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Modeling environmental, spatial, temporal, and operational effects on blue shark by-catches in the Mediterranean long-line fishery

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Summary

A study was conducted from 1998 to 2001 on blue shark (*Prionace glauca*) by-catch of the Italian and Greek surface-drifting swordfish long-line fisheries in the Mediterranean Sea. The focus was on examining whether catches are related to some environmental, spatial, temporal or operational parameters and to what extent, applying generalized linear model (GLM) approaches. Analyses indicated that most appropriate for the dataset was the Delta-lognormal model, which is a binomial error distribution for the probability of a non-zero catch and lognormal error for positive catch rates. Spatial and temporal factors were the most influential regarding blue shark distribution and abundance, with a considerable interaction between them; the modeled environmental factors were of minor importance. Spatial distribution revealed a strong longitudinal gradient whereby blue shark occurrences increased in an east to west direction, whereas catches by latitude were higher in southern- and northern-most regions. Blue sharks were more frequently encountered in autumn and in distant open waters; however, the likelihood of making a larger catch peaked in late spring–early summer and in the vicinity of land. Catch rates differed significantly depending on the fishing gear configuration. Deeper settings (> 20 m), more resilient lines and use of fish attractants increased the probability of *P. glauca* capture.

Introduction

Blue shark (*Prionace glauca*, Linnaeus 1758) is a large pelagic oceanic species of the family Carcharhinidae that inhabits clear and deep waters in tropical, subtropical and temperate areas. *P. glauca* is often found in large aggregations, not tightly organized schools, and frequently close to or at the surface (Compagno, 1984; Castro et al., 1999). While blue shark is among the most abundant, widespread, fecund and faster-growing of the elasmobranchs, it is also one of the most heavily fished sharks in the world (Castro et al., 1999). The impact of annual fisheries mortality (mainly as by-catch), estimated at 10–20 million individuals, is likely having an effect on the world population, but monitoring data are inadequate to assess the scale of any population decline (Stevens, 2000). Highly migratory in nature, it is known to make seasonal reproductive migrations following changes in water temperature and currents (Nakano, 1994; Stevens, 1999). The effect of oceanographic factors on the inter-annual variability of blue shark catch rates is an important focal point of current research, which uses data derived from satellite remote sensors together with commercial fishing catch reports. Information on possible interactions might facilitate the interpretation of abundance indices variability and the management of several blue shark populations. Applications of non-parametric generalized additive models (GAMs), incorporating environmental data to analyze fishery performance trends in the Pacific Ocean, have determined that blue shark catch rates are significantly affected by spatial, temporal and environmental parameters (Bigelow et al., 1999; Walsh and Kleiber, 2001). Analogous approaches to standardize shark catch rates applying Generalized Linear Models (GLMs) have been recently used in the Atlantic Ocean (Cortés, 2002; Nakano and Clarke, 2005) and southern Australian waters (Punt et al., 2000).

The Mediterranean Sea seems to be a relatively overlooked area of research for blue shark and sharks in general. Blue sharks constitute a major by-catch of long-line fisheries targeting swordfish or tunas, much of which is poorly documented and where data are rarely incorporated into national and international statistics (Buencuerpo et al., 1998; Megalofonou et al., 2005a,b; Gilman et al., 2007). The available historical data from swordfish fisheries indicate that the Mediterranean blue shark is in general decline (Saldo et al., 2007). For fisheries management purposes the Mediterranean population is considered as independent of the North Atlantic population; however, the extent of exchange between these populations (if any) is poorly understood (Soldo et al., 2007).

Since the late 1960s the large pelagic fishery in the eastern Mediterranean Sea operates mainly with Italian and Greek long-line fleets primarily targeting swordfish (De Metrio et al., 1988). The Italian fleet comprises approximately 1200 vessels carrying out activities from late February to December. In Greece, about 100 vessels are involved on a regular basis from February to the end of September, but with several boats fishing occasionally during summer. Blue sharks comprise a significant portion of the total catch, reaching as much as 20% in the Italian fleet and 4% in the Greek fleet (Megalofonou et al., 2005a,b). In the past, an attempt to associate fishery datasets with several plausible factors affecting blue shark distribution and abundance in the Mediterranean was never undertaken, not only due to the lack of consistent operational and environmental data, but also as a result of sharks being considered a low research priority for most fisheries. Only after 2002 and with the intention to put into effect the European Union regulation 1543/2000, Italy and Greece initiated monitoring of fisheries activities. To date, logbooks kept on fishing vessels are unreliable because of lack of surveys by port authorities. In this paper, the influence of specific environmental, spatial, temporal, and operational parameters on catch rates of blue sharks in the eastern Mediterranean was studied using GLM approaches. GLMs were initially applied to identify the most significant factors affecting blue shark catches and thereafter to quantify their contribution to blue shark distribution and relative abundance.

