1 DOI: https://doi.org/10.1016/j.ecolind.2016.05.035 2 Modelling the spatial distribution of the striped dolphin (Stenella coeruleoalba) and 3 4 common bottlenose dolphin (Tursiops truncates) in the Gulf of Taranto (Northern 5 Ionian Sea, Central-eastern Mediterranean Sea) Carlucci R., Fanizza C., Cipriano G., Paoli C., Russo T.*, Vassallo P. 6 7 Laboratory of Experimental Ecology and Aquaculture - Dept. of Biology -8 University of Rome Tor Vergata, via della Ricerca Scientifica snc, 00133, Rome, 9 Italy 10 11 12 Abstract: 13 14 Introduction 15 The Marine Strategy Framework Directive (MSFD), the Maritime Spatial Planning Directive 16 (MSPD) and the Common Fisheries Policy (CFP) are the main EU policies incorporating the 17 ecosystem-based management (EBM) framework to human activities as a significant contribution to achieving the goals of the Biodiversity Strategy for the EU marine environments 18 19 (European Environment Agency, 2015). The main issue for the EU policy is to embank the loss 20 of biodiversity in a holistic pathway, maintaining marine habitats as a whole in a healthy, clean, productive and resilient condition. Such an approach will allow supporting habitats' 21 functioning and, consequently, to benefit by the delivery of ecosystem services. In particular, 22 the implementation of any management action aimed at marine biodiversity conservation, has 23 24 to be founded on: 1) the knowledge of the spatial distribution of target species and extension

of critical habitats as well as 2) their overlapping with human activities, pressure and impacts.

26 In fact, a key insight of ecosystem-based management is that human activities often affect the marine environment in complex ways. This is highly relevant in the Mediterranean Sea, the 27 largest and deepest enclosed sea on earth, defined as a sort of ocean in miniature acting as a 28 marine biodiversity hot spot hosting the 7% to the world's marine biodiversity (Coll et al., 29 30 2012). Mediterranean sea diversity has been severely altered by different anthropic pressures 31 through time then resulting particularly vulnerable. Anthropogenic pressures include, for 32 example, increasing use of the coastal areas, eutrophication, pollution and dumping, marine traffic, alien species, global warming and they are expected to increase in the future (CIESM, 33 1997; Bianchi and Morri, 2000; Myers et al., 2000; Coll et al., 2010 and 2012). The presence of 34 different environmental and human drivers of change generates cumulative impacts at 35 36 different spatial and temporal scales (Coll et al., 2012). This condition represents the main 37 obstacle when striving to protect marine mammals. In Mediterranean coastal areasdolphins 38 and whales, suffering habitats fragmentation and loss (Simmonds and Nunny, 2002) or the 39 alterations in distribution and availability of resources (Learmonth et al., 2006; Gambaiani et al., 2009; MacLeod, 2009), could also be exposed to high levels of local anthropogenic impact, 40 such as fishing, shipping collision, noise from military sonar or seismic surveys (Bearzi, 2002; 41 42 Roussel, 2002; Hildebrand, 2005; Nowacek et al., 2007; Fossi and Lauriano, 2008; Dolman et 43 al., 2010), chemical pollution including marine litter (Kannan et al., 2002; Fossi et al., 2003; 44 <mark>on et al., 2004</mark>; Aguillar and Borrel, 2005; <mark>Triantafillou, 2008</mark>). Up to date, the knowledge about the presence and the distribution of cetaceans in the Mediterranean Sea, as well as their 45 conservation status, is still rather heterogeneous and defective. In particular large areas of the 46 central-eastern regions are still scarcely or totally not surveyed (Notarbartolo di Sciara and 47 48 Birkun, 2010). Concerning the Ionian Sea (Central-eastern Mediterranean Sea), the available 49 information reported the presence of eight different species of cetaceans (Notarbartolo di Sciara et al., 1993; Reeves and Notarbartolo di Sciara, 2006; Notarbartolo di Sciara and Birkun, 50

51 2010). Specifically, more recent observations collected in the framework of a monitoring vessel survey confirmed that the striped dolphin Stenella coeruleoalba regularly inhabits the Northern 52 Ionian Sea, together with the common bottlenose dolphin Tursiops truncatus (Dimatteo et al., 53 2011; Fanizza et al., 2014; Carlucci et al., in press). Despite the presence of adult, juveniles and 54 calves of S. coeruleoalba, no conservation measures to ensure a favorable status and long-term 55 56 survival of the species, are currently enforced in the area, mostly due to shortcomings in the 57 basic scientific information (Fanizza et al., 2014). Conversely, both species could be exposed to high levels of anthropogenic threats such as strikes from merchant traffic, disturbance from 58 high intensity military sonar and exposition to chemical pollution due to the presence of a 59 commercial harbor (Taranto harbor) (Marsili and Focardi, 1997; Cardellicchio et al., 2000). In 60 addition, recently seismic surveys were permitted in order to detect possible offshore gas/oil 61 62 deposits in the Northern Ionian Sea. These activities were allowed without taking into account 63 that the striped dolphin and common bottlenose dolphin were both assessed as vulnerable 64 species with evidence of suspected decline in subpopulation within the ACCOBAMS regions (Agreement on the Conservation of Cetaceans of the Black Sea, Mediterranean Sea and 65 Contiguous Atlantic Area) (Reeves and Notarbartolo di Sciara, 2006). Hence, the need for 66 67 identifying the critical habitats for S. coeruleoalba and T. truncatus in the Northern Ionian Sea 68 become even more urgent. The habitats characterization should be matched with the 69 identification of the distribution of the main anthropogenic threats in order to better support potential alternative management strategies (Ahmadi-Nedushan et al., 2006; Halpern et al., 70 2008). 71 In the last thirty years, the advances in the regression analyzes provided by generalized linear 72 73 models (GLMs) and generalized additive models (GAMs) allowed the development of ecological 74 models increasing our understanding of ecological systems (Guisan et al., 2002). Lastly, 75 Random Forest technique (Breiman et al., 1984), based on an automatic combination of decision

