LETTER

WILEY **Conservation Letters**
A journal of the Society for Conservation Biology · Open Access

A risk-based forecast of extreme mortality events in small cetaceans: Using stranding data to inform conservation practice

Colin Bouchard[1,2] (iD) | Cameron Bracken[3] | Willy Dabin[1] | Olivier Van Canneyt[1] | Vincent Ridoux[1,4] | Jérôme Spitz[1] | Matthieu Authier[1,5]

[1]Observatoire Pelagis, UMS 3462, Université de La Rochelle, cnrs, La Rochelle, France

[2]UMR Ecobiop, UMR 1224, INRA, University of Pau and Pays de l'Adour, Saint-Pée sur Nivelle, France

[3]Bonneville Power Administration, Portland, Oregon

[4]Centre d'Étude Biologiques de Chizé, UMS 7372, Université de La Rochelle, cnrs, Villiers-en-bois, France

[5]Adera, Pessac Cedex, France

Correspondence
Colin Bouchard, Observatoire Pelagis, UMS 3462, Université de La Rochelle, CNRS, La Rochelle, France.
Email: colin.bouchard@icloud.com

Abstract

Effective conservation requires monitoring and pro-active risk assessments. We studied the effects of at-sea mortality events (ASMEs) in marine mammals over two decades (1990–2012) and built a risk-based indicator for the European Union's Marine Strategy Framework Directive. Strandings of harbor porpoises (*Phocoena phocoena*), short-beaked common dolphins (*Delphinus delphis*), and striped dolphins (*Stenella coeruleoalba*) along French coastlines were analyzed using Extreme Value Theory (EVT). EVT operationalizes what is an extreme ASME, and allows the probabilistic forecasting of the expected maximum number of dead animals assuming constant pressures. For the period 2013–2018, we forecast the strandings of 80 harbor porpoises, 860 common dolphins, and 57 striped dolphins in extreme ASMEs. Comparison of these forecasts with observed strandings informs whether pressures are increasing, decreasing, or stable. Applying probabilistic methods to stranding data facilitates the building of risk-based indicators, required under the Marine Strategy Framework Directive, to monitor the effect of pressures on marine mammals.

KEYWORDS

bycatch, conservation, extreme events, Extreme Value Theory, forecasting, marine mammals, Marine Strategic Framework Directive, mortality

1 | INTRODUCTION

In the Anthropocene, anthropogenic pressures (Maxwell, Fuller, Brooks, & Watson, 2016; Steffen, Broadgate, Deutsch, Gaffney, & Ludwig, 2015) and extreme environmental events (Ummenhofer & Meehl, 2017) erode biodiversity. A high intensity and historically low occurrence define such extreme environmental events. Previous works on extreme events have focused on their retrospective identification and underlying causes (Barbraud, Delord, & Weimerskirch, 2015; Solow, 2017). The latter can be very difficult to investigate, espe-

cially in ecology where collecting the necessary long-term data is challenging (Anonymous 2017). The consequences of extreme events, however, can be observed through mass die-offs or other extreme ecological responses (Barbraud et al., 2015; Chambert, Rotella, & Garrott, 2012; Gutschick & BassiriRad, 2010; Ummenhofer & Meehl, 2017).

The term "extreme" may describe the consequences of an event on an ecosystem. Studying extreme environmental events through their consequences, rather than their causes, is relevant for biodiversity conservation to emphasize proactive rather than reactive policies. By analogy, catastrophic flood

levels are forecast to estimate their consequences (Coles & Pericchi, 2003) despite many uncertainties in hydrological processes (Beven, 2016). Forecasting has become an imperative for biodiversity conservation in the Anthropocene (Clark et al., 2001; Cook, Inayatullah, Burgman, Sutherland, & Wintle, 2014), but many hurdles remain, especially in the marine realm (Parsons et al., 2014).

The European Marine Strategy Framework Directive (MSFD, 2008/56/EC[1]) aims to maintain or restore "Good Environmental Status" of marine ecosystems by 2020. This conservation plan is based on a set of indicators, mostly describing and assessing the status of ecosystem components. Routinely comparing ecological forecasts to observed data is useful to decision-making in directives like the MSFD (Dietze et al., 2018); it allows researchers and decision-makers to track how pressures change as new policies are implemented. Risk assessments based on the consequences of extreme environmental events and their occurrence probabilities are thus required to supplement status-based indicators (Gibbs & Browman, 2015).