Materials and methods

Study area and data collection

In the four-year period 1998–2001, sampling was carried out using a network of fishing ports in the Adriatic Sea, Ionian Sea, Aegean Sea and Levantine Basin. Observers collected data while stationed either at pilot fishing ports or on board fishing vessels targeting swordfish. In total, 33 fishing vessels operating from 16 major fishing ports were monitored from 550 fishing sets in Greece and 200 sets in Italy. The fleets utilized two types of fishing gear: the traditional swordfish long-line (SWO-LL_T) and the 'American type' swordfish long-line (SWO-LL_A). The main difference between the two types of gear is the fish attractant chemical light stick attached to branch lines one meter above the bait in the SWO-LL_A (Megalofonou et al., 2005a). Both are categorized as surface-drifting fishing gear, but their fishing depths vary considerably: SWO-LL_T rarely exceeds 20 m depth, whereas SWO-LL_A targets depths between 15 and 50 m. Setting begins in the evening and the operation ends before midnight. Retrieval commences at dawn each day and can last for several hours, depending on the length of the gear, the conditions of the sea and the quantity of fish caught. Observers performed duties that included gathering of fishing and operational data, fish identification and measurements, and recording of spatial and temporal variables. Fishing and operational data included the name of the fishing boat, gear used, fishing sets per trip and fishing effort for each fishing set in the number of hooks, and number and weight of fish caught per fishing set by species. Spatio-temporal variable data included the date and geographical coordinates of each fishing set. Sea surface temperature (SST), *Lunar index*, *Bathymetry* and *Distance from coast* data were assigned to all fishing sets based on the exact date and coordinates (Damalas et al., 2007). To investigate trends in resource abundance of sharks, standardized estimates of nominal catch-per-unit-effort (CPUE), calculated as the number of fish ⁄ 1000 hooks, were used.

Statistical analyses – modeling

Fishery performance (CPUE) was modeled in S-PLUS software package (Insightful Inc.) as a function of categorical and continuous effects using Generalized Linear Model (GLM) approaches (McCullagh and Nelder, 1989; Chambers and Hastie, 1997; Maunder and Punt., 2004; Venables and Dichmont, 2004). As blue sharks were non-target species, the distribution of catches was skewed, including many zero or low values and few large-catch observations. For the estimation of mean CPUE in an attempt to account for this variability, the 'Delta-model' (Ortiz and Arocha, 2004) was applied with the general form (Maunder and Punt., 2004):

$$\Pr(Y = y) = \begin{cases} w, & \mathrm{y = 0,} \\ (1 - w)f(y) & \text{otherwise} \end{cases} \quad (1)$$

where w is the probability of a zero observation and $f(y)$ the error-distribution of catch rates from positive catch sets (Pr = probability, y = response variable). It was assumed that the two sub-models refer to different processes. In the first sub-model, the probability of a zero catch is the probability of encountering a school. In the second sub-model, the distribution of the positive catch sets is the probability of the school size (Maunder and Punt., 2004). Identification of the underlying probability distribution for the errors in the dependent variable (positive catches of blue shark) was performed using the Akaike information criterion (AIC) to discriminate among error distributions (Burnham and Anderson, 2002). Several available error distributions, with their corresponding link functions, were investigated: normal (gaussian), lognormal, Gamma, and Poisson. The Poisson distribution specifically was assumed to be the number of blue sharks caught per fishing set, with effort used as an offset. In order to compare models assuming different error distributions, the same number of parameters for each model (all variables plus interactions) was used. After calculating AIC scores for each candidate model, the standard procedure to discriminate among several distributions was based on the computation of the corresponding 'Akaike weights':

$$w_i = \frac{\exp(-(1/2)\Delta_i)}{\sum_{r=1}^{R} \exp(-(1/2)\Delta_i)} \quad (2)$$

that represent the relative weight of evidence for the ith model in the context of R candidate models. Δ_i is the difference between the value of AIC for the ith model and the smallest AIC value for all candidate models. Usually the model with the highest Akaike weight is selected as the 'best' model (Dick, 2004). An evidence ratio (ER) by structural model pairs suggested by Burnham and Anderson (2002) was used:

$$\mathrm{ER} = \frac{\exp(-1/2)\Delta_k)}{\exp(-1/2)\Delta_j)} \quad (3)$$

where Δ_i is as described previously and the subscripts k, j correspond to the kth and jth model, respectively. The larger the ER values, the larger the evidence against the jth model in favor of the kth model. Explanatory factors influencing catch rates incorporated in the model were identified applying a stepwise GLM model building (Chambers and Hastie, 1997). Models were built by adding new terms and seeing how much they improved the fit, and by dropping terms that did not degrade the fit significantly. The initial model was the 'minimal model' consisting only of the overall mean. Adding or removing a new term was decided based on an observed reduction in the AIC. The final model was produced when no further steps could decrease the criterion. Additionally, a P-value based on the appropriate test statistic (chi squared or F) was used to evaluate the significance of each additional factor.

Results

Nominal CPUE

Between April 1998 and September 2001, the observers reported a catch of 412 blue sharks in swordfish long-line operations during 745 fishing days, 472 of which were sampled at landing ports and 273 onboard (Figs 1 and 2). Blue shark was the most abundant by-catch, reaching an overall 5.8% of the total catch in number of fish. In total, no blue sharks were caught in 402 out of 483 American type swordfish long-line sets and 147 out of 262 traditional swordfish long-line sets (overall there were non-zero catches in only 26.3% of the sets). Monthly nominal CPUE values (Table 1) ranged from 0.00 to 1.25 blue sharks ⁄ 1000 hooks for the traditional swordfish long-line and from 0.18 to 0.96 for the 'American-type' swordfish long-line.

