

Table S1. Sampling effort. Number of days, number of mother-calf pairs (follows) and total 5 min intervals sampled by gulf each year. GN: Golfo Nuevo and GSJ: Golfo San José.

Fig. S1. Distributions of \hat{R} and the effective sample size for all the parameters in the joint model fitted for Gull Attack Pressure on Calf (GAPC), Gull Attack Pressure on Mother (GAPM) and Gull Attack Frequency (GAF).

Fig. S2. Posterior predictive checks for (A) Gull Attack Pressure on Calf (GAPC), (B) Gull Attack Pressure on Mother (GAPM) and (C) Gull Attack Frequency (GAF). Squares are observed means, empty points are observed daily data (rates for GAPC and GAPM, and proportion for GAF), coloured points are the posterior means for the annual averages by gulf, and coloured bars show their 95% credible intervals. The rightmost values in each panel show the average across years (observed and estimated). Grey bars are the 95% highest density intervals for the posterior predictive distribution in each year, where ~95% of the data points should be found.

Table S2. GAPC model parameters and estimated calf mortality by year and gulf. Posterior distribution means, standard deviations (sd), 2.5% and 97.5% percentiles, \hat{R} and effective sample size. β_0 are the intercepts, β_1 the slopes for the gull attack covariate (GAPC: gull attack pressure on calves), and β_2 the slope for the SST anomalies. All these parameters are presented at *logit* scale and having fitted the model with standardised covariates. *scale* is the Beta-Binomial dispersion parameter (see extended Methods) and p represents the probability of dying — calf mortality — by year and gulf. Subscripts indicate the gulf (GN: Golfo Nuevo, GSJ: Golfo San José) and the year.

Table S3. GAPM model parameters and estimated calf mortality by year and gulf. Posterior distribution means, standard deviations (sd), 2.5% and 97.5% percentiles, \hat{R} and effective sample size. β_0 are the intercepts, β_1 the slopes for the gull attack covariate (GAPM: gull attack pressure on mothers), and β_2 the slope for the SST anomalies. All these parameters are presented at *logit* scale and having fitted the model with standardised covariates. *scale* is the Beta-Binomial dispersion parameter (see extended Methods) and p represents the probability of dying — calf mortality — by year and gulf. Subscripts indicate the gulf (GN: Golfo Nuevo, GSJ: Golfo San José) and the year.

Table S4. GAF model parameters and estimated calf mortality by year and gulf. Posterior distribution means, standard deviations (sd), 2.5% and 97.5% percentiles, \hat{R} and effective sample size. β_0 are the intercepts, β_1 the slopes for the gull attack covariate (GAF: gull attack frequency), and β_2 the slope for the SST anomalies. All these parameters are presented at *logit* scale and having fitted the model with standardised covariates. *scale* is the Beta-Binomial dispersion parameter (see extended Methods) and p represents the probability of dying — calf mortality — by year and gulf. Subscripts indicate the gulf (GN: Golfo Nuevo, GSJ: Golfo San José) and the year.

PGN, 2019	0.074	0.021	0.039	0.121	1	30000
PGSJ, 2004	0.117	0.04	0.05	0.207	1	26084
PGJS, 2005	0.06	0.021	0.025	0.108	$\mathbf{1}$	6967
PGSJ, 2006	0.11	0.033	0.054	0.182	$\mathbf{1}$	3526
PGSJ, 2007	0.068	0.023	0.03	0.119	$\mathbf{1}$	12214
PGSJ, 2008	0.258	0.042	0.181	0.346	$\mathbf{1}$	4900
PGSJ, 2009	0.174	0.04	0.104	0.261	$\mathbf{1}$	2005
PGSJ, 2010	0.151	0.035	0.088	0.227	$\mathbf{1}$	9916
PGSJ, 2011	0.162	0.042	0.089	0.252	$\mathbf{1}$	30000
PGSJ, 2012	0.145	0.034	0.084	0.219	$\mathbf{1}$	30000
PGSJ, 2013	0.141	0.035	0.08	0.216	1	30000
PGSJ, 2014	0.079	0.028	0.033	0.141	$\mathbf{1}$	30000
PGSJ, 2015	0.161	0.043	0.086	0.253	1	30000
PGSJ, 2016	0.056	0.027	0.015	0.118	1	2614
PGSJ, 2017	0.105	0.031	0.052	0.174	$\mathbf{1}$	30000
PGSJ, 2018	0.06	0.022	0.023	0.108	$\mathbf{1}$	29410
PGSJ, 2019	0.02	0.016	0.001	0.061	$\mathbf{1}$	30000
deviance	163.489	8.106	149.653	181.389	$\mathbf{1}$	30000

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Fig. S3. Posterior predictive checks for GAPC (A), GAPM (B) and GAF (C) mortality models. Black dots represent the mean of the posterior predictive distribution of the number of dead calves by year and gulf, and ribbons are the 95% highest density intervals. Empty dots are the observed number of dead calves by year and gulf.