Studying mortality events is of critical importance due to their potentially disproportionate impact on population abundance (Chambert et al., 2012; Denny, Hunt, Miller, & Harley, 2009; Fey et al., 2015; Gross, Mittelbach, & Reynolds, 2005), and in the case of top predators, on ecosystems (Sergio et al., 2008). Small cetaceans face many pressures (Bossart, 2011; Burek, Gulland, & O'Hara, 2008; Gulland & Hall, 2007; Pierce et al., 2008), including bycatch by fisheries (Dolman, Baulch, Evans, Read, & Ritter, 2016; Read, Drinker, & Northridge, 2006; Reeves, McClellan, & Werner, 2013). High levels of additional induced mortality can disrupt population dynamics and even lead to species extinction (Taylor et al., 2017).

Monitoring temporal variations in the abundance of cetaceans has proven a difficult endeavor (Jewell et al., 2012). Historically, strandings have provided a wealth of information on cetaceans, including mass die-offs, despite uncertainties about their underlying causes. Hohn, Rotstein, and Byrd (2013) developed a retrospective method to detect extreme at-sea mortality events (ASMEs) from marine mammal strandings with a 7-day lag. Forecasting extreme ASMEs—rare but potentially disastrous events—requires models that focus on maxima, not on averages (Burgman et al., 2012; Davison & Huser, 2015). Extreme Value Theory (EVT) provides the appropriate statistical framework to model past extremes and forecast future extremes (Coles, 2001; Davison & Huser, 2015). EVT includes Peak-Over-Threshold and Block-Maxima methods. The latter relies on the Generalized Extreme Value (GEV) distribution and enables the extrapolation of probabilities of future events assuming that the causes of these events remain the same.

This study aimed to develop a risk-based indicator for small cetaceans by building a statistical model using EVT to identify extreme ASMEs based on stranding data and forecast their probable magnitude in the future. Using stranding data along French coasts, we illustrate our proposed risk-based indicator for three small cetacean species experiencing various pressures. We first calibrate models to past stranding data (1990–2012), then use the models for forecasting over the MSFD reporting cycle (2013–2018). These forecasts multiplied by their probability are used as risk-based indicators and are compared to actual stranding data (2013–2016). Such comparisons enable policymakers to assess whether pressures are changing as new policies are implemented.

2 | METHODS

2.1 | Study area and study species

The MSFD applies an ecosystem-based management approach to the conservation of marine waters. Four spatial units, or marine regions, are defined by the directive: the Baltic Sea, the North East Atlantic Ocean, the Mediterranean Sea, and the Black Sea. Each region represents an ecosystem and can be further divided into subregions.

We used stranding data of three small cetacean species, each one characteristic of an MSFD marine subregion: the harbor porpoise (*Phocoena phocoena*) in the English Channel (Greater North Sea), the short beaked common dolphin (*Delphinus delphis*) in the Bay of Biscay (Bay of Biscay and Iberian coast), and the striped dolphin (*Stenella coeruleoalba*) in the North Western Mediterranean Sea (Western Mediterranean Sea, Figure 1). Daily counts of dead animals on the beaches from 1990 to 2016, a period with constant reporting rates (Authier et al., 2014), were tallied. Carcasses were examined by trained volunteers of the French marine mammal stranding network, following European and French regulations on stranded cetaceans. Fresh carcasses, animals estimated to have died less than 48 hr prior to the examination, were examined for marks or wounds diagnostic of bycatch (Kuiken, 1994).

