

# Trawling regime influences longline seabird bycatch in the Mediterranean: new insights from a small-scale fishery

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## Supplement 1. Methodology and supplementary results

### Methodology

According to the zero-inflated Poisson model (ZIP), bycatch can be modelled through 2 distinct processes, i.e. binary and Poisson (Lambert 1992). The ZIP model takes into account 2 different groups: (1) an out-of-risk group of shearwaters not attending vessels for which the probability of capture is always zero and (2) a risk group of shearwaters attending vessels for which the probability of capture could be equal to or different from zero, following a Poisson distribution. Both the probability of being at risk and the probability of being entangled in a longline are allowed to depend on covariates through the canonical link. The corresponding equations used to fit the models are shown in the main paper. We used the Stata software to fit the Generalized Linear Models (GLM) and the R package glmmADMB to fit all Generalized Linear Mixed Models (GLMMs).

The corrected Akaike's information criteria ( $AIC_c$ ) was used as a model selection criterion (Burnham & Anderson 2004) since the maximum number of estimable parameters  $K$  was large relative to sample size  $n$  ( $n/K = 29.6$ ). The model with the lowest  $AIC_c$  was considered to be the best compromise between model deviance and model complexity (i.e. the number of model parameters). However, absolute  $AIC_c$  values are only useful for model ranking and the relevant parameter for model selection becomes the amount of Kullback-Leibler information loss ( $\Delta_i$ ) (Burnham & Anderson 2004):

$$\Delta_i = AIC_{c i} - AIC_{c \min}$$

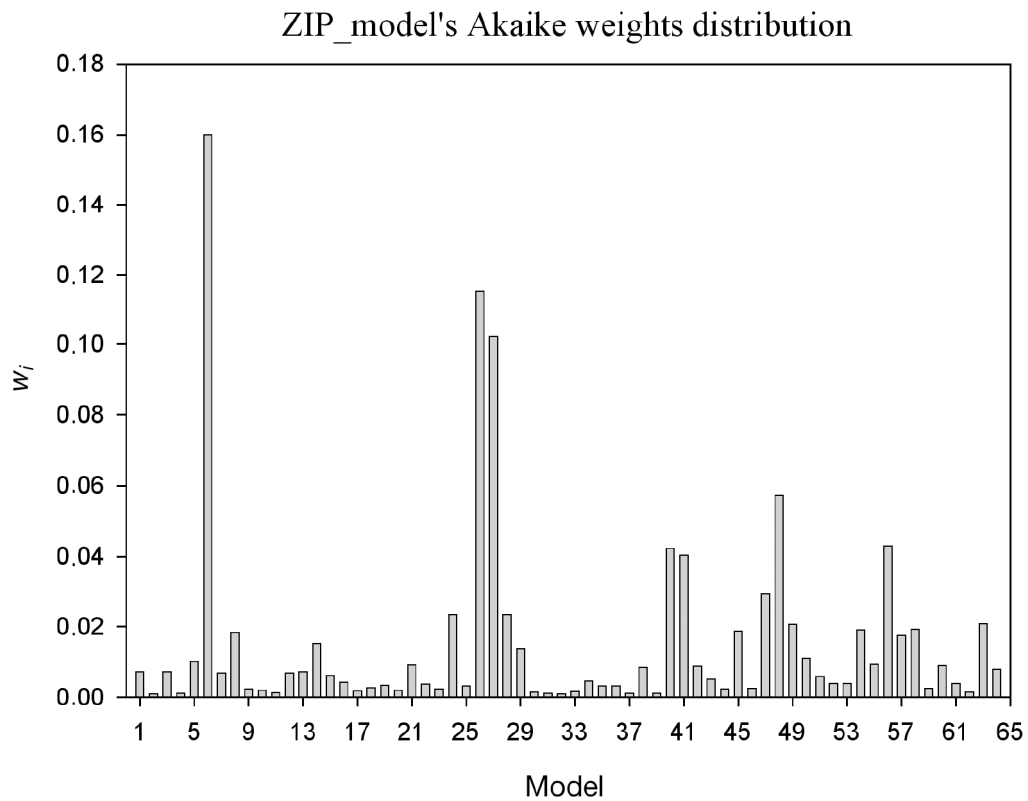
where  $AIC_{c \min}$  is the minimum  $AIC_c$  value among all models considered. The lower the  $\Delta_i$ , the better the fit of the model (Burnham & Anderson 2004).