76 trees was also applied in comparison with other regression techniques, resulting more reliable and accurate in predicting habitat uses (Oui serve PER FORZA un riferimento/citazione). In 77 particular, recent developments in spatial modeling have allowed predicting the 78 presence/absence or the abundance of a species by means of a set of predictor variables, 79 80 highlighting the relative importance of habitats (Baumgartner, 1997; Moses and Finn, 1997; Tynan, 2004; Phillips et al., 2006; Redfern et al., 2006; Thorne et al., 2012). In particular, such 81 82 approaches are increasingly becoming essential to identify critical habitats enhancing the 83 protection of threatened species, mostly in coastal areas where the potential for conflicts is high (Edren et al., 2010; Best et al., 2012; Thorne et al., 2012). 84 In this study, the spatial pattern of S. coeruleoalba and T. truncatus in the Gulf of Taranto 85 86 (Northern Ionian Sea, Central-eastern Mediterranean Sea) was modeled aiming at: 1) assessing 87 the distribution of S. coeruleoalba and T. truncatus in the gulf of Taranto2) identifying the 88 driving forces influencing the distribution of these top predators and, in turn, 3) suggesting 89 suggestions and practices for their conservation and management. At these purposes, different 90 predictive variables were considered. Physiographic features, reckoned as important for cetaceans' distribution both in the Atlantic oceans (Watts and Gaskin, 1986; Selzer and Payne, 91 92 1988; Gowans and Whitehead, 1995; Baumgartner, 1997; Bailey and Thompson, 2006) and 93 more recently in the Mediterranean Sea (Azzellino et al., 2008; Blasi and Boitani, 2012, Marini 94 et al., 2015), were taken into account together with the human activities existing in the basin, suggesting an innovative approach to habitat modeling. Thus, eight predictive indirect 95 variables were identified for modeling the spatial distribution of both striped and common 96 97 bottlenose dolphins in the Gulf of Taranto: depth, slope, distance from coast, canyon, areas of 98 navy exercises, routes of merchant traffic, fishing areas, industrial activities. In particular, these 99 predictive variables were employed to determine the presence/absence probability by means of generalized additive model (GAM) and Random Forest (RF). 100

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Materials and methods

Study area

The Gulf of Taranto in the Northern Ionian Sea (Central Mediterranean Sea) stretches from 104 105 Punta Alice to Punta Mèliso (Figure 1). In particular, the basin is the extension of a Southern-106 Apenninic orogenic system characterized by very complex bottom topography. In fact, the 107 western sector is characterized by a narrow continental shelf with a steep slope and several channels, while the eastern showed terraces declining toward the "Taranto Valley", a NW-SE 108 submarine canyon with no clear bathymetric connection to a major river system (Rossi and 109 110 Gabbianelli, 1978; Pescatore and Senatore, 1986; Harris and Whiteway, 2011). This singular 111 morphology involves a complex distribution of water masses with a mixing of surface and dense 112 bottom waters (Sellschopp and Álvarez, 2003) and occurrence of upwelling currents with high seasonal variability (Bakun and Agostini, 2001; Milligan and Cattaneo, 2007). 113 The coastal area in the Gulf of Taranto is characterized by a high level of urbanization (Ladisa 114 et al., 2010). In addition, the coastal zone nearby the harbor of Taranto is devoted to many 115 116 different activities among which an intense commercial shipping throughout main defined 117 commercial routes stands out (https://www.marinetraffic.com/it/) together with the presence 118 of heavy industries (Ben Meftah et al., 2008). Different areas are employed to the execution of navy exercises such as naval, submarine and shooting ones. Their geographical coordinates and 119 120 characteristics were gathered by consulting the decree provided by National Coast Guards and 121 "Notice Skippers" from 2009 2014 to to 122 (http://www.guardiacostiera.gov.it/taranto/Pages/ordinanze.aspx). 123 An intense fishing activity is also recorded in the basin with trawlers, long-liners, gillnetters 124 and purse seiners distributed in different fishing harbors along the coasts (Carlucci et al., in 125 press).

Distribution of fishing activities

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128 Different fishing activities are present in the basin since trawlers, long-liners, gillnetters and purse seiners are distributed in different fishing harbours along the coasts (Carlucci et al., in 129 130 press). The data provided by the Vessel Monitoring System (VMS) were used, in this study, to assess the amount and the distribution of fishing effort for all the fishing vessels with length 131 132 over all (LOA) larger than 12 m. The original VMS data were provided by by the Italian Ministry for Agricultural, Food and Forestry Policies (MAFFP) within the activities planned for 133 the Data Collection Framework Program in Fisheries Sector (DCF) and were processed within 134 135 the R-environment using the standard procedures provided by the VMSbase platform (Russo 136 et al., 2014a). In summary, VMS data for each fishing vessel operating in the area were 137 cleaned, interpolated (Russo et al., 2011a) and linked to external database (i.e. Logbook and 138 the Community Fishing Fleet Register available at: 139 http://ec.europa.eu/fisheries/fleet/index.cfm) to assess the fishing gear (Russo et al., 2011b). 140 Then, after complete reconstruction and classification of the fishing activity for each vessel, 141 the fishing set positions for each vessel/day of activity were finally inferred using speed and 142 depth filters (Russo et al., 2014a). These fishing set positions were finally used to compute the 143 spatial distribution of the fishing effort, for the different gears, on a XxX Km square grid, for each year of the temporal range 2006-2014. Given that VMS data for the current year (2015) 144 were not already available, the expected distribution of the fishing effort for the year 2015 145 was estimated from the previous years. Namely, for each cell, one-year ahead forecasts of the 146 147 effort have been obtained from the estimates of an ARMA model (see Box et al., 2015) fitted 148 on the available observations. Estimates have been obtained using the R package "forecast" 149 (Hyndman, 2015).