Fig. S4. Month of death models assessment. (A) Quantile-quantile plots of the DHARMa residuals against the expected quantiles in a Uniform(0, 1) distribution (Hartig 2022). (**B**) DHARMa residuals as a function of predicted values (rank-transformed). Based on these diagnostics, all models show a good fit to data. GAPC: gull attack on calves; GAPM: gull attack on mothers; GAF: gull attack frequency.

Fig. S5. Probability of calves dying at Golfo Nuevo (A) and Golfo San José (B) as a function of sea surface temperature (SST) anomalies. This probability is the probability of a calf (or a pool of calves) dying in its first months of life at PV given the SST anomalies values in the feeding ground. SST anomalies correspond to the average of SST anomalies at Islas Georgias del Sur/South Georgia feeding area in August, September and October in the year prior to the calving season. The black line shows the posterior mean of the calf mortality in an average year, while the thinner coloured ribbon shows its 95% credible intervals. The wider dashed ribbon is the 95% prediction interval, showing where we expect to find calf mortality considering unexplained inter-annual variation. Points represent the observed calf mortality. Gull-attack indexes were fixed at their means. GAPC: gull attack on calves; GAPM: gull attack on mothers; GAF: gull attack frequency.

Table S5. Comparing gull attack on calves (GAPC) and gull attack on mothers (GAPM) effects on the probability of calves dying. Here are presented the mean increments of calf mortality when GAPC and GAPM increase from the minimum observed GAPM value to its maximum. 95% credible intervals are presented in brackets. Details on their calculation are available in the Methods section of the Supplementary Information.

Table S6. Probability of calves dying in an average year. Predictions were computed fixing the covariates values at their means (each gull-attack index and SST anomalies). Point estimates are posterior means; their 95% credible intervals are shown in brackets. GAPC: gull attack on calves; GAPM: gull attack on mothers; GAF: gull attack frequency.

Table S7. Probability of calves dying when no attacks had been recorded. Predictions were computed fixing the gull-attack indexes at 0 and SST anomalies at its mean. Point estimates are posterior means; their 95% credible intervals are shown in brackets. GAPC: gull attack on calves; GAPM: gull attack on mothers; GAF: gull attack frequency.

Text S1. Extended Methods

Generalised linear mixed model for gull attack pressure and frequency

Model fitting and priors

We fitted a joint model for gull attack pressure and gull attack frequency to improve the estimation of year-level random effects considering that the effects of these gull-attack indexes were correlated. We modelled the number of attacks per hour either on mothers or calves (GAP), and the proportion of interval with attacks on the mother-calf pair (GAF). In the GAP part of the model was defined as follows:

$$
GAN_{gmyd} \sim NegBin(\mu_{gmyd}, \phi)
$$

$$
log(\mu_{gmyd}) = \alpha_{gm} + \varepsilon_{GY,gy} + \varepsilon_{GMY,gmy} + log(h_{gyd})
$$

$$
\phi = 1/\tau
$$

$$
\tau \sim Half\text{-Normal}(5)
$$

$$
\alpha_{gm} \sim Normal(log(7), 10)
$$

$$
\varepsilon_{GMY,gmy} \sim Normal(0, \sigma_{GMY,gm})
$$

$$
\sigma_{GY,g} \sim Half\text{-Normal}(2)
$$

$$
\sigma_{GMY,gm} \sim Half\text{-Normal}(2)
$$

GAN_{gmyd} is the gull attacks number (count) on gulf $g \in$ {Golfo Nuevo,Golfo San José}, on either mother or calf ($m \in \{$ mother,calf}), year $y \in \{1, ..., 15\}$ (1995 and 2004 to 2019) and observation date d. h_{grad} are the daily observation hours, and as its logarithm is included in the linear predictor for μ_{amvd} , the latter is interpreted as the expected number of attacks on mothers or calves per hour at date *d*, gulf *g* and year *y*, that is gull attack pressure. ϕ is an inverse-dispersion parameter of the Negative Binomial distribution, as parameterised in the *neg_binomial_2* Stan function (Stan Development Team 2020a). Uppercase subscripts as GM, GMY or GY are used here to name parameters related to interactions of the factors gulf (G), mother-calf (M) and year (Y). For example, $\varepsilon_{GMY,gmy}$ is a random effect interaction term for gulf, mother-calf and year. It has one parameter for every combination of these variables. Its standard deviation varies between gulfs and between mother-calf, so $\sigma_{GMY,am}$ represents the variability between years within the gulf and mothercalf combinations (so there are 4 $\sigma_{GMY,gm}$ values). α_{gm} encompasses the interaction between gulf and mother-calf, treated as a fixed effect, having one parameter for every combination of these factors.