The likelihood  $L(g_i | data)$  of model  $g_i$ , given the data, can be calculated as  $\exp(-\Delta_i/2)$ , for  $i=1, 2, \dots, R$  for each of the  $R$  models in the subset (Burnham & Anderson 2004). The likelihood of each individual model was compared to the total sum of the likelihood of all models to calculate Akaike weights  $w_i$ , defined as:

$$w_i = \frac{e^{-\frac{\Delta_i}{2}}}{\sum_{i=1}^R e^{-\frac{\Delta_i}{2}}}$$

where  $w_i$  is the probability that model  $i$  is the best model for the data (Burnham & Anderson 2002, 2004). Akaike weights  $w_i$  are scaled to sum 1.

Fig. S1. Histogram of Akaike weights for the ZIP models fitted in an exploratory analysis



## Number of hooks as a predictor variable

Number of per set hooks is extensively used as a measure of fishing effort in the bycatch literature (Belda & Sánchez 2001, Bugoni et al. 2008b) and it was initially included as one more predictor variable in the ZIP models, the results of which are shown in Table S1. The linear predictor coefficient for this variable is zero. The same result is obtained whenever the number of hooks per set is included as an additional variable. The  $AIC_c$  value when the number of hooks is included as an additional variable is similar to those obtained for the selected models in the main paper ( $AIC_c = 195$ ,  $K = 9$ ). Even though number of hooks has been considered as a bycatch predictor (Bugoni et al. 2008a, Dietrich et al. 2009), we found that this variable did not affect bycatch in our case. However, setting duration should be correlated with the number of hooks and, therefore, bycatch is expected to change with this quantity; hence, the number of hooks was included as an offset variable in the model (forcing hooks predictor coefficient to be 1). Those results are given in the main paper.

Table S1. Linear predictor coefficients when number of hooks is included as an additional variable in the models. Analyses were performed using the Stata software

Variables	Coefficient ( $\pm$ SE)	
	$\beta_{0i}$ for Binary	$\beta_{1i}$ for Poisson
Day	$-0.8 \pm 1.6$	$-1.5 \pm 0.7$
Night	$4.6 \pm 2.8$	$1.4 \pm 0.7$
Trawling allowance	$-4.1 \pm 2.7$	$-2.2 \pm 0.6$
Incubation	$3.7 \pm 1.5$	
Chick-rearing	$0.8 \pm 0.9$	
Hooks	$0.0001 \pm 0.0008$	$-0.00008 \pm 0.0004$
Constant ( $\alpha_1$ )	$-0.3 \pm 1.1$	$0.5 \pm 0.5$

Table S2. *Calonectris diomedea*. Shearwater bycatch per unit effort (BPUE), number of shearwaters attending vessels and other relevant quantities per year

Year	Attending	Dead	Alive	Bycatch	Hooks	BPUE	
						(bycatch/hooks)	Attending/hooks
1998	249	12	0	12	18950	0.0006332	0.01314
1999	83	1	0	1	32086	0.0000312	0.00259
2000	52	2	0	2	15600	0.0001282	0.00333
2001	44	2	0	2	28096	0.0000712	0.00157
2003	348	3	4	7	6550	0.0010687	0.05313
2004	302	10	0	10	64176	0.0001558	0.00471
2005	10	0	0	0	2242	0.0000000	0.00446

### Year as a random variable

Given that our sampling effort has been very unbalanced with respect to year (Table S2), we introduced year as a random variable. Table S3 shows that when year is included as a random variable,  $AIC_c$ s are considerably higher than those corresponding to the set of models selected (Table 3 in the main paper). Also, some unidentifiable parameters arise in 2005 (see Table S4), presumably due to the small sampling effort during that year (Table 1 in the main paper, Table S2).