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153 Investigated cetaceans species

Striped dolphin (Stenella coeruleoalba, Meyen, 1833)

155 The striped dolphin is a cosmopolitan species, preferentially inhabiting highly productive waters off the continental shelf (Perrin at al., 1994a; Notarbartolo di Sciara et al., 1993; Forcada 156 157 et al., 1994; Frantzis et al., 2003; Gannier, 2005). In the Mediterranean Sea, S. coeruleoalba is distributed both inshore and offshore (Aguilar, 2000; Gaspari et al., 2007). The striped dolphin 158 159 (S. coeruleoalba) is the most abundant cetacean species in the western Mediterranean with a 160 decreasing W-E gradient in the abundance observed, probably reflecting the reducing in the 161 productivity of the easternmost basins (Notarbartolo di Sciara and Birkun, 2010). 162 The Red List of the IUCN classifies Mediterranean striped dolphin Mediterranean subpopulation as vulnerable since it is suspected a 30% reduction in population size occurred 163 164 over the last three generations due to a decline in quality of habitat, affecting food availability, incidental mortality in fisheries and the effects of pathogens and pollutants (Aguilar and 165 166 Gaspari, 2012; Notarbartolo di Sciara et al., 2007).

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Bottlenose dolphin (Tursiops truncatus)

The bottlenose dolphin consists of two ecotypes, one coastal and the other pelagic with different morphological and ecological characteristics (Mead and Potter, 1995; Notarbartolo di Sciara and Demma, 2004; Reeves and Notarbartolo di Sciara, 2006). In the Mediterranean Sea, *T. truncatus* is preferentially distributed within the limits of the continental shelf, also inhabiting estuaries, bays and lagoons and generally show a residential attitude (Reynolds et al. 2000, Wells and Scott, 2002; Bearzi et al., 2008). However, the bottlenose dolphin can be also found in deeper waters above the shelf-break in the western Mediterranean (Forcada et al.,

2004; Cañadas and Hammond, 2006). The bottlenose dolphin generally constitutes small groups, which tends to be wider passing from coastal to offshore waters (Bearzi et al., 1997; Cañadas and Hammond, 2006). The shallow water preference of the bottlenose dolphin could be related to the feeding habits of the species, preying mostly on benthic and demersal fishes. Due to these attitude *T. truncatus* is subjected to various anthropogenic threats and then it has been included in the IUCN red list of threatened species being listed among species under the "least concern" category and classified as Vulnerable in the last IUCN report on the Status of Cetaceans in the Mediterranean and Black Sea (Marini et al., 2015; Reeves and Notarbartolo di Sciara, 2006).

Data collection

Data employed for the development of the prediction models were collected in a specific sector of the Gulf of Taranto (hereinafter named "survey area", Figure 1) 640 km² wide. The survey area was selected both for the heterogeneity of forcing factors acting in this specific sector of the Gulf of Taranto and for logistics reasons since it is comprised between the harbors of Taranto and Policoro allowing daily trips of the area. Further sightings (validation dataset), beyond those collected in the survey area and collected in other, independent research campaigns, have been employed for the validation of the presence/absence prediction when projected on the whole study area.

Commentato [TR1]: E' il posto giusto per questo titolo?

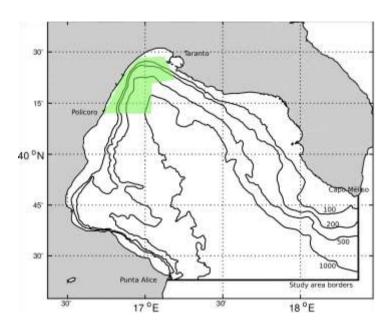


Figure 1 – Map of the study area located in the Gulf of Taranto (Northern Ionian Sea, Central Mediterranean Sea) with main isobaths. The survey area is marked in green.

Sightings of both *S. coeruleoalba* and *T. truncatus* were collected according to a standardized vessel-based survey carried out from 2009 to 2015. In particular, until 2012 surveys were carried out with a rib boat, replaced by means of a 12 m catamaran in the following years. The sampling effort was set to about 5 h/days along 35 nautical miles. Speed was maintained between 7 and 8 knots and trips occurred only in favorable weather conditions (Douglas scale \leq 3 and Beaufort scale \leq 4). Sightings data for both *S. coeruleoalba* and *T. truncatus* were collected following the line transect distance sampling according to the methodology proposed in Buckland et al. (2001). In particular, the random transect was adopted using the software Distance 6.0 (Thomas et al., 2010), with an equal coverage probability design in each sampling area. The observation team on board consisted at least of three people with specific experience

in the recognition of marine mammals. One was an independent observer searching for targets around 180°, while the others searched in a sector from the track-line to 90°. Observer teams rotated each 90 minutes. Once a target was sighted, 7×50 binoculars were used to identify species and in the meanwhile during sightings, observers were recommended to adopt responsible behavior in order to prevent collisions and possible injuries to dolphins. Observers had to maintain a minimum safe distance of 5–10 m from dolphins lowering speed or interrupting navigation. In order to verify identification of the species, video-photo records were gathered. Documents were focused on body markers. Date, daytime, sea weather conditions, geographic coordinates, depth (m), group size, perpendicular distance (in NM) of the target to the track-line and behavior were recorded.

Data processing

The entire Gulf of Taranto area was divided into a regular grid composed by 109720 square cells (422 horizontal and 260 vertical cells)) of about 450 x 450 m. A dependent variable (response) is assigned to each cell identifying the cell as a presence cell if at least a sighting occurred (absence cell otherwise). Moreover, a set of 8 explanatory variables were calculated as reported in Table 1.