The model for GAF was specified as follows:

$$
GAl_{gyd} \sim \text{Binomial}(\pi_{gyd}, \text{NI}_{gyd})
$$

$$
\text{logit}(\pi_{gyd}) = \gamma_g + \delta_{GY,gy} + \delta_{GYD,gyd}
$$

$$
\gamma_g \sim \text{Normal}(0,2)
$$

$$
\delta_{GYD,gyd} \sim \text{Normal}(0, \tau_{GYD})
$$

$$
\tau_{GYD} \sim \text{Half-Normal}(1.5).
$$

 GAI_{gyd} is the number of observation intervals (5 min) where there was at least one attack to mother or calf on gulf g , year y and observation date d . NI is the number of observation intervals and π_{gyd} the attack probability that can be interpreted as the expected gull attack frequency (GAF). $\delta_{GYD,gyd}$ is the observation-level random effect, and it was included to account for overdispersion in the response relative to a Binomial distribution.

 $\varepsilon_{GY,gy}$ and $\delta_{GY,gy}$ are the year-level random effects within gulfs for the linear predictors in GAP and GAF models, respectively. To model the correlation between GAP and GAF, we defined the vector $\eta_{gy} = [\varepsilon_{GY,gy}, \delta_{GY,gy}]'$ with a hierarchical bivariate Normal prior:

$$
\eta_{gy} \sim \text{MVN}(0, \Sigma_g)
$$
\n
$$
\Sigma_{g,ij} = \begin{cases}\n\rho \sigma_{GY,g} \tau_{GY,g} \text{for } i \neq j \\
\sigma_{GY,g}^2 \text{for } i = j = 1 \\
\tau_{GY,g}^2 \text{for } i = j = 2\n\end{cases}
$$
\n
$$
\sigma_{GY,g} \sim \text{Half-Normal}(2)
$$
\n
$$
\tau_{GY,g} \sim \text{Half-Normal}(1.5)
$$
\n
$$
\rho \sim \text{Unif}(-1,1)
$$

 ρ is the correlation between GAP and GAF random effects. Notice that the variance between years for each variable changes between gulfs.

Normal distributions are parameterised with mean and standard deviation, and Half-Normal distributions have an implicit mean $= 0$. MVN stands for Multivariate Normal.

The weakly informative priors used in this model were chosen based on simulations.

Temporal correlation in attacks

It would be appropriate to consider that attacks show a temporal correlation, as many are observed in consecutive 5 min discrete intervals. However, the database with attack records at 5 min temporal resolution was smaller than the dataset with the daily summaries. We preferred to use the latter because the aim of this study is to assess variations in the mean of the attack indexes, not focusing on the kelp gulls' behaviour. A possible consequence of our approach is that our current models underestimate the uncertainty around parameters. A more detailed analysis of kelp gull attack behaviour considering its temporal correlation (with the smaller dataset) will be presented in a separate article focused on whales' behaviour.

1995 database and data between 1996 and 2003

For 1995 we had less observation dates than for the period 2004-2019. As our model gives similar weight to observations with varying number of observation intervals (NI_{qyd} or h_{qyd}), observations with low NI could easily show extreme gull attack number (GAN) or gull attack intervals (GAI) and bias the year-gulf-mother/calf average. To avoid this, we identified one date in each gulf in 1995 having low NI and we merged it with the observations made in the date with lower NI between the 2 closest ones. In this way, the 1995 averages were less biased by noisy observations.

Between 1996 and 2003 we only could get year-level summaries for GAF (proportions) and we do not have any information about GAP. Consequently, we did not include those values in the models, but included them in the correspond figure (Fig. 2C).

Calf mortality and gull attack model

SST anomalies in Islas Georgias del Sur/South Georgia

The reproductive success of southern right whales off the South Atlantic is positively correlated with their prey availability in Islas Georgias del Sur/South Georgia Islands (Leaper et al. 2006, Seyboth et al. 2016). This suggests that calf mortality might be at least partially explained by declines in the density of Antarctic krill (*Euphasia superba*) during the summer prior to the calving season, when pregnant females feed. Data on krill density in Islas Georgias del Sur/South Georgia are available only until 2016 (Atkinson et al. 2017), while our calf mortality data spans from 2004 to 2019. In order to use all of our data, we decided to work with a proxy for krill density.

