

Predicting bottlenose dolphin distribution along Liguria coast (northwestern Mediterranean Sea) through different modeling techniques and indirect predictors



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ARTICLE INFO

Article history:

Received 21 May 2014

Received in revised form

20 October 2014

Accepted 7 November 2014

Available online

Keywords:

Tursiops truncatus

Habitat modeling

GLM

GAM

Random forest

Pelagos sanctuary

Ligurian coast

ABSTRACT

Habitat modeling is an important tool to investigate the quality of the habitat for a species within a certain area, to predict species distribution and to understand the ecological processes behind it. Many species have been investigated by means of habitat modeling techniques mainly to address effective management and protection policies and cetaceans play an important role in this context. The bottlenose dolphin (*Tursiops truncatus*) has been investigated with habitat modeling techniques since 1997. The objectives of this work were to predict the distribution of bottlenose dolphin in a coastal area through the use of static morphological features and to compare the prediction performances of three different modeling techniques: Generalized Linear Model (GLM), Generalized Additive Model (GAM) and Random Forest (RF). Four static variables were tested: depth, bottom slope, distance from 100 m bathymetric contour and distance from coast. RF revealed itself both the most accurate and the most precise modeling technique with very high distribution probabilities predicted in presence cells (90.4% of mean predicted probabilities) and with 66.7% of presence cells with a predicted probability comprised between 90% and 100%. The bottlenose distribution obtained with RF allowed the identification of specific areas with particularly high presence probability along the coastal zone; the recognition of these core areas may be the starting point to develop effective management practices to improve *T. truncatus* protection.

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1. Introduction

Habitat modeling for marine mammals has made considerable advances in the past decades. The application of statistical models to understand and predict relationships between species and their environment has become more and more frequent in the literature (Redfern et al., 2006). Habitat models have a number of important applications for the conservation and management of wild species (Guisan and Zimmermann, 2000; Thomas et al., 2004; Thuiller et al., 2004; Redfern et al., 2006; Kremen et al., 2008; Mouton et al., 2011). In particular, habitat models can be used (i) to predict species occurrence on the basis of habitat variables, (ii) to improve the understanding of species-habitat relationships and (iii) to quantify habitat requirements (Ahmadi-Nedushan et al., 2006).

Habitat modeling techniques are based on the assumption that, for each species, there is an ideal set of environmental variables (signature) that makes the presence of animals more likely. Guisan and Zimmerman (2000) classified variables into three main categories: 1) resources (e.g. matter and energy consumed); 2) condition variables (e.g. variables of physiological importance, pH, temperature) and 3) indirect variables (e.g. depth, slope, distance from coast). While resources and condition variables are expected to change in time, indirect variables are often static variables mainly associated with geomorphologic characteristics of the (investigated) area and thus represent a solid base to understand and to predict animals' distribution and preferences. Many studies have shown that cetacean distribution can be closely linked to underwater topography such as water depth and seabed gradient (Watts and Gaskin, 1986; Ross et al., 1987; Selzer and Payne, 1988; Frankel et al., 1995; Gowans and Whitehead, 1995; Baumgartner, 1997; Raum-Suryan and Harvey, 1998; Karczmarski et al., 2000; Ferguson and Barlow, 2001; Bailey and Thompson, 2006; Ferguson et al., 2006; Azzellino et al., 2008; Blasi and Boitani, 2012).

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Aiming at outlining relationships between cetaceans' presence and environmental variables, a number of different techniques have been applied to cetacean–habitat modeling (Redfern et al., 2006). Most studies exploring the relationship of distribution patterns with environmental variables are based on statistical regression, in which the presence/absence or abundance of cetaceans is regressed with a set of predictor variables (Baumgartner, 1997; Moses and Finn, 1997; Tynan, 2004). An important statistical development of the last thirty years has been the advances in regression analysis provided by generalized linear models (GLMs) and generalized additive models (GAMs) (Guisan et al., 2002). These statistical approaches are able to verify the existence of respectively linear and non-linear relationships between a response variable and a set of predictor variables. The ability of these tools to handle non-linear data allowed the development of ecological models that better represent the underlying data, and hence increase our understanding of ecological systems (Guisan et al., 2002). More recently, new techniques based on machine learning techniques have been applied in a number of different fields aiming at more reliable and accurate prediction of habitat uses. Among these Random Forest (RF) models (Breiman, 2001; Cutler et al., 2007) are a machine learning technique based on an automatic combination of decision trees (Breiman et al., 1984). Several studies applied random forest technique to habitat modeling (Cutler et al., 2007; Siroky, 2009; Kampichler et al., 2010) demonstrating the possibility to apply this methodology for studies on species distribution.

This study is focused on the application and comparison of different techniques for the analysis of the distribution of common bottlenose dolphin (*Tursiops truncatus* Montagu, 1821). Bottlenose dolphins are known to be among the most widely distributed cetaceans, occurring in both hemispheres (Wells and Scott, 2009). In Mediterranean, the bottlenose dolphin distribution is commonly confined to the continental shelf within the 200 m isobath, with a preference for shallow waters of less than 100 m depth and show a residential attitude with excursions usually within a distance of 80 km (50 km on average) (Gnone et al., 2011). 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 (Voliani and Volpi, 1990; Orsi Relini et al., 1994; Silva and Sequeira, 1997; Mioković et al., 1999; Blanco et al., 2001; Santos et al., 2001). Since they mainly behave as coastal cetaceans, bottlenose dolphins are increasingly exposed to a variety of human activities through the proliferation of littoral development. Threats to dolphins in near-shore environments include the loss of suitable habitat, increasing vessel traffic and tourism, entanglement in fishing gear or in marine debris, noise pollution, environmental contaminants and disease. This is why bottlenose dolphin 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 (Reeves and Notarbartolo di Sciara, 2006).

Since the conservation of a species depends on the understanding of the relationship between populations and their habitat (Candas et al., 2005), modeling *T. truncatus* distribution may help to understand which habitats are used with higher frequency, which environmental features (biotic or abiotic) are the most important determinants for the species distribution and, in turn, suggest and develop management practices to improve their conservation.

The aim of this study is the identification of the more reliable technique to predict the relationship between a set of indirect variables and the distribution of the bottlenose dolphin.

The spatial distribution of *T. truncatus* was investigated in the east Ligurian coast (north-west Mediterranean Sea) by means of three different statistic techniques: GLM, GAM and RF.