Table 1: Description of the explanatory variables applied for the determination of striped and bottlenose dolphins' distributions

Variable	Calculation method	Acronym
	Depth values are derived from EMODnet	
Depth	Bathymetry dataset provided by the	Depth
	European Marine Observation and Data	

	Network	
	(http://www.emodnet.eu/bathymetry)	
Slope	Maximum rate of depth variation between adjacent cells	Slope
Distance from coast	Minimum distance of the cell center from the coastline	Coast
Distance from canyon	Minimum distance of the cell center from the main axes of the "Taranto Canyon" (Figure 2)	Canyon
Distance from navy exercise area	Minimum distance of the cell center from the areas of navy exercises (Figure 2)	Navy
Distance from the merchant shipping routes	Minimum distance of the cell center from the main merchant routes recorded towards the Taranto harbor (Figure 2)	Commercial
Distance from fisheries	Minimum distance of the cell center from the areas with recorded trawl fishing effort	Fishery
Distance from the industrial area	Minimum distance of the cell center from the areas identified as specifically addressed to heavy industrial activities (Figure 2)	Industry

Some of the adopted explanatory variables were already applied in many studies on the distribution of dolphins and whales (Bailey and Thompson, 2006; Torres et al. 2008; Marini et al., 2015; Panigada et al., 2008; Azzellino et al., 2008; Fiori et al., 2014). A few explanatory

variables have been specifically introduced in this study due to the peculiarity of the area and the strong anthropic features of the Gulf of Taranto (i.e. navy, commercial, fishery and industry). These latter are here considered as proxies of impacts and disturbances that may have an influence on shaping the distribution of cetaceans. In particular, distance from the industrial area is intended as a proxy of the pollution effect on cetaceans' distribution, distance from the commercial routes and from areas of navy exercises are employed as measures of the effect of noise disturbance and, finally, distance from fisheries as a measure of the competition or synergies for the food resources.

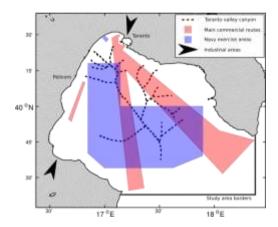


Figure 2 – Location of canyon main axes as identified by Senatore (1987) and anthropic variables identified in the study area.

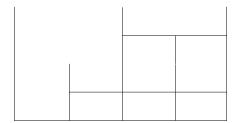
Spatial analyzes

Usually, techniques applied for modeling the spatial distribution of dolphin and whales are based on the collection of presence-absence data. But, obtaining reliable and accurate absence data for cetaceans is problematic due to their mobility and ability to spend underwater time being undetectable to observers. Thus, although recurrent samplings may reduce this uncertainty, the separation of true from false absences is difficult and leads to uncertainty when

interpreting results (Hall, 2000; Martin et al., 2005). In fact, the inclusion of false absences in predictive modeling could substantially bias analysis (Hirzel et al. 2002), indicating the need of the use of alternative approaches to modeling spatial distribution of species when there is no reliable absence data (zero inflated). Statistical adjustment to face this intrinsic uncertainty have been developed and, to this aim, in this study we applied a zero inflated correction recently proposed and applied in similar studies (Azzellino et al., 2012; Fiori et al., 2014; Marini et al., 2015). It consists in the selection of random sets of cells where the number of absence cells was equal to the number of presence cells. This approach is reported to satisfactorily cope with zero-inflated data avoiding the application of more sophisticated methods such as the hurdle-Negative Binomial and zero-inflated mixture-Negative Binomial models (Hall, 2000). In fact, the adopted procedure has the advantage to carry into the analysis a unique zero inflated correction that could be applied to both GAM and RF modeling, avoiding the introduction of further differentiations among methodologies.

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can be specified as:

Generalized additive model

variables affect the distribution of *S. coeruleoalba* and *T. truncatus* in the study area. When data are related to certain variables but the relationships fall to be simply linear, additive modeling may be a useful tool to improve predictive accuracy. GAM relates the dependent variable to a combination of functions of explanatory variables. The coefficients of the combination are identified in order to generate the best fit (maximum likelihood) between the model outputs and the calibration data set (Hastie and Tibshirani, 1990). GAM technique was recently employed to model cetaceans distribution (Forney et al., 2012; Tardin et al., 2013) and in some cases also at Mediterranean level (i.e. Tepsich et al., 2014, Marini et al., 2015).

The dependent variable in this study was spatial distribution of the presence of striped and bottlenose dolphins in each cell Y_i (binominal variable, i.e. presence or absence) where 1 is the presence and 0 is the absence. As a consequence, the presence/absence of dolphins in each

spatial cell (Y_i) follows a Bernoulli distribution with P_i (probability of presence/absence) and

A statistical approach based on additive model (GAM) was applied to determine if the selected

289 $Y_i = B(1, P_i)$

where $P_i = P_i = e^{g(x_i)}/(1 - e^{g(x_i)})$ being P_i comprised between 0 and 1 and where $g(x_i) = \alpha + f_i(x_j)$ +...+ $f_n(x_n)$ is a combination of smoothing functions (splines) $f_j(x_j)$ of explanatory variables (smoothers). x_j are the explanatory variables, that in our case are: depth, slope and distance from coast, canyon, industry, fisheries, commercial routes and navy exercise areas. f_j are the best smoothing functions, that were estimated by maximum likelihood and that are a fit of data most representative than a straight line.

Generalized additive models (GAM) allow a data driven approach by fitting smoothed nonlinear functions of explanatory variables without imposing parametric constraints (Hastie and Tibshirani, 1990). The greatest benefit of using GAMs resides in their flexibility in capturing non-linear species-habitat relationships. In GAM, there is a link function used to establish a relationship between the mean of response variable and the smooth function of explanatory variable. As a consequence, the association between response and explanatory variables derives from data itself and not from the model, because it does not assume any kind of parametric assumption (Yee and Mitchel, 1991). In this study GAM regression and smoother terms were derived using penalized regression splines using the MGCV library for freeware R (Wood, 2006) with a binomial distribution (family=binomial, link function=logit) of dependent variable (presence/absence of cetaceans in each spatial cell). Smoothness selection was based on an Un-Biased Risk Estimator (UBRE). The numerical output of the model show significant variables, selected by means of a chisquared test with a significance level for the selection of the explanatory variable fixed at 5%. Significant explanatory variables were selected by means of a Backward Elimination method that starts from a model of size p (being p the total number of variables) and eliminates not significant variables in a step by step procedure. When a variables is selected a significant nonlinear relationship exists within this variable and the presence/absence of cetaceans. Output presents also the degrees of freedom of a smoother, sometimes called effective number of parameters, is an indication of the amount of smoothing. The smoothers are calibrated so that a smoother with one degree of freedom gives an approximate straight line. The default value in R is for four degrees of freedom, which approximately coincides with the smoothing of a third-order polynomial (Zuur et al., 2007; Liu, 2008). The model also gives information about the deviance, that is the explained variance or the residual sum of squares. This is equivalent to the R² in linear regression. To help visual interpretation smoothing curves, graphically representing the relationship between the response variable and the explanatory variables, are shown: the y-axis show the