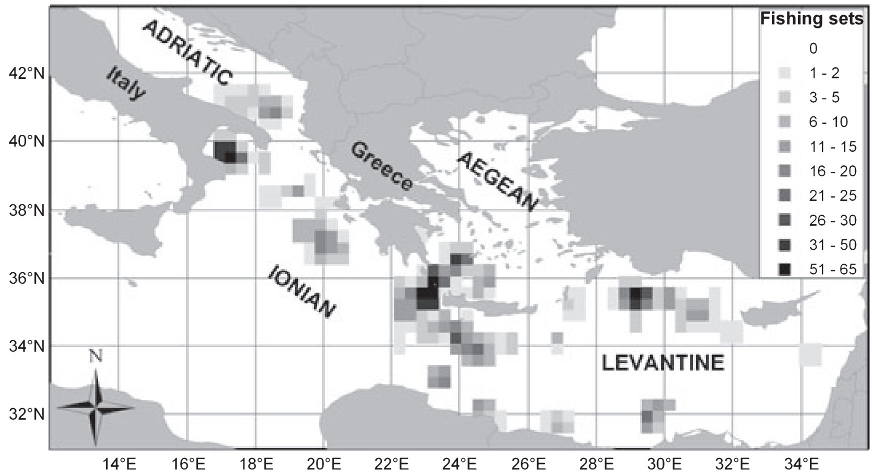

Fig. 1. Map of studied area and spatial distribution of fishing effort, eastern Mediterranean Sea, 1998–2001 (Spatial resolution of fishing effort 1 ⁄ 3 of a degree)

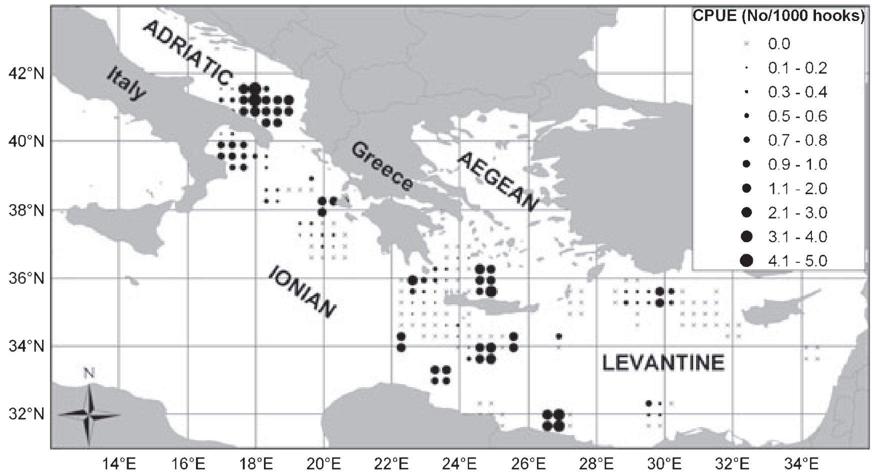

Fig. 2. Geographical distribution of blue shark (*P. glauca*) CPUE (no. ⁄ 1000 hooks), eastern Mediterranean Sea, 1998–2001 (Spatial resolution of fishing effort 1 ⁄ 3 of a degree)

Table 1
Effort (number of hooks), blue sharks captured, and nominal CPUE values (no. fish ⁄ 1000 hooks) by fishing gear and month for blue sharks, *P. glauca*, caught in Mediterranean Sea, 1998–2001

		Month								
Fishing gear		Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Total
SWO-LL$_T$	No. hooks	1150	850	30,450	35,080	124,930	123,360	61,540	22,150	399,510
	No. sharks	0	0	8	44	156	66	18	18	310
	CPUE	0.00	0.00	0.26	1.25	1.25	0.53	0.29	0.81	0.78
SWO-LL$_A$	No. hooks	8880	13,200	28,200	40,290	62,700	37,800	40,740	–	231,810
	No. sharks	2	4	5	13	21	18	39	–	102
	CPUE	0.23	0.30	0.18	0.32	0.34	0.48	0.96	–	0.44
Total	No. hooks	10,030	14,050	58,650	75,370	187,630	161,160	102,280	22,150	631,320
	No. sharks	2	4	13	57	177	84	57	18	412
	CPUE	0.20	0.28	0.22	0.76	0.94	0.52	0.56	0.81	0.65

Selection of error-model and explanatory variables

Nine variables were included in the GLM model, the first six being continuous and the last three categorical:

$$g\,(\mathrm{CPUE\ or}N) = c + a_1\,Latitude + a_2\,Longitude + a_3\,\mathrm{SST} + a_4\,Bathymetry + a_5\,Distance\ from\ coast + a_6\,Lunar\ index + a_7\,Month + a_8\,Year + a_9\,Fishing\ Gear\ type + a_k\,INTER_k + \varepsilon \quad (4)$$

where g was the link function, 'CPUE' the number (N) of shark caught per 1000 hooks, a_i the unknown coefficients, $INTER_k$ any combination of interactions between *Fishing Gear type* and variables expressing time (*Month, Year*) or area (*Latitude, Longitude*), c a constant and ε a random error term. Especially for the initial Delta sub-model concerning the probability of obtaining a zero catch assuming a binomial error distribution with *logit* as the link function, we recoded CPUE to the binary variable *Presence*, so that it was assigned a value of 0 when no blue sharks were present in the catch, and a value of 1 if otherwise (Bernoulli-type 0 ⁄ 1 measurements).