The study area is completely included in the International Pelagos Sanctuary for the protection of marine mammals (Notarbartolo di Sciara et al., 2008). The Pelagos Sanctuary is a 90.000 km² Marine Protected Area (MPA) established in 2002 by a joint declaration between the Governments of France, Italy and Principality of Monaco (Notarbartolo di Sciara et al., 2008). The Sanctuary hosts eight resident cetacean species: *Balaenoptera physalus*, *Physeter macrocephalus*, *Grampus griseus*, *Globicephala melas*, *Tursiops truncatus*, *Stenella coeruleoalba*, *Delphinus delphis* and *Ziphius cavirostris*. Compared to other Mediterranean regions, the area is characterized by high levels of offshore primary productivity maintained by upwelling circulation (Viale, 1991; Barale and Zin, 2000). Moreover, all MPA is characterized by the strong presence of human activities generating possible threats for cetaceans, that varies from acoustic (i.e. vessel noise, military sonar exercise, seismic survey) (Notarbartolo di Sciara et al., 2008) and chemical pollution (Monaci et al., 1998; Aguilar, 2000; Fossi et al., 2003), habitat degradation, entanglement in fishing gear, disturbance by boat i.e. whale watching, pleasure and fishing boats (Jahoda et al., 2003), and collisions with vessels (Panigada et al., 2006).

For this study four predictive physiographic variables were identified: depth, distance from coast, distance from 100m bathymetry and slope. These were tested by means of the three chosen techniques aiming at the best prediction of *T. truncatus* distribution and at the identification of the most influencing variables determining the animals' distribution.

2. Materials and methods

2.1. Study area

The study area is located in the Ligurian Sea (NW Italy) and stretches from the eastward limits of the city of Genoa (9° 06' 04" E – 44° 22' 38.21" N) to Punta Bianca, La Spezia (9° 58' 24.19" E – 44° 02' 50.28" N). This area is characterized by a marked bathymetric heterogeneity with a small and extremely steep continental shelf in the western sector and a bathymetric profile more and more smoothed moving eastward (Fig. 1). As a consequence the edge of the platform (~200 m depth) runs almost parallel to the coastline at a distance of about 10 km from Portofino promontory to Cinque Terre while in the western sector it moves offshore reaching more than 25 km wideness.

The area is characterized by a marked seasonal variability in the main current field which is also highly influenced by waters flowing northward on both sides of Corsica in roughly equivalent fluxes and connecting in the Gulf of Genoa. These flows interact in a turbulent way and mix together to form the Ligurian current (Millot, 1987). This current moves westward remaining close to the coast and then continues along the Provence continental shelf (Taupier-Letage and Millot, 1986). The strong counterclockwise circulation at the centre of the Ligurian Sea causes the coastal upwelling of deep waters that supports a spring primary production, higher than the average for the western Mediterranean, with mesotrophic conditions in March–May and oligotrophic conditions in the summer and winter months (Viettia et al., 2010).

A high level of urbanization characterizes the coastline except for small portions such as Portofino and Cinque Terre where both terrestrial and marine protected areas have been established in the late nineties.

The area has undergone an impressive amount of development in the last century. This phenomenon has been mainly driven by the construction of massive infrastructures (commercial harbors, roads and railways) and later by an impressive increase (started in the 1960s) in tourism pressure and population density on the coastal

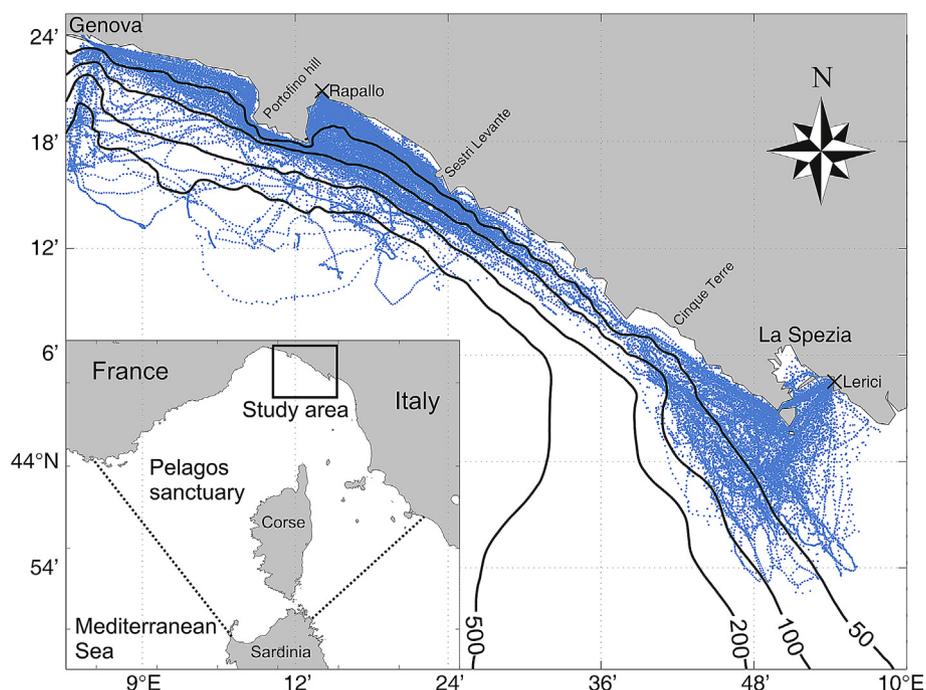


Fig. 1. Study area (blue dots represent the tracks held from 2005 to 2012). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

strip. Since then, local economy of many small resorts has become strongly dependent on summertime, domestic, family-oriented and (sun-) bathing tourism (Vassallo et al., 2009). As a consequence, pleasure boat traffic is intense through the year with marked seasonal pick during summer season. Twenty small marinas and a commercial harbor (La Spezia) are distributed along the considered coastline for a total of approx 6200 moorings. A number of professional fisheries operate both inshore and offshore. In coastal waters fishing activity is carried out mainly with set nets, while on the continental slope the most widely practiced fishing techniques are based on trawl nets (Orsi Relini, 1984). A negative interaction exists between bottlenose dolphin and artisanal fishery in inshore waters (Fossa et al., 2011), while a random association between bottlenose dolphin and trawlers seems to occur in some parts of the study area (Bellingeri et al., 2011).