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influence predicted by GAM on presence/absence of cetaceans in function of each smoother, whose range of variability is displayed on the x-axis. The higher is the y value in the smoothing curve, the more it is probable the presence of cetaceans in the corresponding value of the explanatory variable considered.

Models' performances verification

Models performances were evaluated within the survey area for the verification of the model reliability. Performances were tested comparing predicted to observed values and reporting the true and false presences (a and b respectively in Table Tabella) and the true and false absences (c and d respectively in Table Tabella) at different cut-off values (Allouche et al., 2006).

Table 3: An error matrix used to evaluate the predictive accuracy of presence-absence models. a, number of cells for which presence was correctly predicted by the model; b, number of cells for which the species was not found but the model predicted presence; c, number of cells for which the species was found but the model predicted absence; d, number of cells for which absence was correctly predicted by the model.

		Obse	rved
		Presence	Absence
Predicted	Presence	a	b
Tredicted	Absence	С	d

Values in **Errore.** L'origine riferimento non è stata trovata. allow the calculation of a set of model accuracy metrics among which sensitivity and specificity. Sensitivity is calculated as the ratio among true presences and total presences (a/(a+c)) and thus counting for the probability

344 that the model will correctly classify a presence. Specificity is computed as the ratio among true absences and total absences (b/(b+d)) measuring the probability that the model will correctly 345 classify an absence (Allouche et al., 2006). 346 Despite commonly adopted, sensitivity and specificity have been also reported as often 347 348 dependent upon prevalence (the overall proportion of presences). Recently, the true skill 349 statistic (TSS=sensitivity+specificity-1), a new measure for the performance of presence-350 absence distribution models, have been proposed and is expected to correct for this 351 dependency (Allouche et al., 2006). To select the optimal cut-off probability value, we applied the Youden Index method (Fluss et 352 353 al., 2005) applied to the receiver operating characteristic (ROC) curve (Fielding and Bell, 1997). 354 ROC curve is obtained plotting false-positive rate (1-specificity) on the horizontal axis and the 355 true-positive rate (sensitivity) on the vertical axis for various cut-off values. The Youden Index 356 method allows the determination of the optimal cut-off point using the maximum vertical 357 distance of ROC curve from the chance line (where false positive rate = true positive rate). In 358 fact, Youden index maximizes the difference between sensitivity and 1-specificity. Thus, by 359 maximizing Sensitivity + Specificity across various cut-off points, the optimal cut-off point is 360 calculated (Hajian-Tilaki, 2013). Once the optimal cutoff was identified, the model is projected 361 to the entire study area, the suitable habitat areas are plotted and validated with an 362 independent set of data collected outside the survey area borders (validation dataset).

364 Random forest

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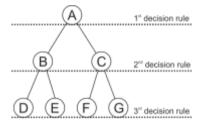
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Random Forest (RF) is based on regression tree methodology, able to model a response variable from a number of explanatory variables by subdividing a dataset in subgroups. Subgroups originate from recursive partitions based on decision rules that allow dividing successively each part into smaller data portions.

This can be represented as a binary tree, a hierarchical structure formed by nodes and edges, the latter representing some sort of information flow between adjacent nodes (Figure 3).



372 Figure 3: A complete binary tree with a set of three decision rules.

The random forests (RF) are a classification technique of neural networks (Breiman, 2001) based on regression tree methodology. It differs, as it does not only grow a single tree, but a whole forest of trees.

This is achieved by two means: (1) a random selection of explanatory variables is chosen to grow each tree and (2) each tree is based on a different random data subset, created by bootstrapping (Efron, 1979). Finally the "splitting" optimal in comparison with real data is identified and selected as predictor.

The data portion used as training subset is known as the "in-bag" data, whereas the rest is called the "out-of-bag" data. The latter are not used to build the tree, but provide estimates of generalization errors (Breiman, 2001). The mean square error calculated from prediction with the test dataset averaged over all trees is called the out-of-bag error. As forest size increases, this generalization error always converges (Breiman, 2001). The number of trees therefore needs to be set sufficiently high (800 in this case). In particular, RF implicitly deals with over fitting issue as decision trees are fitted to random samples of the data. In addition, RF performs splits in random subsets of the variable space, allowing to predict distribution on the whole dataset (Kehoe et al., 2012).

The rank importance of each explanatory variable is accounted as the changes in mean square error estimated by leaving a variable out of the model. After the most relevant variables were identified, the following step is consisted in studying the nature of the dependence between the response variable and each explanatory variable. Partial dependence plots were used to graphically characterize relationships between individual explanatory variables and predicted probabilities of presence obtained from RF (Hastie et al. 2001).

Results

A total of 334 daily trips for about 1670 hours of observations and 11690 nautical miles were carried out actively searching for *S. coeruleoalba* and *T. truncatus* in the Gulf of Taranto from 2009 to 2014. In particular, a total of 287 and 37 sightings of striped dolphin and bottlenose dolphin were recorded, respectively (Table 4).

Table 4: Sampling period, daily trips, survey effort, range of depth investigated and number of sightings of *T. truncatus* and *S. coeruleoalba* in the study area.