However, the obtained coefficients (see Table S4) are in agreement with the ones presented in the main paper, e.g. setting time and moratorium. We can therefore conclude that the effect of setting time and trawling moratorium is robust when introducing year random effects, which is not the case for the coefficients corresponding to different breeding periods (Table S4). Therefore, given that the  $AIC_c$  values increase when year is included as a random variable and that there are some unidentified coefficients (see year 2005 in Table S4) we didn't present these models in the main text. These analyses were performed using the R package glmmADMB. In the main text, we present the most parsimonious models that do not take into account year as a random variable.

Table S3. Corrected Akaike's information criteria values ( $AIC_c$ ) for the models when hooks are introduced as a variable and year is introduced as an offset. Explanatory variables are: TR: trawling activity, FT: fishing time, BS: breeding stage, HS: number of hooks per set.  $K$ : number of parameters. Analyses were performed using R package glmmADMB and the function glmm.admb

Model	$K$	$AIC_c$
ZIP(FT,TR,BS,random year)	20	199.8
ZIP(FT,TR,BS,HS,random year)	21	249.8

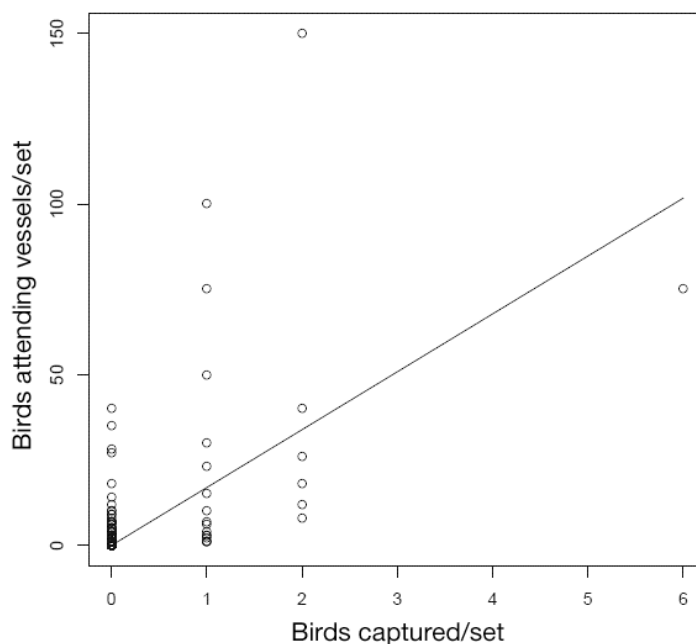
Table S4. *Calonectris diomedea*. Coefficients for models listed in Table S3. The first column corresponds to the model without year as a random variable and is reported here as a reference for comparison. Explanatory variables are: TR: trawling regime, FT: fishing time, BS: breeding stage, HS: number of hooks per set. Analyses were performed using R package glmmADMB