Sea surface temperature (SST) is inversely correlated with krill density (Trathan et al. 2003, Fielding et al. 2014), and has already been used as its proxy in other analyses about reproductive success of marine mammals in Islas Georgias del Sur/South Georgia (Leaper et al. 2006, Seyboth et al. 2016, Forcada et al. 2005). We decided to work with the SST anomalies average between August and October, as winter anomalies are negatively correlated with krill density in summer at Islas Georgias del Sur/South Georgia (Fielding et al. 2014). We obtained the SST data from a 0.25º resolution daily database Reynolds et al. (2008) using Google Earth Engine (Gorelick et al. 2017). For every year between 1982 and 2019, we averaged the August-October daily values from all the pixels within two separately polygons previously used in other studies (Fig. S6) (Leaper et al. 2006, Trathan et al. 2006, Fielding et al. 2014). Then, we subtracted the long-term mean (1982-2011) from the annual values, to express the values as anomalies. We computed the spatial average of the annual anomalies for each polygon, and lastly, we computed the annual average anomaly between both polygons. To include SST anomalies as a predictor of annual calf mortality we assigned the anomalies of the winter (August-October) in year *y-1* to mortality in year *y*, as SST anomalies in winter are related to krill density in summer, which may affect calf mortality in the following spring.

Fig. S6. Polygons used to extract sea surface temperature (SST) anomalies around Islas Georgias del Sur/South Georgia. SST data from August to October was derived from the daily database of Reynolds et al. (2008) and expressed as anomalies. We then calculate the average of the anomalies of both polygons and assigned the values of the winter of year *y-1* to year *y*, as krill density in summer is negatively correlated with krill density in winter (Fielding et al. 2014).

Model fitting and priors

We fitted three separated Beta-Binomial generalised linear models to analyse the effects of gull attacks on calf mortality. The number of dead calves in each gulf during each year was modelled with a Binomial distribution with probability of dying $p_{g,y}$ and size equal to the number of born calves in gulf *g* and year *y*:

$$
deadcalves_{g,y} \sim Binomial(p_{g,y}, borncalves_{g,y})
$$

To account for overdispersion we assumed that $p_{q,y}$, the probability of calves dying at a given year and a give gulf, followed a Beta distribution:

$$
p_{g,y} \sim \text{Beta}(\alpha_{g,y}, \beta_{g,y})
$$

With parameters $\alpha_{g,y}$ and $\beta_{g,y}$ that were defined by $p_{g,y}$'s mean $\theta_{g,y}$ and a precision parameter φ_g :

$$
\alpha_{g,y} = \theta_{g,y} * \varphi_g
$$

$$
\beta_{g,y} = (1 - \theta_{g,y}) * \varphi_g
$$

We modelled $\theta_{a,v}$, the mean probability of dying, with a *logit* link function:

$$
logit(\theta_{g,y}) = \beta_{0,g} + \beta_{1,g} \times GA_{g,y} + \beta_2 \times SST_{y-1}
$$

where $\beta_{0,g}, \beta_{1,g}, \beta_{2}$ are parameters to be estimated, $GA_{g,y}$ is any of the three standardised gullattacks indexes in gulf g during year y , and SST_y is the sea surface temperature anomalies in Islas Georgias del Sur/South Georgia corresponding to year *y-1* (as the SST of the preceding winter is correlated with present krill density; Fielding et al. 2014).

As φ_g is inversely related to the Beta-Binomial variance, we defined it through the *scale* parameter, proportional to the variance:

$$
\varphi_g = 1 / scale_g
$$

We fitted the three models using JAGS through its R interface, jagsUI (Plummer 2003), specifying weakly informative priors for all parameters based on prior predictive checks:

scale_g ~ Gamma(1, 1 / 0.1)
\n
$$
\beta_{0,g} \sim \text{Normal}(0, 1.5)
$$
\n
$$
\beta_{1,g} \sim \text{Normal}(0, 1.5)
$$
\n
$$
\beta_2 \sim \text{Normal}(0, 1.5)
$$

Gamma distributions were parameterised through *shape* and *rate* parameters, and Normal distributions were parameterised with mean and standard deviation.

The covariates were standardised to fit the models. Models parameters are shown in standardised scale in Tables S2, S3 & S4.

Additional references

Atkinson A, Hill SL, Pakhomov EA, Siegel V and others (2017) KRILLBASE: a circumpolar database of Antarctic krill and salp numerical densities, 1926-2016. Earth Syst Sci Data 9: 193-210

Forcada J, Trathan PN, Reid K, Murphy EJ (2005) The effects of global climate variability in pup production of Antarctic fur seals. Ecology 86: 2408-2417

Hartig F (2022) DHARMa: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models. R package version 0.4.6. https://CRAN.R-project.org/package=DHARMa

Trathan PN, Murphy EJ, Forcada J, Croxall JP and others (2006) Physical forcing in the southwest Atlantic: ecosystem control. In: Boyd IL, Wanless S, Camphyusen CJ (eds) Top predators in marine ecosystems: their role in monitoring and management*.* Cambridge University Press, Cambridge, p 28-45