2.2. Bottlenose dolphin

The bottlenose dolphin can be found in all tropical and temperate waters of the world. The limits to the global world scale distribution of the species seem to be related to temperature, directly or indirectly through the distribution of prey (Wells and Scott, 2002). On the finer scale, the bottlenose dolphin is a species displaying strong adaptive ability and an extraordinary behavioral flexibility, using a variety of tactics and strategies of search and capture of prey for different habitats, ranging from individual to highly coordinated group hunting techniques (Wells and Scott, 2002). In addition, deliberately and opportunistically, bottlenose dolphins use different types of fishing nets as an integral part of their feeding strategies, removing the prey directly from the tool (Fertl and Leatherwood, 1997; Pace et al., 1999; Pulcini et al., 2001, 2002; Pace et al., 2003; Lauriano et al., 2004; Blasi and Pace, 2006).

The bottlenose dolphin is one of the most frequently observed cetaceans in the Mediterranean (Reeves and Notarbartolo di Sciara, 2006). Generally it is sighted within the limits of the continental

shelf (~200 m) and forms small subgroups of a few tens of individuals only occasionally more numerous (Connor et al., 2000). Bottlenose dolphins occur in most coastal waters of the basin and have been reliably reported in the waters of Albania, Algeria, Croatia, Cyprus, France, Gibraltar, Greece, Israel, Italy, Montenegro, Morocco, Slovenia, Spain, Tunisia and Turkey. The presence of the bottlenose dolphin in the Pelagos Sanctuary has been reported along the west coast of France (Ripoll et al., 2001; Gannier, 2005), east coast of Liguria (Gnone et al., 2006), north Tuscany (Nutti et al., 2006), Tuscany Archipelago (Rosso et al., 2006; Nutti et al., 2007), west and south coast of Corsica (Dhermain, 2004; Dhermain and Cesarini, 2007), and the north coast of Sardinia (Lauriano, 1997; Fozzi et al., 2001). Occasional sightings have also been reported in the west coast of Liguria (Azzellino et al., 2008; Bearzi et al., 2008). A few attempts have been made to estimate the abundance of the bottlenose dolphin in the Sanctuary; the bottlenose dolphin is more abundant in the eastern portion of the Sanctuary, characterized by a wide continental platform, and along the north-western coasts of Corsica (Gnone et al., 2011).

2.3. Data collection

Data for the model development were collected by means of boat-based survey conducted from 2005 to 2012. A total of 171 sightings were recorded and used to set up and verify the different models (Table 1). The fieldwork was carried out with two 5.10 m long rigid inflatable boats, one moored in Rapallo (Genoa) and one in Lerici (La Spezia). Both units surveyed at an average speed of 8 knots. Sighting effort was conducted only under adequate weather conditions (defined as Douglas sea state 3 or lower).

2.4. Physiographical features

The study area was divided into 1650 cells of about 1 x 1 miles each. In each cell four predictive variables were calculated: 1) depth as average depth of the cell (25 depth point in each cell were

Table 1
Number of surveys, effort under favorable conditions (expressed as nautical miles surveyed and hours spent) and number of bottlenose dolphin sightings in different years.

	Number of surveys	Effort		Number of sightings
		NM	h	
2005	46	931	140	16
2006	50	1843	215	26
2007	50	1506	225	17
2008	49	1530	225	16
2009	50	1383	200	18
2010	49	1490	175	17
2011	60	1806	225	34
2012	48	1296	150	27
Total	402	11786	1556	171

averaged); 2) distance from coast as the minimum distance of the cell centre from coastline (distcoast); 3) distance from 100m bathymetry as minimum distance of the cell centre from the 100 m bathymetry (dist100) and 4) slope as the maximum depth difference recorded between the four corners of the cell. These variables were already used in many studies about cetaceans' distribution and also for bottlenose dolphin (Bailey and Thompson, 2006; Torres et al., 2008).

2.5. Spatial analysis

Traditionally, approaches for modeling cetacean distribution such as Generalized Linear Models (GLMs) and Generalized Additive Models (GAMs) have relied on the collection of presence-absence data. However, these methods assume that the absence data is accurate. Obtaining reliable absence data for cetaceans is problematic. Due to the mobility of marine mammals and their ability to spend time underwater (and therefore undetectable to observers on the surface), there is always a degree of uncertainty associated with cetacean absence data. Recurrent samplings may reduce this uncertainty but the separation of 'true' absences, where animals are actually absent, from 'false' absences, where animals are present but not detected, is difficult and leads to uncertainty when interpreting results (Hall, 2000; Martin et al., 2005). Hirzel and collaborators (Hirzel et al., 2002) suggested that inclusion of these types of 'false' absences in predictive modeling could substantially bias analysis and propose the use of alternative approaches to modeling species' potential distributions 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 already proposed by Azzellino et al., 2012 and Fiori et al., 2014 consisting in the selection of random sets of cells where absence was recorded equal to the number of presence cells. This design is similar, although not identical, to the "two stage sampling design" used in case-control studies (Breslow, 1996; Breslow and Cain, 1988). 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). Moreover, the selected procedure has the advantage to carry into the analysis a unique zero inflated correction that will be applied to the three modeling techniques without distinction, thus avoiding the introduction of further differentiation among methodologies.

2.5.1. Generalized linear model

To determine if the selected variables affect the distribution of *T. truncatus* in the study area a statistical approach based on linear

relationship was tested. Generalized linear models (GLMs) are useful for fitting linear relationships with non-Gaussian data distributions such as presence/absence data (McCullagh and Nelder, 1989). GLM relates the dependent variable to a linear combination of explanatory variables. The coefficients of the linear combination are identified in order to generate the best fit (maximum likelihood) between the model outputs and the calibration data set (Jongman et al., 1987; Nicholls, 1989; Hirzel et al., 2001).

The dependent variable in this study was *T. truncatus* spatial presence 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 *T. truncatus* in each spatial cell (Y_i) follows a Bernoulli distribution with P_i (probability of presence/absence) and can be specified as: $Y_i = B(1, P_i)$ where P_i being P_i comprised between 0 and 1, and where $g(x_i) = \alpha + \beta_1 x_1 + \dots + \beta_n x_n$ is a linear function of explanatory variables. x_j are the explanatory variables, that in our case are depth, distance from coast, distance from 100m bathymetry, slope, and β_j are the coefficients that were estimated by maximum likelihood.