2.2 | Data formatting

Statistical analyses were carried out at month-level. Data were "blocked" prior to EVT modeling (Coles, 2001). We chose a 3-day block length to smooth a possible weekend effect in reporting (due to increased beach attendance, Supporting Information), and to account for ASMEs extending several days. Daily counts of stranded animals were summed over a sliding 3-day window for each month and M_{ij}, the monthly maximum of the ith month in year j, was computed. The response variable was the monthly maximum number of strandings over a 3-day period (Figure 2). The data of the period from 2013 to 2016 were not used to estimate
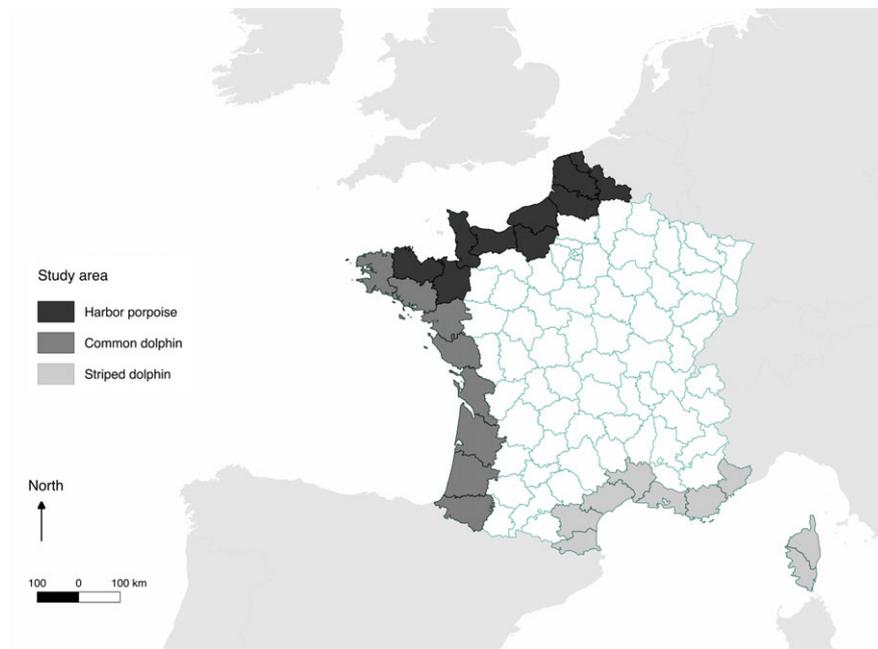
FIGURE 1 Study area map. France borders three MSFD marine sub-regions: the English Channel (Greater North Sea subregion), the Bay of Biscay (Bay of Biscay and Iberian coast subregion), and the North Western Mediterranean Sea (Western Mediterranean Sea subregion)
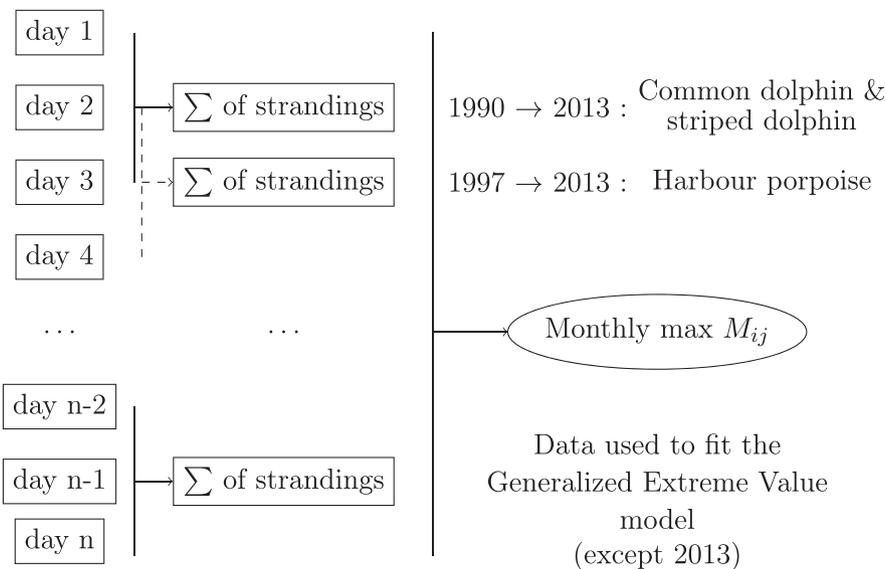

FIGURE 2 Flow chart illustrating data preparation for EVT modeling. Strandings are reported for each day of the study period. These strandings are totaled over a sliding 3-day window and the maximum for each month is extracted

model parameters but were held out for out-of-sample cross-validation.