Analysis revealed that six out of nine variables and *Longitude : Latitude : Year* interaction for the binomial component and five out of nine, plus the *Longitude : Latitude*

: Year : Fishing Gear type interaction for the lognormal component, were significant. Comparison among evidence ratios (ER) for the positive catch sets data gave evidence in favor of the lognormal distribution relative to all the other candidate models, suggesting it as the best approximating distribution for the model (Table 2). Therefore, stepwise GLM model building was applied to the data, assuming a lognormal error distribution. Diagnostic plots verified that the lognormal component approach adequately fit the data (Fig. 3) suggesting that: (i) there is no systematic departure from the assumption of the error distribution and that model misspecification is not occurring (top), (ii) variance changes, but not dramatically, through the range of predicted values (middle) and, (iii) the explanatory variables reduce satisfactorily the variance in the data (bottom). The binomial component of the Delta approach took the following form:

$$\begin{aligned}&\mathit{Presence}\ (\mathit{link} = \mathit{logit}) \sim a_1\,\mathit{Year} + a_2\,\mathit{Month}\\ &+ a_3\,\mathit{Fishing\ Gear\ type} + a_4\,\mathit{poly}\ (\mathit{Latitude},\ \mathit{df} = 2)\\ &+ a_5\,\mathit{Longitude} + a_6\,\mathit{poly}\ (\mathit{Distance\ from\ coast},\ \mathit{df} = 2)\\ &+ a_7\,[\mathit{Longitude} : \mathit{poly}\ (\mathit{Latitude},\ \mathit{df} = 2) : \mathit{Year}],\end{aligned} \tag{5}$$

and the lognormal component of the Delta approach (for positive catch sets) :

$$\begin{aligned}&\log\ (\mathrm{CPUE}) \sim a_1\,\mathit{Year} + a_2\,\mathit{Month} + a_3\mathit{Fishing\ Gear\ type}\\ &+ a_4\,\mathit{poly}\ (\mathit{Distance\ from\ coast},\ \mathit{df} = 3)\\ &+ a_5\,\mathit{poly}\ (\mathit{Latitude},\ \mathit{df} = 2) + a_6\,[\mathit{Longitude} :\\ &\mathit{poly}\ (\mathit{Latitude},\ \mathit{df} = 2) : \mathit{Year} : \mathit{Fishing\ Gear\ type}],\end{aligned} \tag{6}$$

where *poly* are transformations of the explanatory variables (polynomials in this case) and *df* stands for the degrees of freedom of the polynomials (Note: polynomials of up to the third power were investigated, i.e. $df \leq 3$). The detailed deviance results for the two applied sub-models are shown in Tables 3 and 4.

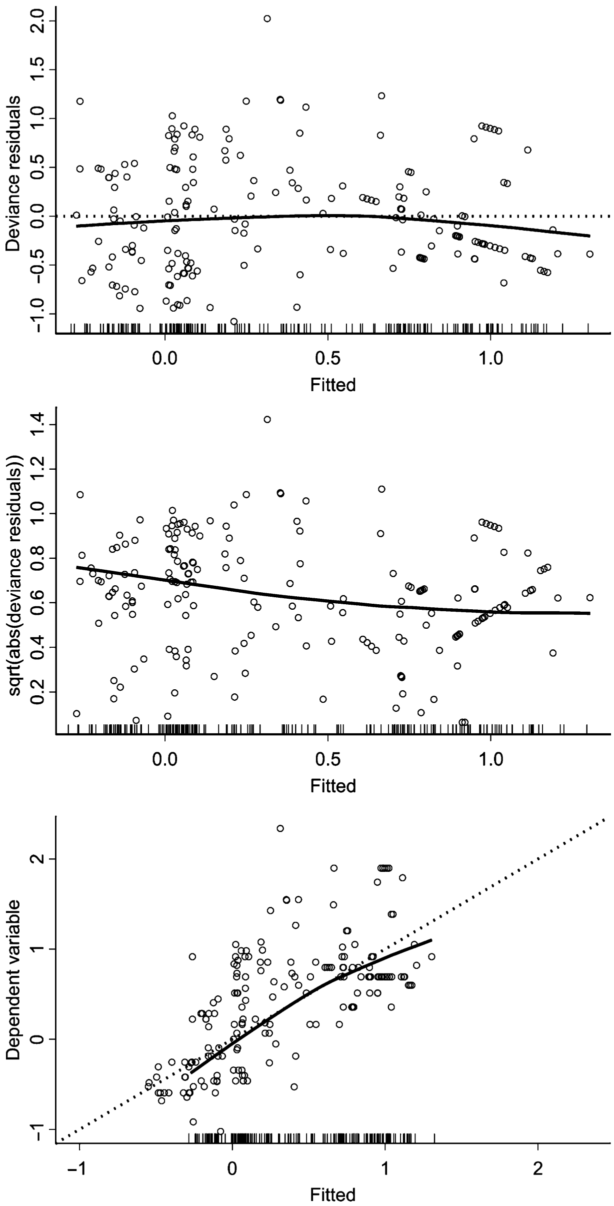

Fig. 3. Diagnostic plots for goodness-of-fit of a Delta-lognormal model for pelagic shark positive catch rates, eastern Mediterranean, 1998–2001. Standardized residuals versus predicted values (top), square root of absolute values of standardized residuals versus predicted values (middle) and observed versus predicted values (bottom). Solid lines are *loess* smoothers through the plotted data

Effects of explanatory variables

From our knowledge to date, blue sharks are not considered as species-forming schools. Thus, the binomial component model described the probability of encountering blue sharks. Once encountered, the lognormal component model quantified the probability of how many would there be as the measure of local abundance.

Encountering blue sharks (presence–absence model)

The first sub-model, i.e. the binomial, included six significant predictor variables: three categorical and three continuous (Table 3). In total, the derived model explained more than 29% of the variance in the probability of encountering blue sharks.