Data were modeled using the freeware R (<http://www.r-project.org>) and a binomial distribution was selected. Initially the model was tested with all four explanatory variables. Later the significance of each explanatory variable was determined and then non-significant variables (at the 5% level) eliminated from the GLM model.

GLM applications to cetacean distribution are becoming common and many studies have been recently published (Cañadas et al., 2002; Praca et al., 2009; Azzellino et al., 2012).

2.5.2. Generalized additive model

GAMs (Hastie and Tibshirani, 1990) are semi-parametric extensions of GLMs. 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.

In GAM β_j slopes employed in GLM linear function of explanatory variables are replaced by smoothing functions (splines) $f_j(x_j)$:

$$g(x_i) = \alpha + f_1(x_1) + \dots + f_n(x_n)$$

that make the GAM able to predict non linear regression with greater accuracy in comparison with GLM. Generalized additive models (GAMs) allow a data driven approach by fitting smoothed non-linear functions of explanatory variables without imposing parametric constraints (Hastie and Tibshirani, 1990). The greatest benefit of using GAMs instead of GLM 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 Mitchell, 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 *T. truncatus* in each spatial cell). Smoothness selection was based on an Un-Biased Risk Estimator (UBRE).

As in GLM significant explanatory variables have been selected by means of trial and errors procedures and a significance level for the selection of the explanatory variable fixed at 5%.

GAMs have been 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).

2.5.3. Random forest

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 (Fig. 2).

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). Moreover, in this way, RF implicitly deals with over fitting issue as decision trees are fitted to random samples of the data and perform splits in random subsets of the variable space and then are used to predict distribution on the whole dataset (Kehoe et al., 2012). Later, most relevant variables have been identified. In particular, the importance of each explanatory variable is accounted as the changes in mean square error that is realized by leaving a variable out of the model.

After the most relevant variables have been identified, the next step is to attempt to understand the nature of the dependence of response variable on each explanatory variable. Partial dependence plots (Hastie et al., 2001) may be used to graphically characterize relationships between individual explanatory variables and predicted probabilities of presence obtained from RF.

Despite RFs were never applied to model cetacean distribution, many approaches have been proposed in environmental studies to classify habitat (Parravicini et al., 2012; Rodriguez-Galiano et al., 2012; Ghosh et al., 2014) and to identify spatial distributions (Oliveira et al., 2012; Tinkham et al., 2014) by developing random forests.

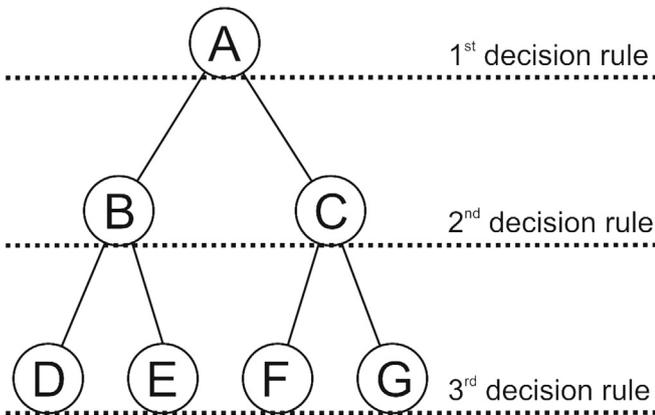


Fig. 2. A complete binary tree with a set of three decision rules.

3. Results

3.1. GLM results

The GLM identified the distribution of bottlenose dolphins significantly affected by three over four variables: depth, distance from coast and distance from 100 m bathymetry (Table 2).

Table 2 shows the resulting estimates for intercept and slope of the linear regression (estimate) and the statistical outputs of the ANOVA test (Std. Error, t-value and P-value) applied to reject the null hypothesis that all parameters are equal to zero. The predicted probability resulted positively affected by depth increase while an opposite relationship was assessed for both distance from coast and distance from 100 m isobath. The resulting predictive probability map is reported in Fig. 3 and showed the highest probabilities gathered near the coast and for the most part within the 50 m bathymetry line. The GLM output probabilities turned quickly to low values moving toward open sea even if several sightings were recorded far from coast mainly in the eastern part of the study area.

3.2. GAM results

The significant test applied to verify the smoother terms (a Chi squared method was applied) showed again distance from coast, distance from 100 m bathymetry and depth as the three significant variables affecting the bottlenose dolphin distribution (Table 3).

The smoothers showed different estimated degrees of freedom assessing the dependency from distance from coast as almost linear while more heterogeneous relationships were detected by the smoothers of distance from 100 m isobath and of depth.

Fig. 4 shows the GAM-predicted smooth splines for the sightings as functions of distance from coast, distance from 100 m bathymetry and depth where the values in parentheses represent the degrees of freedom for the nonlinear regression. Distance from coast had a continuous decreasing effect on the distribution probability moving offshore, while, distance from 100 m isobath and depth showed maximum values until a distance of 10 km and a depth of 200 m and a more rapid decrease at increasing values over those thresholds.

The GAM graphical output of predicted probabilities is reported in Fig. 5. The highest probabilities were displayed slightly moved offshore if compared with GLM map (Fig. 3) and were mainly located between 50 and 100 m isobaths establishing a continuous pattern of high sighting probabilities that crossed the entire study area from north-west to south-east.

3.3. Random forest results

Random forest identified the bottlenose dolphins' distribution driven principally by variations in depth followed by distance from coast and 100 m bathymetry respectively (Fig. 6). Once again slope resulted poorly important for the determination of dolphins' distribution.

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 bottlenose

Table 2
GLM numerical results, parameter of linear relationship.