	Daily	Survey	Survey	Range			
Sampling period	trips	Effort	Effort	Depth	Number of sightings		
		(NM)	(hours)	(m)			
		-	_		Stenella	Tursiops	
					coeruleoalba	truncatus	
April-August 2009	13	455	65	93-500	11	1	
April-August 2010	24	840	120	180-	27	3	
. 0				636			

Commentato [P2]: Da rivederere a seguito dell'introduzione dei dati 2015

January-	61	2135	305	15-665	54	9
November 2011						
January-August	50	1750	250	20-694	42	6
2012	30	1730	250	20 071	12	
June-December	73	2555	365	6-882	64	5
2013	, 0	2000	000	0 002	0.1	Ü
May-December	113	3955	565	5-1000	89	13
2014				3 1300		
				5-		_

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Total	334	11690	1670		287	37
				1000		

An information summary about sightings of striped dolphin and bottlenose dolphin is shown in

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Stenella coeruleoalba resulted the most frequently sighted species (88.6% of total sightings)

with a frequency occurrence between 0.84 to 1.13 from 2009 to 2014. Observations occurred

with a mean aggregation number of 47 ± 39 specimens, in a depth range between 15 and 1000

m with a mean depth of 428±163 m. Encounter rate varied between 0.023 and 0.032

Tursiops truncatus presented a percentage occurrence of total sightings of 11.4% and frequency

occurrence between 0.07 to 0.15 from 2009 to 2014. Observations occurred with a mean

aggregation number of 12±10 specimens, in a depth range between 5 m to 586 m with a mean

depth recorded 141±157 m. Encounter rate varied from 0.002 to 0.004.

Table 5

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Table 5: Sampling period, encounter rate (sightings per survey effort in nm), frequency of occurrence

(number of sightings per daily trip), mean aggregation number (number of individuals per sighting) \square

Commentato [P3]: 2015

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standard deviation) and range of depth of sightings of *S. coeruleoalba* and *T. truncatus*, in the study area.

		Stenella	Stenella coeruleoalba Tursiops truncatus					
		Frequen	Mean	Rang		Frequen	Maan	Rang
Samplin	Encount	cy of	aggregati	e dept	Encount	cy of	Mean aggregatio	e dept
g period	er rate	occurenc	on	h	er rate	occurenc	n number	h
		e	number	(m)		e		(m)
April- August 2009	0.024	0.85	46268	200- 500	0.002	0.08	10	93
April- August 2010	0.032	1.13	49291	200- 636	0.004	0.13	1121	180- 419
January- Novemb er 2011	0.025	0.89	43238	15- 665	0.004	0.15	16261	36- 586
January- August 2012	0.024	0.84	46268	22- 694	0.003	0.12	21777	20- 500
June- Decembe r 2013	0.025	0.88	62228	117- 882	0.002	0.07	622	6- 421

May-

r 2014

 Decembe
 0.023
 0.79
 38287
 0.003
 0.12
 822

 1000
 401

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422 GAM results

GAMs developed for *S. coeruleoalba* and *T. truncatus* reached respectively 34.7% and 23.4% of explained deviance. *S. coeruleoalba* distribution resulted mainly affected by depth, distance from navy exercise area and distance from industrial areas; lower influence but still significant is shown by distance from fisheries (Table 6). Slope, distance from coast, distance from canyon, distance from the merchant shipping routes were not significant variables and then are not considered. The habitat identified by the GAM was characterized by depth over 250 m; distances from fishery areas exceeding 32 km; distances from navy exercise area greater than 6 km and distance from industrial areas ranging from 5 to 25 km (Figure 4).

Table 6: GAM numerical results, reported statistics include the estimated degrees of freedom (edf) and significant values of test based on model deviance.

S. coeruleoalba						T. trunco	itus	
	Estimate	Std. err.	p-val			Estimate	Std. err.	p-val
(Intercept)	-2.130	0.1285	<0.001		(Intercept)	-2.213	0.399	<0.001
	Ap	proximat	e significa	n	ce of smooth	terms:	'	'
	edf	Chi.sq	p-val			edf	Chi.sq	p-val
f(fishery)	0.621	2.735	0.033		f(fishery)	0.887	7.501	0.036
f(depth)	2.716	70.252	<0.001		f(depth)	0.705	2.926	0.004
f(navy)	1.169	68.747	<0.001		f(industry)	2.658	10.839	0.001
f(industry)	2.329	15.178	<0.001					

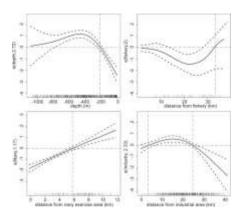


Figure 4: Generalized additive model (GAM) predicted smooth splines of the response variable presence/absence of striped dolphin as a function of the explanatory variables (see Table 6). The degrees of freedom for non-linear fits are in parentheses on the y-axis. Tick marks above the x-axis indicate the distribution of sightings. Dotted lines represent the 95% confidence intervals of the smooth spline functions.

T. truncatus distribution resulted mainly affected by distance from fishery, depth and distance from industry (Table 6). Slope, distance from coast, distance from canyon, distance from the merchant shipping routes, distance from navy exercise area were not significant variables and then are not considered. The GAM identified the *T. truncatus* habitat as characterized by depth lower than 300 m, distances from fishery areas lower than 10 km, and distance from industrial area ranging from 15 to 25 km with a second peak at distances higher than 40 km (Figure 5).

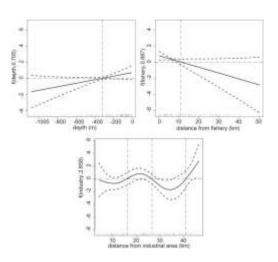


Figure 5: Generalized additive model (GAM) predicted smooth splines of the response variable presence/absence of bottlenose dolphin as a function of the explanatory variables (Table 6). The degrees of freedom for non-linear fits are in parentheses on the y-axis. Tick marks above the x-axis indicate the distribution of sightings. Dotted lines represent the 95% confidence intervals of the smooth spline functions.