Table 2
AIC results, Akaike weights (w_i) and evidence ratios (ER) for several error distributions in a GLM for factors affecting blue shark, *P. glauca*, positive catch rates, Mediterranean Sea, 1998–2001

Model	AIC	Δ_i	w_i Akaike weights	ER[1]
Delta-gaussian	215.27	165.71	10×10^{-4}	10E+04
Delta-gamma	51.29	1.73	0.29	2.4
Delta-lognormal	49.56	0.00	0.70	1.0
Delta-poisson	143.40	93.84	10×10^{-4}	10E+04

Explanatory variables for each error distribution were the same for consistency and comparison purposes.
[1]ERs calculated for each distribution relative to the lognormal distribution. Poisson distribution fitted using number of blue sharks caught as the response variable.

Geographical location had the greatest effect on encountering *P. glauca*. *Latitude* and *Longitude* explained 30.3% and 7.6% of the total deviance, respectively, while their interaction with *Year* contributed an additional 10.8% (Fig. 4). The effect of *Longitude* indicated a strong gradient in the presence of blue sharks, the probability increasing in a westerly direction (Fig. 4, bottom left), while the *Latitude* effect was bimodal with two separate peaks located to the extreme north and south of the studied area (Fig. 4, top left).

Temporal factors (*Year* and *Month*) explained 19.2% and 16.4% of the total deviance, respectively. The fitted probability of encountering blue sharks as a function of *Month*, revealed an overall seasonal increasing trend from spring to autumn

Table 3
Stepwise generalized linear model building for factors affecting blue shark, *P. glauca*, catches, Mediterranean Sea, 1998–2001

Model structure terms added	Residual *df*	Residual deviance	Df	Deviance decrement	Cumulative deviance explained	% of total deviance explained	P (Chi)	AIC
NULL	744	858.63						860.63
+ as.factor (*Year*)	741	810.45	3	48.18	5.61	19.18	0.0000	816.00
+ as.factor (*Month*)	734	769.32	7	41.13	10.40	16.38	0.0000	780.00
+ as.factor (*Fishing gear type*)	733	740.42	1	28.9	13.77	11.51	0.0000	754.70
+ *poly* (*Latitude*, *df* = *2*)	731	664.41	2	76.01	22.62	30.26	0.0000	688.17
+ *Longitude*	730	645.40	1	19.01	24.83	7.57	0.0000	671.53
+ *poly* (*Distance from coast*, *df* = *2*)	728	634.54	2	10.86	26.10	4.32	0.0044	662.02
+ *Longitude : poly* (*Latitude*, *df* = *2*) *: as.factor* (*Year*)	720	607.48	8	27.06	29.26	10.77	0.0007	637.83

Sub-model 1: Delta-binomial probability of a non-zero catch.

Table 4
Stepwise generalized linear model building for factors affecting blue shark CPUE, Mediterranean Sea, 1998–2001

Model structure terms added	Residual *df*	Residual deviance	Df	Deviance decrement	Cumulative deviance explained	% of total deviance explained	P (F)	AIC
NULL	195	98.48						99.49
+ as.factor (*Year*)	192	87.16	3	11.32	11.50	23.14	0.0000	70.53
+ as.factor (*Month*)	185	80.34	7	6.82	18.43	13.94	0.0026	66.56
+ as.factor (*Fishing Gear type*)	184	65.11	1	15.23	33.89	31.13	0.0000	62.46
+ *poly* (*Distance from coast*, *df* = 3)	181	60.61	3	4.50	38.46	9.20	0.0021	59.36
+ *poly* (*Latitude*, *df* = 2)	179	56.63	2	3.98	42.50	8.14	0.0015	52.12
+ *Longitude : poly* (*Latitude*, *df* = 2) *: as.factor* (*Year*) *: as.factor* (*Fishing Gear type*)	165	49.56	14	7.07	49.68	14.45	0.0063	49.75

Sub-model 2: Delta-lognormal positive sets.