	Estimate	Std. error	t-value	P-value
(Intercept)	3.11244	0.517918	6.01	1.86E-09
depth	0.015525	0.004103	3.784	1.54E-04
distcoast	-0.12221	0.040664	-3.005	2.65E-03
dist100	-0.19274	0.053716	-3.588	3.33E-04

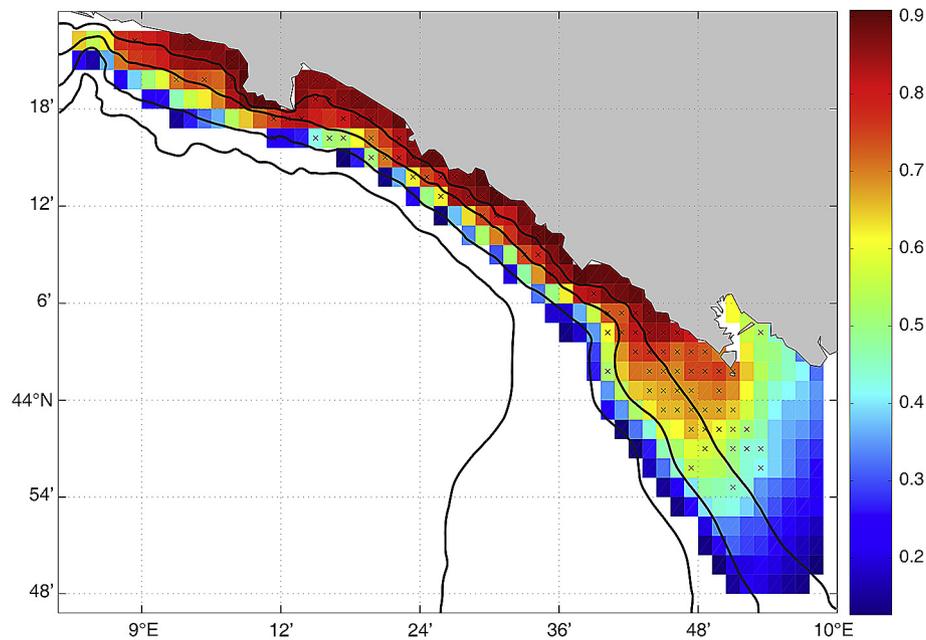


Fig. 3. *T. truncatus* predictive map based on GLM. Cells with sightings are shown with black dots; black lines identify the main isobaths.

dolphin signature in the East Ligurian coast is determined by a depth lower than 150 m, a distance from coast and from 100 m isobath lower than 12 km. The univariate partial dependence plots for the three most important variables (Fig. 7) showed that depth (at 150 m) and distance from 100 m bathymetry (at 12 km) had an evident threshold effect on the sighting distribution. On the contrary, the relationship found between distance from coast and the sighting distribution showed a tendency to increase with a smoother trend starting from 15 km from coast (Fig. 7).

The RF resulting map of distribution (Fig. 8) highlighted the presence of a few spots of parcels where the probability of sighting was very high (close to Portofino promontory, along the coast of Sestri Levante and in front of Cinque Terre National park), where the values of the driving variables resulted especially favorable to the presence of *T. truncatus*.

3.4. Models verification

Aiming at the identification of the more accurate and reliable method for the determination of the preferred habitat by *T. truncatus* a simple verification procedure is here proposed. The presence probabilities obtained from each model are compared considering cells where at least a sighting was recorded (presence cells). The most reliable model is expected to show the highest value of average probability calculated in presence cells (high accuracy) as well as the distribution of probabilities shifted towards higher probability values (i.e. close to the unit) (high precision). In Fig. 9 the number of sightings corresponding to different predicted

probabilities is showed. RF resulted both the most accurate and the most precise with the highest average probability value (90.4% of mean predicted probabilities in presence cells) and with 66.7% of presence cells with a predicted probability between 90% and 100%.

4. Discussion

This study aimed at developing a reliable habitat modeling procedure suite for the characterization of bottlenose dolphin distribution in a coastal zone along the Ligurian coast. By means of the application of three different models (GLM, GAM and RF) two main results were obtained: 1) to identify most relevant explanatory variables among a set initially chosen and 2) to test different modeling techniques on a database covering a eight years period of observations.

Among the four variables employed, depth, minimum distance from coast and minimum distance from 100 m bathymetry, turned out to significantly affect the distribution of bottlenose dolphin whatever modeling technique was applied. On the contrary slope, which is commonly applied in other studies on cetaceans' distribution (e.g. Cañadas et al., 2002; Pirotta et al., 2011; Azzellino et al., 2012) never brought significant improvement to predicted distribution. In the study area bottlenose dolphin distribution resulted concentrated near the 100 m isobath and distribution is never predicted over 200 m depth with a clear threshold value identified. This is partially in accord with other studies on *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.

A secondary factor affecting distribution is the distance from coast, with the highest distribution probabilities detected at few kilometers from coast (~3 km). This may be due to the balance between, on one side, the appeal of shallow zones in terms of prey abundance and easiness of catch and, on the other side, the threads due to increasing human disturbance more and more evident at decreasing distance from coast (Allen and Read, 2000).

Finally, the selection of preferential habitats is also driven by a limited range of movement around the 100 m bathymetry with

Table 3
GAM numerical results, reported statistics include the estimated degrees of freedom (edf) and significant values of test based on model deviance.

	Estimate	Std. Error	P-value
Intercept	-60.81	138.71	0.661
Approximate significance of smooth terms:			
	edf	Chi.sq	p-value
f(distcoast)	1.468	25.45	7.80E-06
f(dist100)	2.084	17.55	1.61E-05
f(depth)	3.478	13.28	7.62E-04