2.3 | Model building

The GEV distribution has three parameters (Coles, 2001): location (μ, mean), scale ($\sigma, > 0$), and shape (ξ). The shape parameter, ξ, is estimated from the data and determines the GEV distribution (Gumbel, Weibull or Fréchet, see Supporting Information). Temporal variation in the stranding intensity (μ_{ij}) were tested through four model specifications ($\mathcal{M}_{\text{Null}}$ −

$\mathcal{M}_3$). A null model with no temporal variation ($\mathcal{M}_{\text{Null}}$, a simple GEV distribution) was first tested. In other specifications, additive year (j) and month (i) random effects were included. The GEV likelihood for datum y_{ij} is (Coles, 2001; see Supporting Information for priors and model fitting):

$$\ell\left(\mu_{ij}, \sigma, \xi \mid y_{ij}\right) = -\log\sigma - \left(1 + \frac{1}{\xi}\right)\log\left[1 + \xi\left(\frac{y_{ij} - \mu_{ij}}{\sigma}\right)\right]$$

$$-\log\left[1 + \xi\left(\frac{y_{ij} - \mu_{ij}}{\sigma}\right)\right]^{-1/\xi}$$

with $y_{ij} = \log(1 + M_{ij})$ and:

$$\mathcal{M}_{\mathrm{Null}}: \mu_{ij} = \text{intercept}$$

$$\mathcal{M}_1: \mu_{ij} = \text{intercept} + \alpha_j + \beta_i \quad ; \alpha_j \sim \mathcal{N}\left(0, \sigma_{\mathrm{year}}^2\right), \beta_i \sim \mathcal{N}\left(0, \sigma_{\mathrm{month}}^2\right)$$

$$\mathcal{M}_2: \mu_{ij} = \text{intercept} + \text{slope} \times j + \beta_i \quad ; \beta_i \sim \mathcal{N}\left(0, \sigma_{\mathrm{month}}^2\right)$$

$$\mathcal{M}_3: \mu_{ij} = \text{intercept} + \text{slope} \times j + \alpha_j + \beta_i \quad ; \alpha_j \sim \mathcal{N}\left(0, \sigma_{\mathrm{year}}^2\right), \ \beta_i \sim \mathcal{N}\left(0, \sigma_{\mathrm{month}}^2\right)$$

The WAIC was used for model selection (see Supporting Information). Parameters from the best model were used to forecast the return level $y_{\mathrm{pred},T}$, the value expected to be exceeded on average once every time interval T (Guillou, Naveau, Diebolt, & Ribereau, 2009). The return level corresponds to the expected maximum of stranded dolphins over a 3-day period in each month (T) of an MSFD cycle ($T \in [1:72]$ months):

$$y_{\mathrm{pred},T} =$$

$$\begin{cases} \mu - \left(\frac{\sigma}{\xi}\right)[1 - \{-\log(1-p)\}^{-\xi}] & \text{with} \quad p = \frac{1}{T} \quad \text{and} \quad \xi \neq 0 \\ \mu - \sigma \log\{-\log(1-p)\} & \text{with} \quad \xi = 0 \end{cases}$$

2.4 | Risk assessment

A risk is the product of the likelihood of an event and its consequences (Gibbs & Browman, 2015). For each monthly forecast between 2013 and 2018, the risk was the product of the forecast level $y_{\mathrm{pred},T}$ (number of dead individuals) and the corresponding occurrence probability: $p_T = \frac{1}{T}$ (Coles, 2001). The risk measure can be compared across species, as well as across months within species.

2.5 | Cross-validation

Forecasts for the 2013–2016 period were compared to observed data: 2,000 posterior values were used to calculate 95% highest posterior density (HPD) intervals. Because predicting maxima was the target, a model forecast should be lower than or equal to the observed data. Upon validation, the selected GEV model was used to forecast the return level for the first MSFD cycle (2013–2018). Return levels were also corrected by buoyancy probability (Section 11 in Supporting Information).

3 | RESULTS

3.1 | Stranding data (1990–2012)

The number of harbor porpoise strandings in the English Channel per year has increased since the 1990s. In 1997, only eight stranded individuals were reported, in contrast to 195 individuals in 2012. Common dolphin strandings in the Bay of Biscay increased from 125 to 323 individuals during the 1990–2012 period, with a peak of 476 individuals in 2000. Year-to-year variations were larger in common dolphins than in harbor porpoises (Figure 3). Strandings of striped dolphins peaked in 1990 (139 individuals), and the lowest number was in 1999 (five individuals) with weak evidence of an increase over the study period. Fresh deaths were largely attributed to bycatch for common dolphins and harbor porpoises; both sexes seemed similarly impacted (Figure 3).