Variables	Coefficient ( $\pm$ SE)		
	$\beta$ for Binary and Poisson		
	ZIP (FT, TR, BS, HS)	ZIP (FT, TR, BS, random year)	ZIP (FT, TR, BS, HS, random year)
Day	-1.1 $\pm$ 0.6	-1.0 $\pm$ 0.6	-1.1 $\pm$ 0.6
Night	-0.3 $\pm$ 0.5	-0.2 $\pm$ 0.5	-0.6 $\pm$ 0.5
Trawling allowance	-1.2 $\pm$ 0.5	-1.6 $\pm$ 0.5	-1.1 $\pm$ 0.5
Incubation	-0.17 $\pm$ 0.8	0.4 $\pm$ 1	-0.5 $\pm$ 0.8
Chick-rearing	-0.16 $\pm$ 0.8	-0.1 $\pm$ 0.8	-1.4 $\pm$ 0.9
Hooks	0.00004 $\pm$ 0.0004		0.0007 $\pm$ 0.0003
1999		-5 $\pm$ 1	-3.4 $\pm$ 0.9
2000		-2.2 $\pm$ 0.8	-1.9 $\pm$ 0.9
2001		-2.8 $\pm$ 0.9	-2.0 $\pm$ 0.8
2003		-0.03 $\pm$ 0.9	-1.2 $\pm$ 0.9
2004		-1.6 $\pm$ 0.6	-2.0 $\pm$ 0.6
2005		-43 $\pm$ 352570	-18 $\pm$ 3066
Constant ( $\alpha_1$ )	1.09 $\pm$ 1.04	3 $\pm$ 1	3.6 $\pm$ 1

### Attendance and bycatch

Even though we observed a strong positive linear correlation between bycatch and birds attending vessels (Pearson correlation = 0.6; 95% confidence interval: 0.49 to 0.66), we can not establish a simple linear relationship between bycatch and number of birds attending vessels, given the high dispersion in the data (Fig. S2). According to Fig. S2, bycatch could be maximum for an intermediate level of attendance, presumably due to overlapping in the competition for resources when density of birds attending vessels is very high or simply because of the lack of consideration of other species that might also be competing with shearwaters. Moreover, it has been reported elsewhere that Cory's shearwater abundance behind trawlers is not a good indicator of their discard consumption rate in the western Mediterranean (Martínez-Abraín et al. 2002).

Fig. S2. *Calonectris diomedea*. Birds attending vessels per set as a function of the number of captures per set. The black line corresponds to a linear fit



Instead of explicitly including the number of birds attending vessels into the model, we implicitly included this quantity through the ZIP model, assuming that the probability of presence/absence of birds in the region of bycatch is linearly related with our explanatory variables, e.g. trawling moratoria, breeding-stage and fishing time. In this way, we avoid the use of the high dispersion data shown in Fig. S2 by using more accurate data like breeding stage, fishing time and trawling moratoria periods.

It is well known that some of these factors affect the number of birds attending vessels. For instance, the frequency of foraging trips could increase during the chick-rearing period (Weimerskirch & Lys 2000). The number of birds attending vessels increases during sunrise (Belda & Sánchez 2001), presumably due to the higher need for food after night fasting. Recent studies indicate that seabird activity increases during sunrise and sunset (Péron et al. 2010). Also, changes in seabird foraging behaviour seem to be related to fishing activities (Bartumeus et al. 2010), the time distribution as well as the length of foraging trips being affected by trawling moratoria in the north-western Mediterranean. We therefore hypothesise that birds could be attracted by longlines in the absence of trawlers (i.e. during trawling moratoria, including weekends and calendar holidays), increasing the probability of attending vessels during this period.

In the following, we checked for a possible linear relationship between the probability of attendance and the mentioned set of explanatory variables. According to Eq. (1a) in the main paper,  $(1 - \Phi)$  is the probability of presence of seabirds in the region of bycatch. A plot of  $(1 - \Phi)$  versus number of birds attending vessels is presented in Fig. S3. If we fit a linear model between these quantities we obtain:

## Coefficients

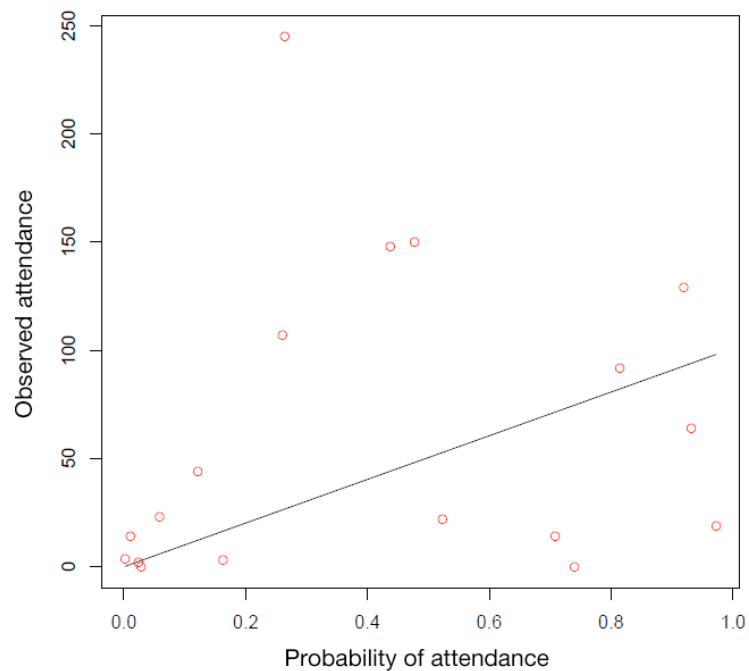
$\text{lm}(\text{formula} = \text{Observed attendance} \sim (1 - \Phi) - 1)$

Estimate Std. Error  $t$  value  $\text{Pr}(>|t|)$

100.89 32.72 3.084 0.00673 \*\*

which clearly reflects that the modelled probability can be interpreted as the probability of birds attending vessels and can be modelled as a linear function of the explanatory variables, i.e. trawling moratoria, breeding-stage and fishing time. The fit was done using R package Stats (Fig. S3).

Fig. S3. *Calonectris diomedea*. Probability of seabirds attending vessels vs. observed attendance per set. The black line corresponds to a linear fit



## Interaction terms

Given our relatively small sample size and the important unbalanced sampling effort in our dataset, we did not consider interaction terms.

However to our knowledge, trawling moratoria do not interact with breeding stage.

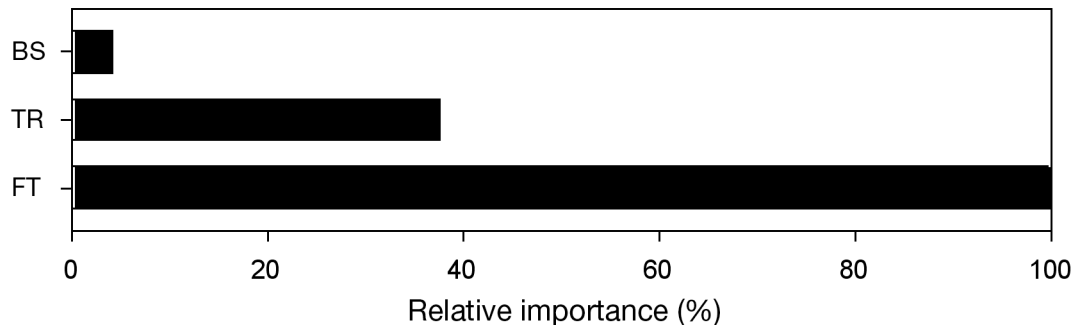
Breeding stage and fishing time occur at different temporal scales and therefore an interaction would be unfeasible in this case.

Finally, given that trawling is not performed at night we could expect some degree of interaction between trawling moratoria and setting time. However due to the unbalanced sampling effort, we couldn't test this interaction, better observer programmes would be essential to test it.

## Ranking variable importance

We calculated the relative importance (in %) for each variable included within the best subset of models by summing up the rescaled Akaike weights for all models containing that variable (McAlpine et al. 2008). Overall, the relative importance of individual variables was: fishing time > trawling regime > breeding stage.

Fig. S4. Ranking of explanatory variables included in best subset of models by sum of Akaike weights ( $\sum w_i$ ) for ZIP model. Explanatory variables are: TR: trawling activity, FT: fishing time, BS: breeding stage



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