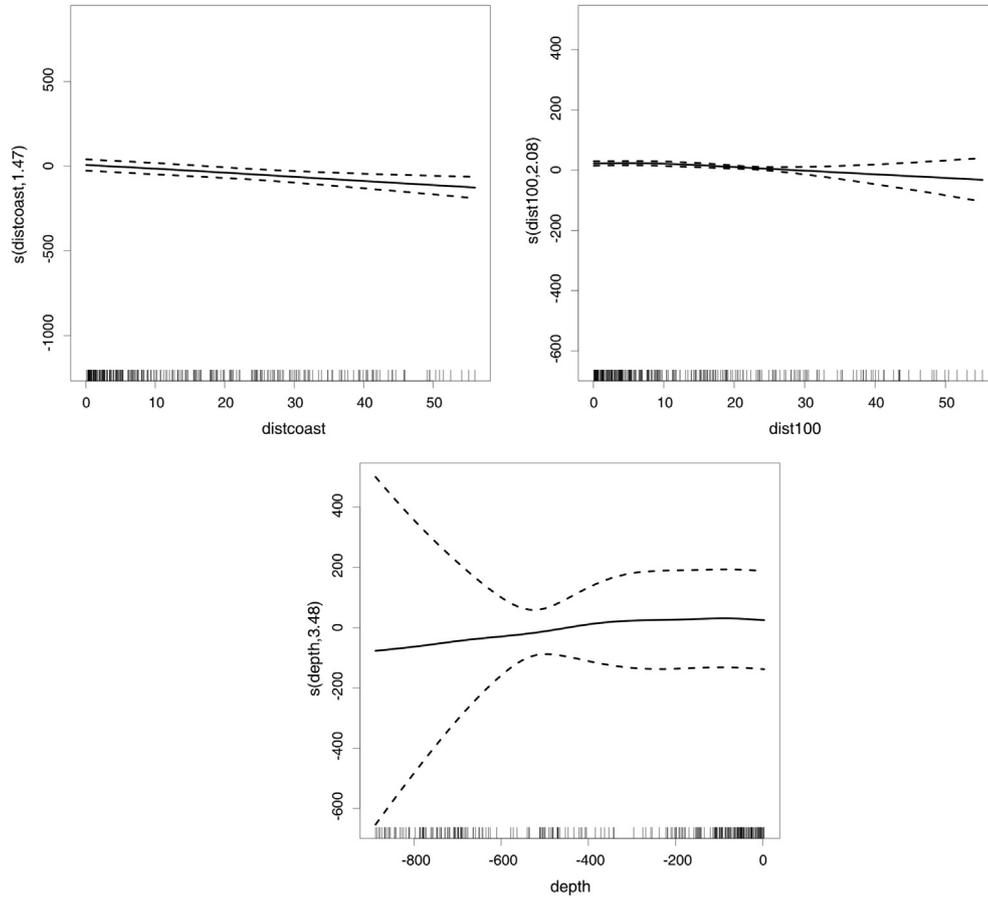


Fig. 4. GAM-predicted smooth splines for bottlenose dolphin sightings as function of distance from coast, distance from 100 m bathymetry and depth. Dashed curves indicate 2 standard error bounds.

highest predicted values detected within 5 km and very low presence predicted at distance greater than 12 km.

Regarding the applied modeling techniques, predicted bottlenose dolphin distributions revealed clear differences with

increasing accuracy and precision moving from GLM, to GAM and finally to RF. When modeling distribution, RF outperformed other data-driven methods and this is in good accord with what assessed by other researches (Cutler et al., 2007; Virkkala et al., 2010). RF is

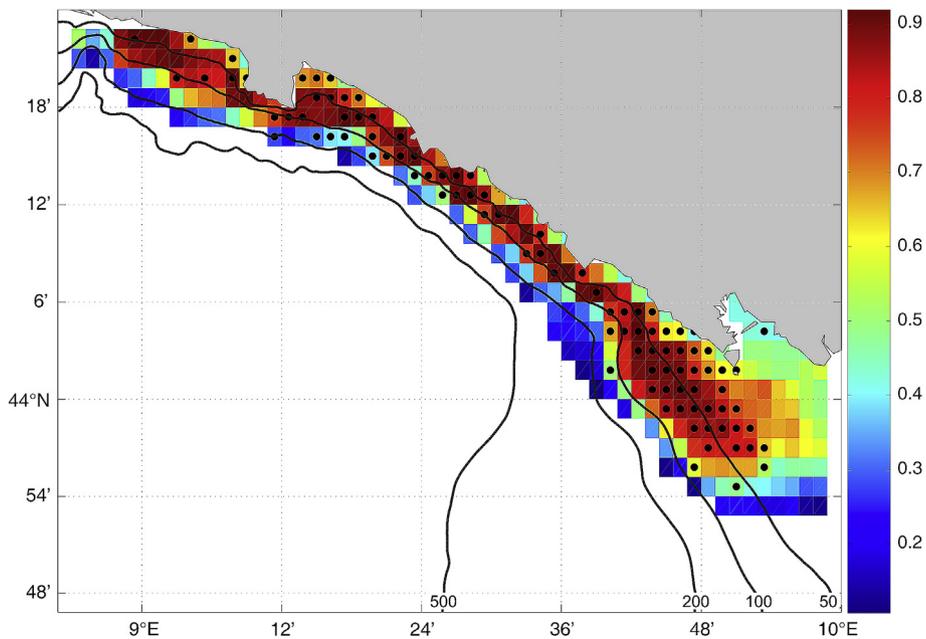


Fig. 5. *T. truncatus* predictive map based on GAM. Cells with sightings are shown with black dots; black lines identify the main isobaths.

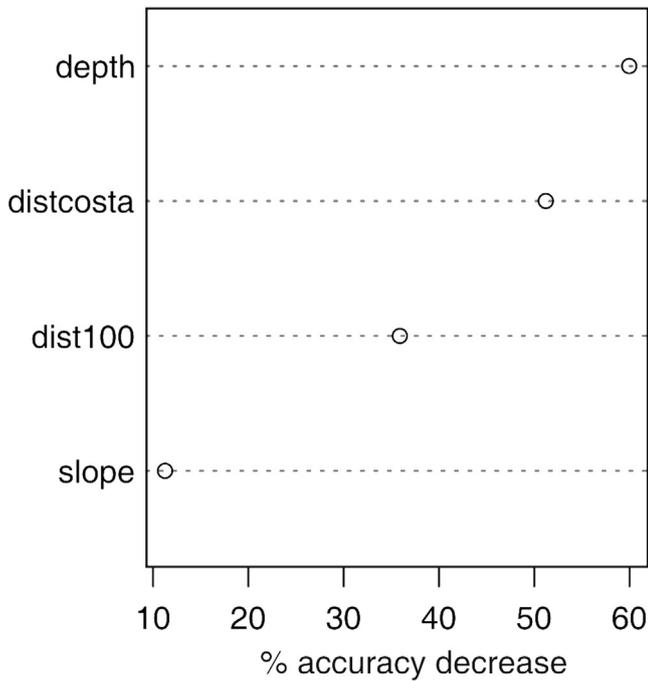


Fig. 6. Importance scores of the explanatory variables used in the model. Importance is quantified as % increase in mean square error of the RF model when that explanatory variable is removed.

based on multiple individual classification and regression trees, already successfully used for environmental mapping and management (Pesch et al., 2011; Parravicini et al., 2012) also because it is particularly appropriate in identifying and modeling complex interactions among multiple variables (Loh, 2008).