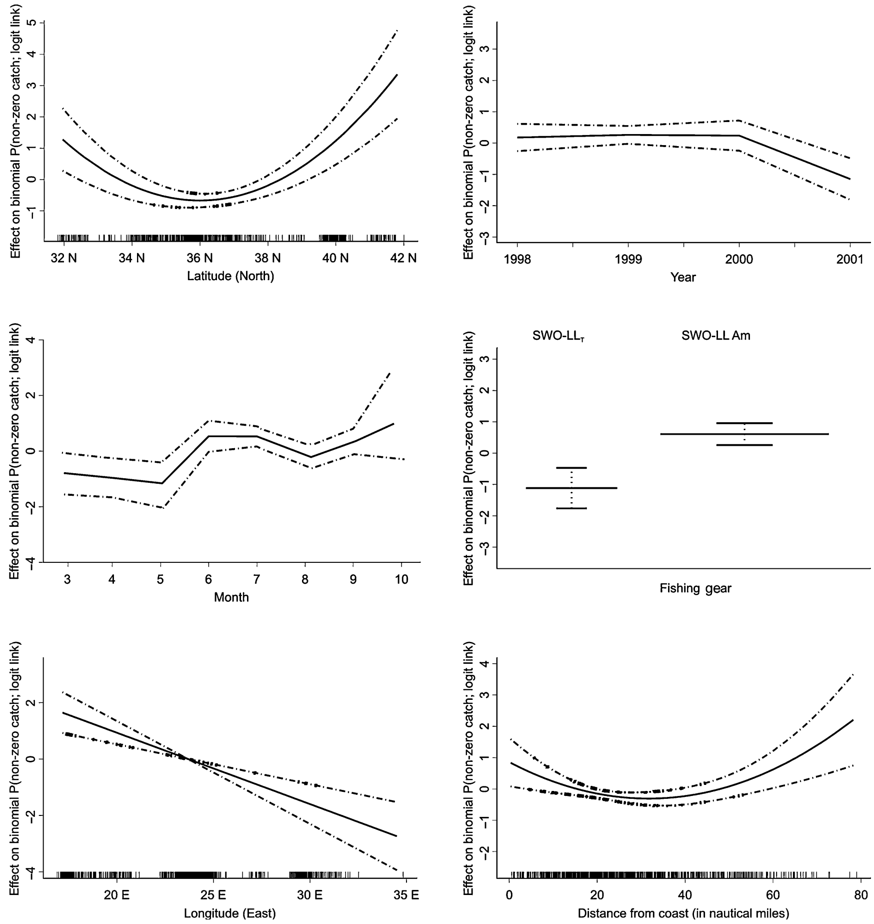

Fig. 4. Generalized linear model (GLM) derived effects of *Latitude, Year, Month, Fishing Gear type, Longitude* and *Distance from the coast* on the Delta-binomial probability of encountering blue sharks. Dashed lines indicate 95% confidence bands. Relative density of data points shown by the ‘rug’ on the *x*-axis

(Fig. 4, middle-left). The interesting peak at the end of spring–start of summer is linked to local abundance, and is described in detail in the next stage of the Delta approach (positive lognormal catch rates). The annual effect demonstrated an insignificant decline for the first three years followed by a significant drop in 2001 (Fig. 4, top right).

The operational factor (*Fishing Gear type*) yielded an 11.5% reduction of total deviance. The 'American type' swordfish long-line turned out to be more effective in obtaining non-zero catches than the traditional swordfish long-line (Fig. 4, middle-right). However, nominal CPUE values indicated that traditional swordfish long-line catches were higher.

Distance from the coast, embracing both spatial and environmental properties as an explanatory variable, was the final principal term in the model. Probability seemed to be stable in a buffer zone between 20 and 50 nautical miles (n.m.), increasing substantially beyond this point to the open sea and to a lesser extent when moving closer to the coast (Fig. 4, bottom-right).

Spatio-temporal interaction (*Latitude : Longitude : Year*) was significant and the probability surface fluctuated in the three dimensional XYZ space (X = *Longitude*, Y = *Latitude*, Z = probability) with an almost constant pattern for all years except for the first year (1998).

Local abundance (positive catch sub-model)

The second sub-model included five significant predictor variables: three categorical and two continuous, and the interaction of *Longitude : Latitude : Year : Fishing Gear type*. The final fitted model explained almost 50% of the deviance (Table 4).

Fishing Gear type effect was the most important variable affecting 'local abundance' of blue sharks, explaining more than 31% of the total deviance in the model. The effect of this parameter was more or less similar in both sub-models. Whether we were interested in the probability of a non-zero catch (binomial component) or how large a catch would be (lognormal component), both models suggested that the 'American type' swordfish long-line was the one to which blue sharks were more vulnerable (Fig. 5, top left).

The plot for *Year* revealed a modest declining trend in catch rates between 1998 and 2001 (Fig. 5, top right). The modeled probability of an elevated blue shark catch by *Month* showed a reverse pattern compared to the probability of encounter, signifying that although blue shark were not likely to be caught during spring (binomial component), the catch during a fishing set taking place at the end of this season was more likely to be large (lognormal component).

Distance from the coast plot (Fig. 5, mid-right), showed a positive trend in favor of coastal areas: an elevated blue shark catch being more likely near the coastline (< 10 n.m.), almost constant until 60 n.m. from land, then declining in the open sea (> 60 n.m.). Spatial predictor (*Latitude*) explained only 8.1% of total deviance, although *Year : Latitude : Longitude* interaction accounted for an extra 14.5%. Catch rates related to *Latitude* demonstrated a reverse pattern compared to the probability of encountering a blue shark. Non-zero catch rates were higher in the south but the probability of a non-zero catch was higher in the north (Fig. 5, bottom). Finally, there was a considerable interaction of spatial, temporal and operational factors (*Latitude : Longitude : Year : Fishing Gear type*). Although the type of gear did not interact with spatio-temporal factors when modelling the probability of encountering a shark, it proved to be appreciably related to them when modelling positive catch rates. Trends of positive CPUEs as a function of *Longitude* were more pronounced in the traditional swordfish long-line.

