1	1	0	0	0,27	4191,23	4257,37
harbour porpoise	Winter	2	0	0	0	1	1	1	0	0,00	4180,92	4260,26
harbour porpoise	Winter	3	1	0	1	1	0	0	0	0,00	4190,94	4261,46
harbour porpoise	Winter	4	1	0	1	0	0	1	0	0,07	4192,03	4262,93
harbour porpoise	Winter	5	1	0	0	1	0	1	0	0,66	4186,46	4263,59
harbour porpoise	Summer	1	1	0	0	1	0	0	1	0,14	15048,28	15082,12
harbour porpoise	Summer	2	1	0	0	1	0	1	0	0,00	15072,06	15099,54
harbour porpoise	Summer	3	1	0	0	1	1	0	0	0,75	15069,64	15099,88
harbour porpoise	Summer	4	1	1	0	1	0	0	0	0,00	15075,35	15101,18
harbour porpoise	Summer	5	1	0	0	1	0	0	0	0,12	15072,68	15103,36
harbour porpoise	Spring	1	0	0	0	1	0	0	1	0,00	3708,12	3735,63
harbour porpoise	Spring	2	0	0	1	1	0	0	1	0,14	3717,58	3738,16
harbour porpoise	Spring	3	0	0	0	1	1	0	1	0,07	3708,35	3738,89
harbour porpoise	Spring	4	1	0	0	1	0	0	1	0,00	3707,99	3741,00
harbour porpoise	Spring	5	0	0	0	1	0	1	0	0,79	3732,11	3741,48
harbour porpoise	Autumn	1	1	0	0	1	0	0	1	0,36	1566,53	1589,76
harbour porpoise	Autumn	2	0	0	0	1	0	1	1	0,00	1571,08	1598,82
harbour porpoise	Autumn	3	0	1	0	1	0	0	1	0,64	1572,51	1599,09
harbour porpoise	Autumn	4	0	0	0	1	1	0	1	0,00	1569,89	1599,12
harbour porpoise	Autumn	5	1	0	1	1	0	0	0	0,00	1580,48	1601,30
striped dolphin	Winter	1	1	1	0	0	0	0	1	0,00	168,45	262,09
striped dolphin	Winter	2	1	1	0	1	1	0	0	0,04	169,26	278,83
striped dolphin	Winter	3	0	0	0	1	1	0	1	0,00	156,87	2799,63
striped dolphin	Winter	4	0	0	0	1	1	0	0	0,01	156,87	4335,75

striped dolphin	Winter	5	0	0	1	0	0	0	1	0,95	156,87	4376,39
striped dolphin	Summer	1	1	0	0	0	0	1	1	0,58	1642,62	1715,40
striped dolphin	Summer	2	1	0	0	0	0	0	1	0,00	1644,24	1721,04
striped dolphin	Summer	3	1	0	1	0	0	0	1	0,17	1644,23	1722,96
striped dolphin	Summer	4	1	0	1	0	0	1	0	0,07	1647,91	1731,76
striped dolphin	Summer	5	1	0	0	0	0	0	0	0,18	1647,87	1734,67
striped dolphin	Spring	1	1	0	1	0	0	1	0	0,03	1237,58	1406,90
striped dolphin	Spring	2	1	0	0	0	0	1	0	0,11	1239,65	1407,09
striped dolphin	Spring	3	1	0	1	1	0	0	0	0,55	1234,82	1407,49
striped dolphin	Spring	4	1	0	1	0	0	0	1	0,00	1237,05	1407,75
striped dolphin	Spring	5	1	0	0	0	0	1	1	0,30	1239,81	1428,02
striped dolphin	Autumn	1	1	0	0	1	0	0	1	0,03	2087,43	2319,37
striped dolphin	Autumn	2	0	0	0	1	0	0	1	0,00	2087,45	2335,20
striped dolphin	Autumn	3	0	0	0	1	0	1	1	0,71	2087,45	2345,05
striped dolphin	Autumn	4	1	0	1	0	0	1	0	0,00	2102,79	2437,04
striped dolphin	Autumn	5	0	0	0	1	1	0	1	0,26	2079,02	2470,40
bottlenose dolphin	Winter	1	0	0	1	1	0	0	1	0,49	2436,19	2489,18
bottlenose dolphin	Winter	2	1	0	0	0	0	0	1	0,51	2437,22	2491,13
bottlenose dolphin	Winter	3	0	0	1	0	0	1	1	0,00	2466,25	2500,05
bottlenose dolphin	Winter	4	0	1	0	0	0	1	1	0,00	2468,22	2501,65
bottlenose dolphin	Winter	5	0	1	0	0	0	0	1	0,00	2468,25	2502,40
bottlenose dolphin	Summer	1	0	0	0	1	0	1	1	0,47	4017,94	4049,82
bottlenose dolphin	Summer	2	0	0	0	1	1	1	0	0,00	4017,94	4050,25
bottlenose dolphin	Summer	3	0	1	0	0	0	1	1	0,00	4014,66	4050,78
bottlenose dolphin	Summer	4	1	0	0	0	0	0	0	0,51	4024,13	4054,10
bottlenose dolphin	Summer	5	0	1	1	0	0	0	0	0,02	4021,77	4054,50
bottlenose dolphin	Spring	1	1	0	0	0	0	0	0	0,00	6082,60	6158,68
bottlenose dolphin	Spring	2	1	0	0	1	1	0	0	0,00	6081,14	6160,54
bottlenose dolphin	Spring	3	0	0	1	1	1	1	0	0,09	6073,31	6163,00
bottlenose dolphin	Spring	4	0	0	1	1	0	1	0	0,41	6059,09	6163,72
bottlenose dolphin	Spring	5	1	0	1	0	0	0	0	0,50	6082,29	6165,19
bottlenose dolphin	Autumn	1	1	0	0	1	1	0	0	0,00	3473,10	3568,53