 RF results

Random forest identified the *S. coeruleoalba* distribution driven principally by depth, distance from industrial areas, distance from coast and distance from navy exercise areas (Figure 6A). On the contrary, slope and distance from fishery resulted poorly important for the determination of *S. coeruleoalba* distribution.

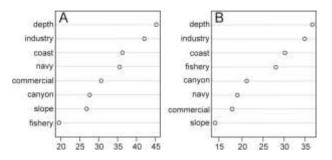


Figure 6: Importance scores of the explanatory variables used in the models (A) striped dolphin; (B) bottlenose dolphin. Importance is quantified as % increase in mean square error of the RF model when that explanatory variable is removed.

The univariate partial dependence plots are a tool to identify, for each considered variable, the range of optimal values expected to increase the presence probability (signature). The influence of depth values on the distribution of striped dolphin is shown in Figure 7A displaying an increasing presence probability at increasing depth reaching maximum values from 300 m depth. A threshold level is clearly detectable with very un-probable presence of striped dolphins at depth lower than 200m. The second most important explicative variable influencing the striped dolphin distribution is distance from industrial zone (Figure 7B) displaying a single presence probability peak between 10 and 25 km from industrial zone and very low presence probability at distances higher than 28 km. Distance from coastline influenced the striped dolphin distribution with very low probabilities at distances lower than 5 km and a steep increase in probability toward 10 km where a plateau is reached and presence probability is maximized Figure 7C. Distance from navy exercise areas has again a relevant effect on striped dolphin distribution. In particular, a continuous increasing trend is detected with maximum presence probabilities detected at distances exceeding 18 km (Figure 7D).

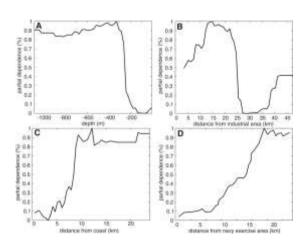


Figure 7: Univariate partial dependence plots of the depth (A), distance from the industrial area (B), distance from coast (C) and distance from navy exercise areas (D) for striped dolphin in the study area.

Also *T. truncatus* distribution is mainly shaped by depth followed by distance from industrial area, distance from coast and distance from fisheries. Once again slope resulted poorly important to discriminate the distribution also for *T. truncatus* (Figure 6B).

Depth resulted the most important explicative variable also for bottlenose dolphin and it revealed an increasing presence probability at depth lower than 300 m with the highest influence around the 100 m bathymetry (Figure 8A). Dependence from industrial areas revealed an increasing presence probability at increasing distance. Bottlenose dolphin revealed a trend with a clear threshold at 40 km and a sudden increase at higher distance (Figure 8B). Distance from coast has again a relevant effect on bottlenose dolphin distribution. Its influence displayed a clear presence probability increase at distance lower than 5 km (Figure 8C). Unlike striped dolphin, bottlenose dolphin resulted attracted by fisheries with a clear dependency

from this variable and the tendency to stay in the close proximity to fishing areas. A threshold

level is detectable with bottlenose dolphin, unlikely to be detected at distances higher than 5 km from fishery activity (Figure 8Figure 8D).

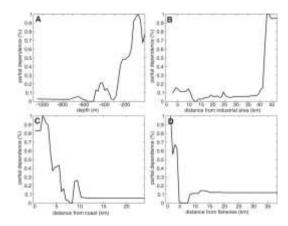


Figure 8: Univariate partial dependence plots of depth (A), distance from industrial areas (B), distance from coast (C) and distance from fishery area (D) for bottlenose dolphin in the study area.

Models' performances verification

Models' reliabilities have been tested within the survey area considering the ability of the predicted distribution to correctly identify the habitat of the considered species. The Youden Index method applied to ROC curves was applied to recognize habitat versus non-habitat areas. The optimal cut-off values and a set of predictive accuracy metrics are reported in Table 7 for each model and for each species.

Table 7: Measures of predictive accuracy calculated as reported in Errore. L'origine riferimento non è stata trovata..

		Cut-off	Sensitivity	Specificity	TSS
GAM	SC	0.30	0.74	0.78	0.52
GAM	TT	0.26	0.72	0.77	0.49
RF	SC	0.51	0.97	0.95	0.92
	TT	0.52	0.95	0.94	0.89

The most reliable model is expected to show the highest values of sensitivity, specificity and TSS thus being able to correctly identify both presences and absences of considered species. RF

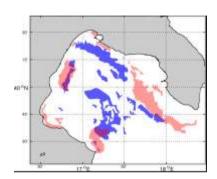
resulted the most reliable model for both striped and bottlenose dolphin.

The information provided by RF prediction together with the selection of the cut-off values

allowed the projection of the expected presence/absence pattern of striped and bottlenose

dolphins in the entire study area and produced the identification of habitat versus non habitat

521 map reported in Figure 9.



523 Figure 9: identification of habitat areas for striped dolphin (blue) and bottlenose dolphin (red).

RF predicted striped dolphin widely present in the central part of the Gulf of Taranto while bottlenose dolphin resulted mainly distributed along the coast with clear coastal hot spots in the western sector and favorable areas moved slightly offshore in the eastern sector, probably allowed by the wider platform present in this sector of the Gulf of Taranto. A clear separation of the habitat is showed with a couple of exception in front of the Policoro harbor and in the south-western sector.

The reliability of the projection on the entire study area has been tested considering the distribution of sightings collected as validation dataset and resulting in true presence rates of 0.73 and 0.77 for striped dolphin and bottlenose dolphin respectively.