In relation to bottlenose dolphin distribution in the Eastern coast of Liguria (NW Mediterranean Sea), RF allowed the identification of hot spots of presence along the coastal zone. Here the values of the three physiographic variables affecting bottlenose dolphin distribution are contemporaneously close to the values identifying the bottlenose dolphin signature.

Physiographic variables may influence the bottlenose dolphin distribution directly or indirectly by acting upon other biotic factors such as prey availability, predator avoidance, or the facilitation of social interaction (Wells et al., 1980; Scott et al., 1990; Wells and Scott, 2002). Although dolphin distribution is unlikely to be directly influenced by any of the physiographic variables considered in the present study, bottlenose dolphins may tend to concentrate in certain areas depending on other variables, such as prey density, that may be affected by considered variables (Davis et al., 2002; Blasi and Boitani, 2012). For example the hot spot areas identified by RF in Ligurian Sea also correspond to preferential nursery areas for hake (*Merluccius merluccius*), one of the preferred preys of bottlenose dolphin (Blanco et al., 2001; Santos et al., 2001). In the Ligurian Sea, in fact, the hake nursery areas are spread along a narrow strip within the depth range 100–250 m, and show several zones with higher densities. Among the areas with highest concentrations, Abella and collaborators (Abella et al., 2008) identified those close to the Portofino Hill and off La Spezia

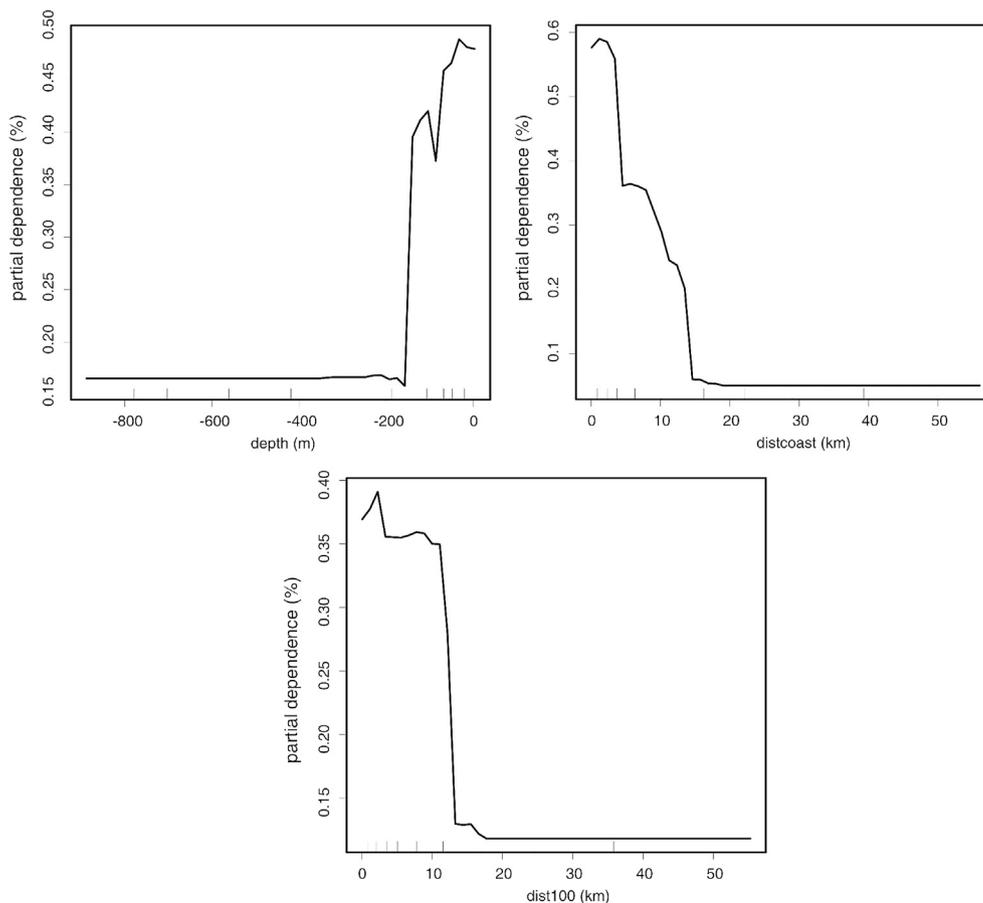


Fig. 7. Univariate partial dependence plots of the three most important variables in the study area.

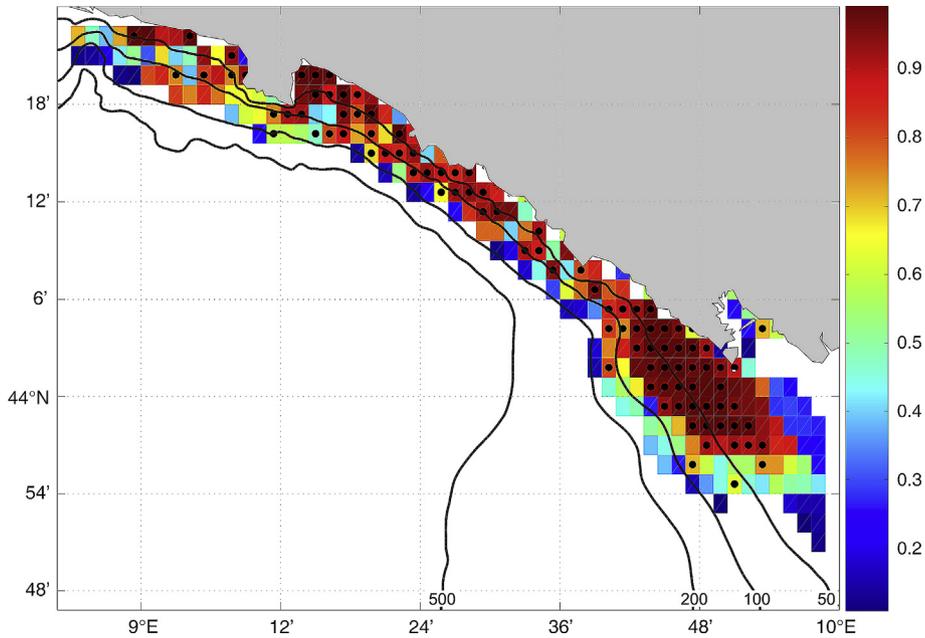


Fig. 8. *T. truncatus* predictive map based on RF. Cells with sightings are shown with black dots; black lines identify the main isobaths.

corresponding to the hot spots identified by RF predicted distribution.