3.2 | Model selection

The most complex model specification ($\mathcal{M}_3$), which incorporated both a yearly trend and random effects, provided the best relative fit (e.g., the lowest WAIC; Supporting Information Table S1). An increasing trend in harbor porpoise and common dolphin strandings was clearly supported. Coefficients of determination for this yearly trend were 0.35 (95%HPD = [0.27, 0.43]), 0.27 ([0.18, 0.36]), and 0.13 ([0.02, 0.24]) for harbor porpoises, common dolphins, and striped dolphins, respectively (Figure 4).

3.3 | Cross-validation

The expected maximum numbers of stranded small cetaceans were predicted for each month of 2013, 2014, 2015, and 2016 (Supporting Information Figures S4–S7). Observed harbor porpoise strandings were close to forecasts in all months of 2013 except May, where strandings exceeded predictions. All other harbor porpoise forecasts were acceptable because observations did not exceed predictions. Observed data for both the common dolphin, and the striped dolphin, were close to, yet always lower than, the predictions: observed maxima never exceeded predicted ones.

3.4 | Return levels (2013–2018)

We forecast the potential extreme ASMEs—maxima of the potential number of stranded small cetaceans over a 3-day period—using the model $\mathcal{M}_3$ for each month over a 6-year time period (MSFD cycle: $T = \text{January } 2013 - \text{December } 2018 = 72 \text{ months}$) and corrected for buoyancy probability to provide an estimate of the total number of dead animals at sea. Forecasts of other models are provided in the Supporting Information.

For harbor porpoises, the highest return levels were expected in April (Figure 5). Monthly variations in strandings were double that of yearly ones (Table 1). The largest return level was forecast for April 2018 from a Weibull distribution ($\xi = -0.37$, 95%HPD $= [-0.46, -0.26]$) at 14, 95%HPD $= [09, 18]$ stranded individuals following a mortality event at sea. Taking buoyancy probability into account,
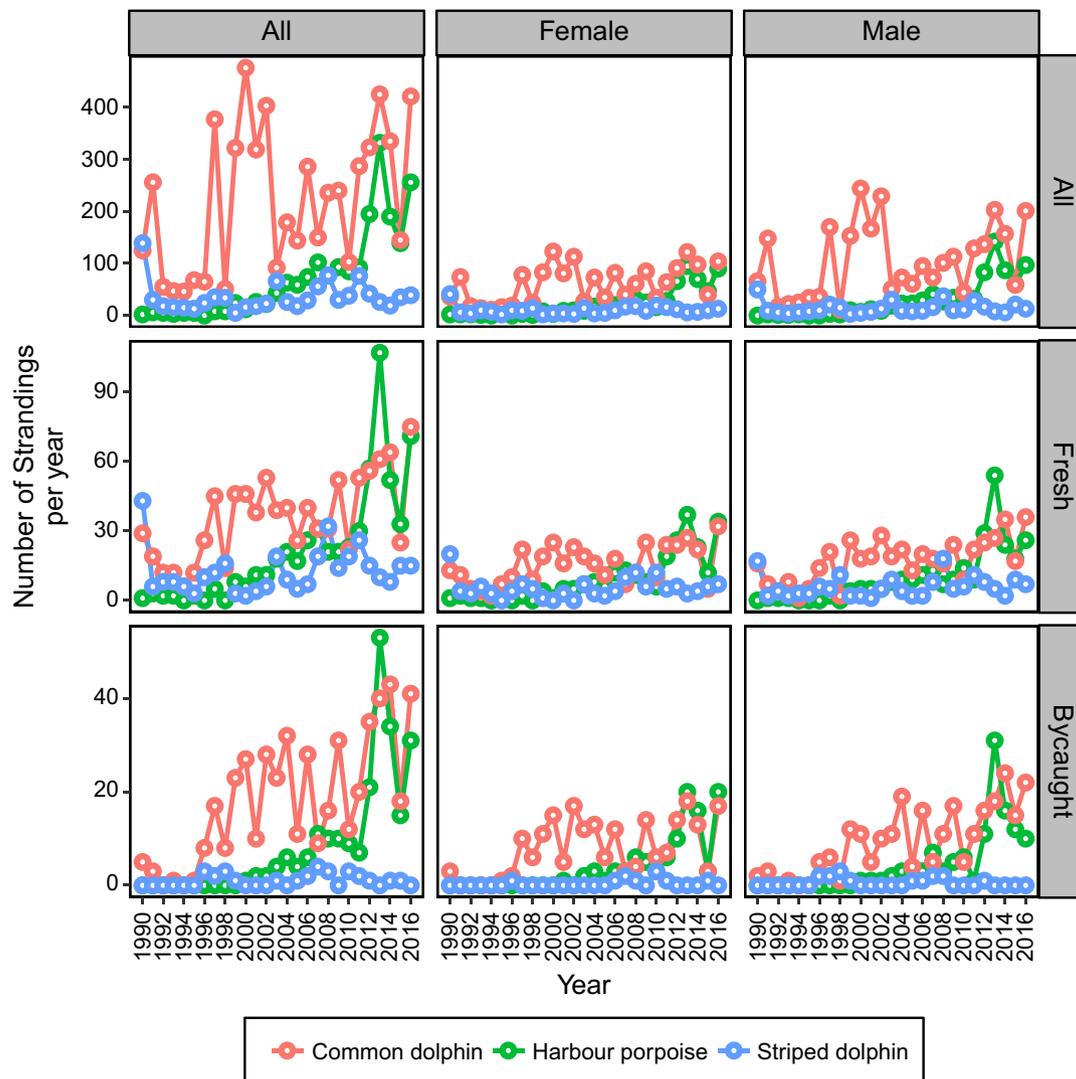
FIGURE 3 Trends in strandings from 1990 to 2016 along French coasts for harbor porpoises (English Channel), short-beaked common dolphins (Bay of Biscay), and striped dolphins (North Western Mediterranean Sea)