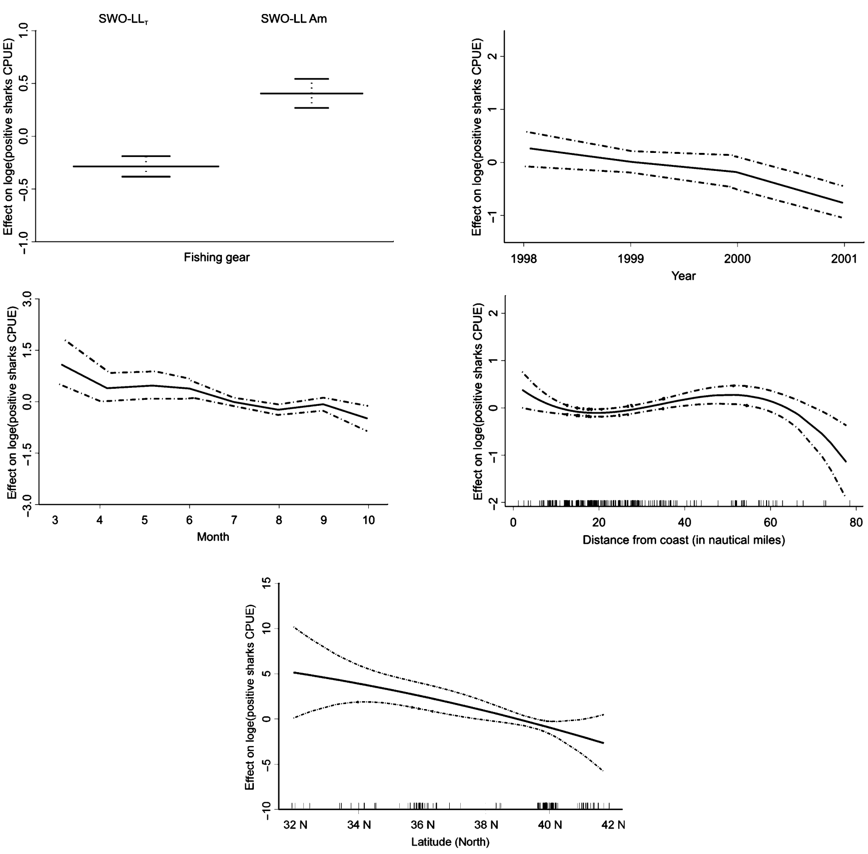

Fig. 5. Generalized linear model (GLM) derived effects of *Fishing Gear type, Year, Month, Distance from the coast* and *Latitude*, on the Delta-lognormal probability of positive sets shark catch rates. Dashed lines indicate 95% confidence bands. Relative density of data points shown by the 'rug' on the x-axis

Discussion

The purpose in modeling Mediterranean blue shark catches was to comprehend how fishery performance varied with a selection of environmental, spatial, temporal and operational factors and subsequently to generate standardized indices of commercial catch rates, which could be useful for regional planning and policy development for conservation and sustainable management of the species. Nominal CPUE values observed in this study were very low compared to analogous values from surveys conducted in the western Mediterranean and Atlantic (Nakano, 1994; Buencuerpo et al., 1998; Hazin et al., 1998; Stone and Dixon, 2001; Nakano and Clarke, 2005). These low values can be attributed to the lower productivity of the area, or lower abundance of sharks due to regional depletion from historical fishing, or both. A comparison of historical CPUE records in kg of fish ⁄ 1000 hooks in the North Ionian Sea with recent records (De Metrio et al., 1984; Megalofonou et al., 2005b) reveals that catch rates over the past 20 years have decreased by an average of 38.5%. Although the time period of the data set (1998–2001) was brief, a declining trend in annual catch rates is apparent. These data together with other available evidence (Gilman et al., 2007; Saldo et al., 2007) point out that the Mediterranean *P. glauca* population is in general decline and is possibly facing a worse scenario than blue shark populations elsewhere in the world. It may be premature to draw strong inferences regarding environmental effects on shark distribution and abundance; even so, our results indicated that spatial, operational and temporal factors played the predominant role in the model, while environmental features were of minor importance probably because the most appropriate environmental variables were not modeled.

Spatial variables affecting catches

GLM analysis, modeling the probability of encountering a blue shark, revealed that *Latitude* had the most profound effect. Elevated probabilities of catching a shark increased northwards, peaking north of the 40th parallel. Strasburg (1958), Nakano (1994), Bigelow et al. (1999) and Walsh and Kleiber (2001) described latitudinal patterns in the northern Pacific (sharks being more abundant to the north). According to Bigelow et al. (1999) this finding was ascribed to: (i) presence of the Sub-Arctic Frontal Zone in the Northern Pacific plus the increased abundance of prey species during spring and summer and, (ii) inefficient exploitation of blue sharks by near-surface gear in the subtropics, since shark tend to shift to deeper, cooler water masses. As the Mediterranean is a semi-enclosed sea and not an open ocean like the Atlantic and Pacific, the aforementioned arguments do not apply in our case. The increased probability of catching a shark in higher latitudes could be attributed to the productivity of the northern areas due to incoming nutrients from European rivers. On the other hand, elevated catch rates in latitudes south of the 34th parallel indicate a persistent presence of blue sharks in this area. Thus, although generally characterized as oligotrophic due to the deep vertical mixing of water masses, local and temporal anomalously very high productive areas have been detected (Siokou-Frangou et al., 2005).

The strong longitudinal component of where blue shark are present, with the probability increasing from east to west, has been confirmed not only for the studied area but also throughout the Mediterranean (Megalofonou et al., 2005b). Additionally, data from the vicinity of the Strait of Gibraltar show that the Atlantic fishing sets were more proliferate than those in the Mediterranean (Buencuerpo et al., 1998; Megalofonou et al., 2005b). Increased productivity and abundance of prey may be the key factor in interpreting the effect of *Longitude*. The higher trophic potential of the western Mediterranean compared to the eastern area supports this assumption (Caddy, 1998).

Operational variables affecting catches

The result for *Fishing Gear type* was expected, as the use of ‘American type’ swordfish long-lines had a significant effect on both the probability of catching a blue shark and of making a large catch during a fishing set. The use of fish attractant chemical light-sticks and thicker, more resilient, lines is a reasonable explanation for increased catches with the ‘American type’ swordfish long-line when compared to the traditional long-line. However, depths at which fishing take place can also affect the catch effort. SWO-LL_A targets deeper waters, often below 50 m, whereas SWO-LL_T depth ranges rarely exceed 20 m (Megalofonou et al., 2005a). It can be assumed that the *Fishing Gear type* variable reflects fish vulnerability rather than their actual abundance.