The application of these methodologies to wider areas aiming at a validation of obtained results will thus require particular attention and probably some further tuning procedures to cope at best with the adaptive character of these animals that may adopt

different behaviors in different areas in function of specific and local threats and opportunities.

Nonetheless the prediction of preferential habitat distribution with a sufficiently fine spatial scale should have important management outcomes. In the context of an effective management of Pelagos Sanctuary, bottlenose dolphins are reported forming

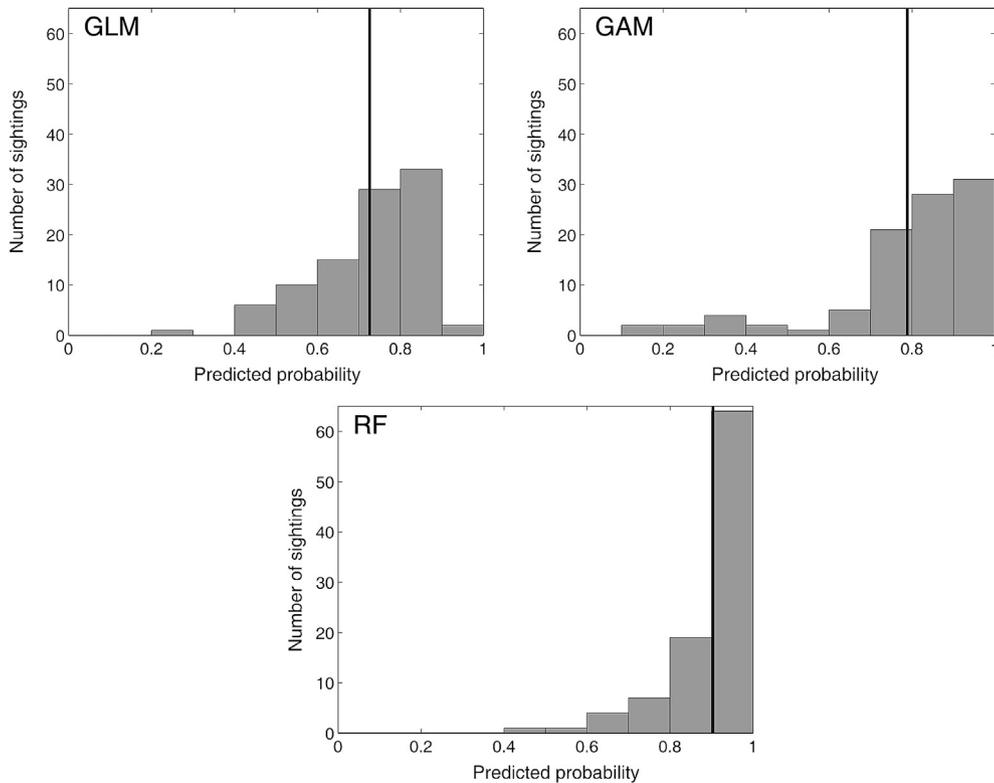


Fig. 9. Histograms of number of sightings in function of predicted probabilities. Black vertical line identifies the average predicted probability in cells where at least a sighting was recorded (presence cells).

discrete populations preferentially distributed over specific favorable areas along the continental shelf (Cañadas et al., 2002; Gnone et al., 2011). Migration between favorable areas is scarcely probable (Gnone et al., 2011) and the excursion range is reported usually within a distance of 80 km (50 km on average). The proposed spatial analysis may be able to identify preferential areas, their reciprocal distance and the presence of corridors between different areas. This is of fundamental interest for the development of effective conservation programs whose aim should be to preserve the most favorable areas and to maintain connections and corridors to allow genetic continuity between (sub) populations.

Conservation programs should be devoted to manage human activities that impact dolphins such as overfishing, conflict with fisheries, disturbance from pleasure boating, habitat degradation with particular attention to preferential areas. These evaluations acquire more and more value given that *T.truncatus* is a top predator and small changes in its ecology can have significant impacts on ecosystems and, vice versa, even small changes of the supporting ecosystem may have significant impact on its abundance and distribution. For instance, Bascompte et al. (2005) stated that the stability of food webs in the marine environment depends on the strength of interactions between top-level predators and their prey. As a consequence monitoring its distribution through time could be useful in order to identify possible threats since top predators can act as indicators on the relative health or state of an ecosystem. That is, avoiding threats to regional populations of coastal dolphins should be viewed as an important component of global biodiversity conservation (Tanabe, 2002; Bascompte et al., 2005; Currey et al., 2009).

5. Conclusion

Habitats are the resources and conditions present in an area that produce occupancy, including survival and reproduction, by a given organism (Thomas, 1979). Habitat selection is a hierarchical process involving a series of innate and learned behavioral decisions made by an animal about what habitat it would use at different scales of the environment (Hutto, 1985). Reliable and spatially explicit analyses of ecological forcing factors that drive the habitat selection and, in turn, shape species distributions are likely to be important tools to identify possible threats to key species as top predators. Since presence and distribution of these species can be interpreted as an indicator on the health or state of an ecosystem, management and conservation procedures should be shaped on the basis of habitat modeling outputs.

In this study we tested three different models (GLM, GAM and RF) and four static, morphological variables for each technique to detect what method is better suited to characterize and what parameter mostly affects the distribution of bottlenose dolphin in the East Ligurian Sea.

Results showed that RF is the technique able to cope at best with observations both in terms of precision and accuracy. This is the first attempt to use this modeling technique for bottlenose dolphin habitat modeling and may shade new light on the development of further applications. In the considered area dolphin's distribution resulted affected by depth, distance from coast and distance from 100 m bathymetry and core areas of very high values of predicted distribution have been identified.

Although, due to the peculiar adaptive characteristics of bottlenose dolphin, the dependence on considered explanatory variables are likely to change if the analysis was applied in other (or wider) areas, the ability of the proposed method to cope with complex, non-linear relationships is expected to provide detailed and accurate information regarding bottlenose dolphin habitat distribution.

Acknowledgments

We would like to thank all students that in these years have collected the data with Delfini Metropolitan project (Acquario di Genova).

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