this corresponded to 80, 95%HPD = [36, 136] individuals at sea (Figure 5).

The highest return levels were expected in February for common dolphins (Figure 5). Monthly variations in strandings were over five times larger than yearly ones (Table 1). Positive estimates were in the HPD interval of: $\xi = -0.06\ [-0.14, 0.03]$, indicating a Gumbel distribution. The largest return level was forecast for February 2018 at 146 [83, 221] stranded individuals, around 50 of which are females. This corresponded to 860 [321, 1, 533] individuals at sea (Figure 5), around 291 of which are females.

For striped dolphins, the highest return levels were expected in October (Figure 5), although seasonality was weak. Yearly strandings were twice as variable compared to monthly strandings (Table 1). Return levels were forecast from a Weibull distribution ($\xi = -0.20\ [-0.31, -0.11]$). The largest return level was forecast for October 2018 at 10 [5, 15]

stranded individuals. This corresponded to 57 [21, 101] individuals at sea (Figure 5).

3.5 | Risk assessment

The computed risk had a different range for each species, the common dolphin displaying the highest risk, and the striped dolphin the lowest (Figure 5). For the common dolphin, a high risk still occurred in 2018 with a value of 11.6.

4 | DISCUSSION

The effect of extreme events on population dynamics is a growing area of conservation research (Barbraud et al., 2015; Chambert et al., 2012; Gutschick & BassiriRad, 2010). We predicted the effects of potential extreme ASMEs on small cetacean strandings along French coasts using EVT (Coles,
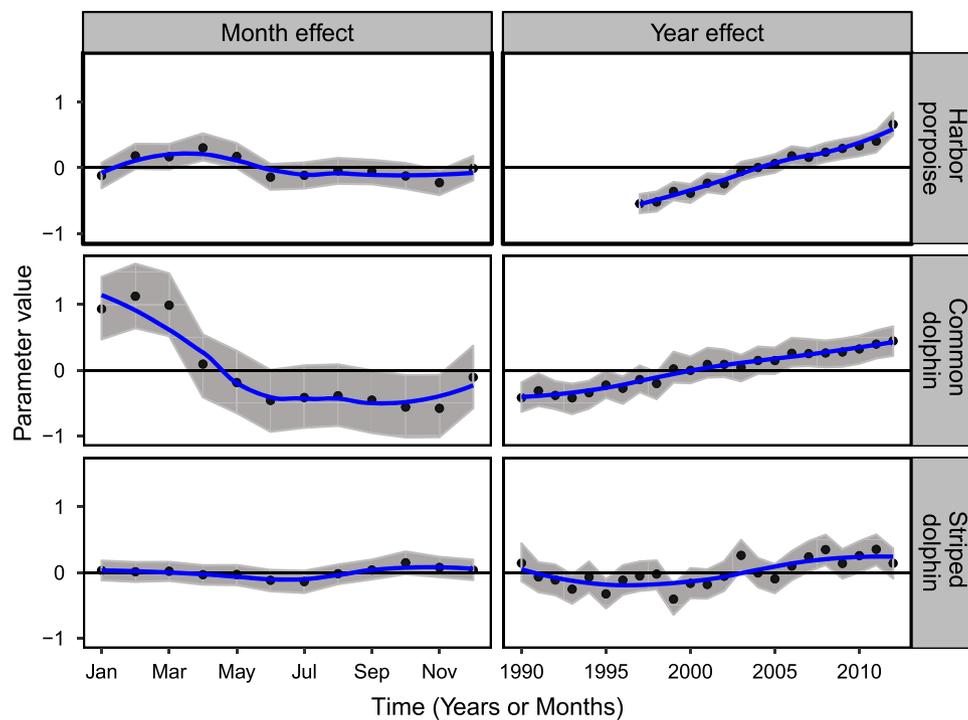
FIGURE 4 Month and year effects of the best model ($\mathcal{M}_3$) estimating extreme mortality events in harbor porpoise, common dolphin, and striped dolphin. The curve corresponds to the mean forecast and the gray area to the 95% HPD interval

2001; Davison & Huser, 2015) and computed their associated risks, which enabled us to compare the predicted and observed figures across months and years for each species. The three species: harbor porpoises, common dolphins, and striped dolphins, each provided a different picture. Return level intensities increased over the study period: the increase was the largest in harbor porpoises and the smallest in striped dolphins. Mortality and the associated risk were the largest for common dolphins. Seasonal variations were greatest in common dolphin strandings and smallest in striped dolphin strandings. These seasonal variations do not overlap with variations in abundance in the study area (Supporting Information).