bottlenose dolphin	Autumn	2	0	0	0	1	0	1	0	0,36	3473,12	3569,37
bottlenose dolphin	Autumn	3	0	0	1	0	0	0	1	0,00	3464,41	3571,03
bottlenose dolphin	Autumn	4	0	0	0	1	1	0	1	0,00	3462,61	3572,47
bottlenose dolphin	Autumn	5	1	0	0	1	0	0	1	0,64	3460,59	3573,31
beaked whales	Winter	1	0	0	0	1	1	1	0	0,00	200,46	435,30
beaked whales	Winter	2	0	0	1	1	1	1	0	0,00	200,46	441,57
beaked whales	Winter	3	0	0	0	1	1	0	1	0,04	200,77	445,02
beaked whales	Winter	4	0	0	1	1	1	0	1	0,96	200,77	452,35
beaked whales	Winter	5	0	0	0	1	1	1	0	0,00	200,46	463,84
beaked whales	Summer	1	1	0	1	0	0	0	1	0,79	699,50	785,22
beaked whales	Summer	2	1	0	1	0	0	0	0	0,21	699,50	788,03
beaked whales	Summer	3	1	0	0	1	1	0	1	0,00	699,50	789,62
beaked whales	Summer	4	1	0	1	1	1	0	0	0,00	699,50	790,67
beaked whales	Summer	5	1	0	0	1	1	0	0	0,00	699,50	794,56
beaked whales	Spring	1	1	1	0	1	0	0	0	0,98	199,55	220,25
beaked whales	Spring	2	1	1	0	1	1	0	0	0,00	203,61	226,22
beaked whales	Spring	3	1	0	0	1	1	0	0	0,00	196,00	229,40
beaked whales	Spring	4	1	0	0	1	0	1	0	0,00	198,04	232,70
beaked whales	Spring	5	1	0	1	1	0	0	0	0,02	198,22	234,92
beaked whales	Autumn	1	1	1	0	0	0	1	0	0,00	337,42	341,66
beaked whales	Autumn	2	1	1	0	1	0	0	0	0,92	337,42	341,85
beaked whales	Autumn	3	1	0	0	1	1	0	0	0,00	338,86	346,04
beaked whales	Autumn	4	1	0	0	0	0	1	0	0,00	338,86	346,28
beaked whales	Autumn	5	1	0	0	0	0	0	0	0,08	338,86	347,00

Bathy:bathymetric depth

Slope : bathymetric gradient

Aspect: seafloor topography

SST: sea surface temperature

SSTgrad: sea surface temperature gradient

EKE: eddy kinetic energy

NPPV: Net primary productivity

AIC: Akaike Information criterion

LOOIC: Leave-One-Out Information criterion

Stacking weights: weights for stacking predictions based on LOOIC

This page is left blank intentionally