Temporal variables affecting catches

Temporal distribution of blue shark catches, indicating higher probability of their capture during summer and autumn, could be attributed to the recruitment of juveniles entering the fishery. Parturition for blue sharks is known to take place from April to July (Pratt, 1979), hence making late autumn and winter a plausible period for the young to enter the fishery. Nakano (1994), however, commented that seasonal abundance of blue sharks largely depends on their migration pattern. Buencuerpo et al. (1998) reported September and April as months with increased shark abundance. Hazin (1994) placed this period in the 3rd and 4th quarters of the year, Bigelow et al. (1999) and Walsh and Kleiber (2001) at the end of the year, and Strasburg (1958) during spring and summer. The Mediterranean is a semi-enclosed temperate sea quite different from other oceans where some seasonal information is known. Compounded by the fact that very little is known about blue shark distribution and migration makes an explanation difficult for the increased probability of achieving larger catch during spring. A tagging program to study the blue shark behavior and migration pattern in the Mediterranean as well as a more detailed examination of catches incorporating biological data such as size, sex and maturity, could elucidate the temporal effect on abundance.

Environmental variables affecting catches

The cause for the positive relation between blue shark occurrence and *Distance from the coast* could be readily justified, as blue shark is an oceanic species. Strasburg (1958) and Hazin (1994) have also shown that blue shark occurrence is positively correlated to *Distance from the coast*. The observed reverse pattern when studying catch rates instead of occurrence could be attributed to the seasonal migratory behavior of the species due to parturition. Casey (1985) reported a rapid and concentrated movement inshore in late spring which, combined with Pratt’s (1979) suggestions on the time frame for giving birth to pups, could be the most likely solution to the puzzling elevated abundance of *P. glauca* in the vicinity of land. Additionally, food availability is another plausible explanation, as the prey of blue shark usually congregate near land, seamounts or banks (Hazin, 1994; Bigelow et al., 1999).

Of note is that the sea surface temperature (SST) was omitted from both models during the fitting procedure as being insignificant. Santos and Miguel (2000) in a review of the effects of environmental conditions cited that 63% of fish behaviors were related to sea surface temperature. However, acoustic telemetry studies on blue sharks have shown that sharks regularly swim below the thermocline where they experience water temperatures much lower than at the sea surface (Carey and Scharold, 1990; Klimley et al., 2002). Thus, SST as an influential factor in blue shark catches is insignificant, since surface temperature may bear very little relationship to their preferred thermal habitat.

Abundance trends

Fitted values for the probability P of a non-zero catch and the expected CPUE, conditional on it being positive, the predicted unconditional CPUE is given as P*CPUE (Stefansson, 1996). Our results suggest a moderate decline of sharks in catches for the the study period (1998–2001). Especially for the last year (2001) the estimated probability of catching a shark in a fishing set was significantly low (Fig. 6). This finding could be linked to such reasons as: (i) inter-annual environmentally driven fluctuations of shark distribution, (ii) mal-apportioned fishing or sampling effort, or (iii) a signal that the population is under intensive fishing pressure. The significant interaction effect of *Latitude : Longitude : Year* in both sub-models mostly supports the second supposition. Italian data (located to the north-west) made up the bulk of observations during the first two years, whereas this situation was reversed in the final 2 years in favor of the Greek data (south-east). Therefore, the strong longitudinal gradient (catches to the west > catches to the east) interacting with the *Year* effect resulted in an increased abundance for the first 2 years.

Comparing the results of an analogous study on eastern Mediterranean swordfish (Damalas et al., 2007) with the current study, *P. glauca* differed considerably from their

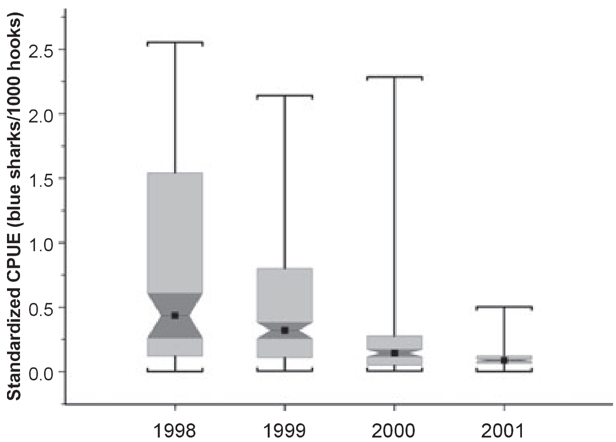

Fig. 6. Generalized Linear Model (GLM) standardized CPUE index of blue shark abundance (number sharks ⁄ 1000 hooks) by *Year* (Lightly shaded box area limits correspond to 25th and 75th percentiles. Dark shaded notched box area indicates 95% confidence bounds around the median, shown as a small solid black box. Whiskers extend to min and max values observed)

pelagic 'co-tenants' in many distributional aspects. Furthermore, the results for Mediterranean swordfish, which form a distinct population, were not in agreement with the results from Atlantic and Pacific ocean surveys. These findings together with the fact that the blue shark population status is still poorly understood corroborate the need for international programs monitoring catch levels as well as the necessity for biological studies of the species in the Mediterranean.

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