Statistical modeling with the GEV distribution requires binning the data into blocks (Coles, 2001). The chosen block length of 3 days allowed smoothing a possible weekend effect in reporting and accommodated for an ASME spanning several days (Section 15 in Supporting Information). The forecasting model was cross-validated with 4 years of data (2013–2016) to assess model predictive accuracy on holdout data, which is how the model will be used if incorporated in management practices. Forecasts can be provided at the beginning of an MSFD cycle and can later be assessed against observations at the close of the cycle. Recent observed common dolphins' mass strandings were similar or closed to our forecasts (forecasts: 134 [75, 209] and 118 [64, 181]; observations: 144 and 62 for February and March 2017; Observatoire Pelagis's unpublished data), asserting the value of ecological forecasting as a support of management directives. Our forecasts for

common dolphin suggest that a potential ASME in 2018 could represent around 20% of the threshold number of deaths due to human activities above which the population would decrease (Mannocci et al., 2012; Section 12 in Supporting Information).

Forecasts and observations for common and striped dolphins were comparable: previously observed variations were sufficient to predict future ones (Cook et al., 2014). The same pressures operating before 2013 were thus still in effect between 2013 and 2016. Past variations did not allow for an accurate forecast for harbor porpoises for May 2013. The recent increase in harbor porpoise strandings suggests that a shift in conditions may have occurred around 2012. This may be due to the displacement of the harbor porpoise population from the northern part of the North Sea down to the English Channel between 1994 and 2005 (Hammond et al., 2013). The considerable lag in effect would need to be explained for this to be a feasible explanation. Another non-mutually exclusive hypothesis is the exacerbation of existing pressures or the appearance of new pressures affecting harbor porpoises in the English Channel, causing an increase in bycatch (Figure 3). It is essential to monitor harbor porpoise populations and the pressures acting on them in the coming years in order to understand the discrepancy between the forecast and observed strandings.