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Discussion

This study aimed at developing a reliable habitat modeling procedure suite for the characterization of striped and bottlenose dolphin distribution in the Gulf of Taranto. By means of the application of two different models (GAM and RF) three main results were obtained: 1) to identify most relevant explanatory variables among a set initially chosen 2) to test the

540 reliability of different regression techniques, and 3) to identify areas to be considered as suitable habitat for dolphins in the Gulf. 541 Table 7 542 543 Human activities, and in turn impacts originating from them, are able to influence the cetaceans 544 distribution both directly and indirectly. Among the eight considered variables some are able to directly influence the distribution (e.g. commercial routes with collision risk) or indirectly 545 546 by acting upon other biotic (e.g. fishery activity with competition for feed resources) or abiotic 547 factors (e.g. navy exercise, commercial routes and industrial zone generating noise and 548 pollution). 549 Nonetheless variables employed, depth, distance from industry and distance from coast, turned 550 out to significantly affect the distribution of both striped dolphin and bottlenose dolphin. On 551 the contrary slope, which is commonly applied in other studies on cetaceans' distribution (Cañadas et al., 2002; Cañadas et al., 2005; Pirotta et al., 2011; Azzellino et al., 2012) never 552 553 brought significant improvement to predicted distribution together with the distance from 554 commercial routes. 555 For both species, two out of four among the most important variables identified during the 556 analysis resulted dependent on human presence and activities. This finding highlighted how heavily human activities act as driving forces in shaping the habitat of marine species 557 outclassing natural, geomorphological parameters that would normally shape the habitat of an 558 559 undisturbed species. 560 Among anthropic variables, distance from industrial zones resulted the most important for the 561 determination of the distribution of the considered species. Both species never showed the 562 peak of probability values close to the industrial areas confirming the existence of these activity 563 as disturbing the distribution of both striped and bottlenose dolphin.

Bottlenose dolphin distribution is also significantly affected by the distance from fishery activities, while striped dolphin resulted unaffected by this variable. In particular, bottlenose dolphin presence resulted particularly probable closer to fishery activity with a sudden increase in presence probability for distances lower than 5 km. This is in accord with what expected since only bottlenose dolphin have been reported as possibly attracted by fishery due to the ability of this species to prey on fish nets (Fertl and Leatherwood 1997; Corkeron et al. 1990; Pace et al. 2003; Chilvers and Corkeron 2001; Wells and Scott 2009; Lauriano et al. 2004; Diaz Lopez 2006; Brotons et al. 2008). On the other hand striped dolphin showed a significant dependency on the distance from navy exercise areas displaying the tendency to be more present at increasing distance and thus to move away from this possible disturbance. Depth and distance from coast resulted the only geomorphologic variables significantly affecting the distribution of both species. In the study area striped dolphin distribution is predicted mainly at depth higher than 350 m and distance from coast greater than 10 km while bottlenose dolphin distribution resulted concentrated near the 100 m isobath and rarely at depth higher than 200 m coupled with distances from coast unlikely to be greater than 5 km. This is in accord with other studies on S. coeruleoalba and T. truncatus habitat distribution in Mediterranean such as Cañadas et al. (2002) and Azzellino et al. (2012), who demonstrated that T. truncatus prefer coastal areas within 400 m while S. coeruleoalba presence probability is expected to increase around 1600-2000 m of depth and thus beyond the continental shelf. Regarding the applied modeling techniques, RF displayed better ability to cope with the observed distribution of both striped dolphin and bottlenose dolphin (Table 7) confirming findings of other researches (Cutler et al., 2007; Virkkala et al., 2010). RF is based on multiple individual classification and regression trees: this technique has already been used successfully for environmental mapping

and management (Pesch et al., 2011; Parravicini et al., 2012) and for characterizing bottlenose

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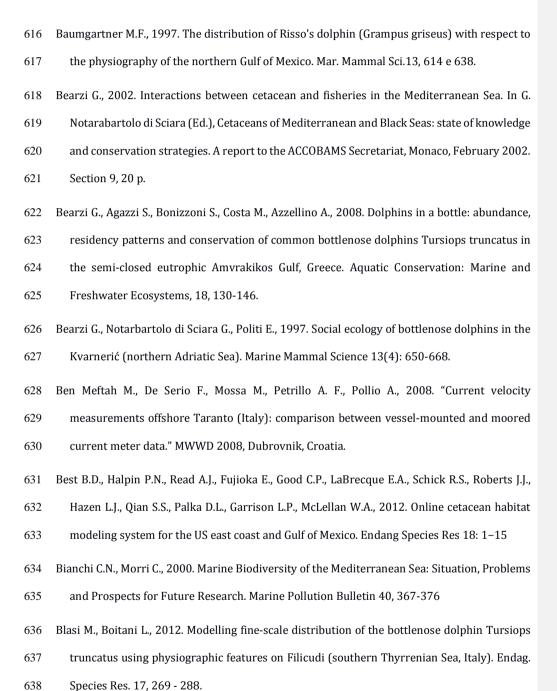
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- 589 distribution (Marini et al., 2015) also because it is particularly appropriate in identifying and modeling
- 590 complex interactions among multiple variables (Loh, 2008).
- 591 Conclusion
- 592 To do

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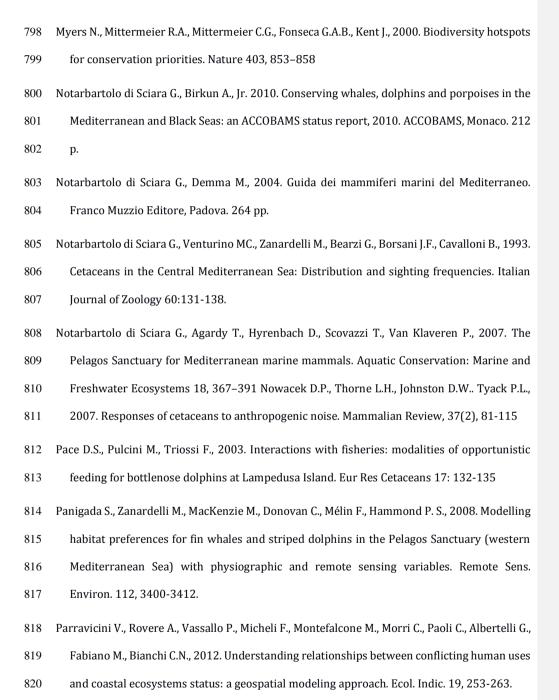
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