For common dolphins and harbor porpoises, monthly variations in the month parameter (β_i) display a peak in late winter/early spring. However, the peak for harbor porpoises is
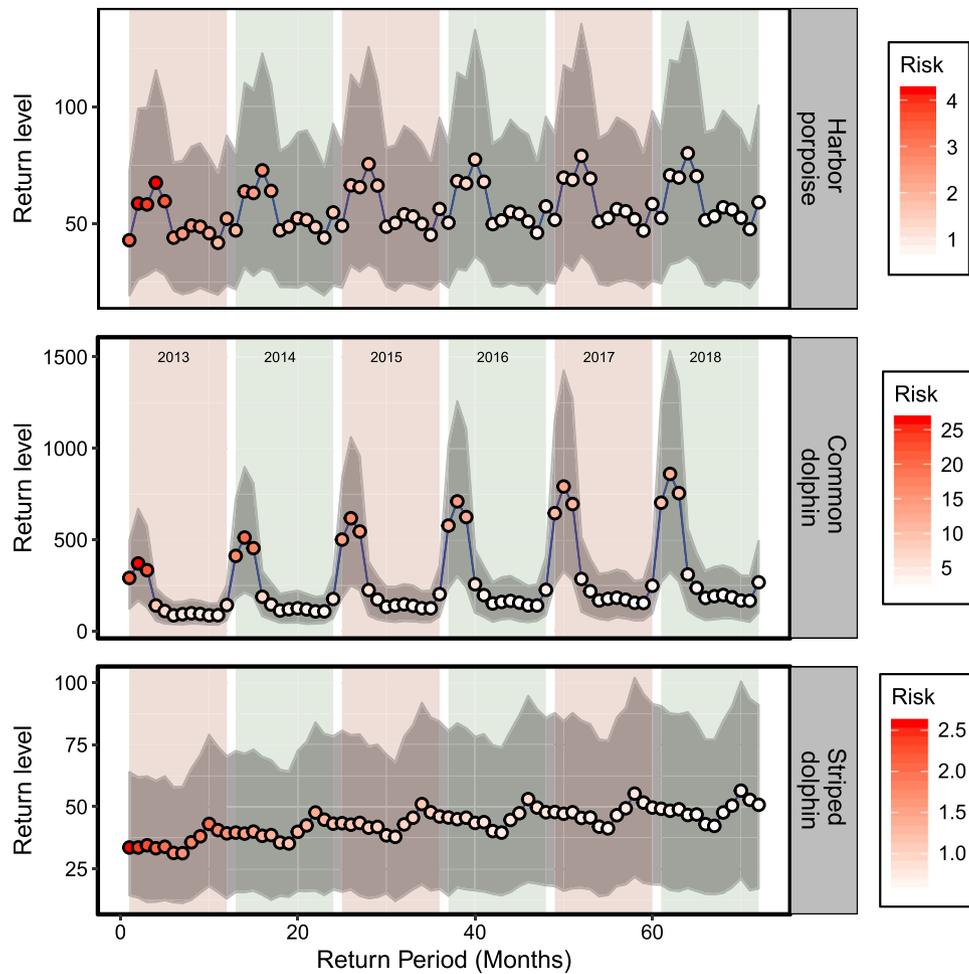
FIGURE 5 Corrected return levels forecast from model $\mathcal{M}_3$ for harbor porpoises, common dolphins, and striped dolphins between January 2013 and December 2018 (MSFD cycle). The curve corresponds to the mean forecast and the gray area to the 95% HPD interval. The associated risk is color-coded for each estimated return level

TABLE 1 Estimated standard deviations of month and year effects for harbor porpoises, common dolphins, and striped dolphins. Posterior means and 95% highest posterior density intervals from model $\mathcal{M}_3$ are reported

Standard deviation	Harbor porpoises	Common dolphins	Striped dolphins
σ_{month}	0.21 [0.11,0.36]	0.72 [0.46,1.13]	0.12 [0.03,0.23]
σ_{year}	0.09 [0.02,0.19]	0.11 [0.01,0.24]	0.21 [0.13,0.31]

2 months later than that of common dolphins (Figure 4). The seasonality can reflect fishery activities e.g. winter seabass trawling in the Bay of Biscay (Peltier et al., 2016) versus passive fishing gears in the Channel. A large number of stranded individuals had evidence of bycatch (Figure 3; Authier et al., 2014; Peltier et al., 2016), suggesting that bycatch substantially contributed to the observed mortality (Section 14 in Supporting Information). Yearly trends of common dolphins and harbor porpoises were qualitatively similar (Figure 4). For striped dolphins, yearly variations were higher than monthly ones, indicating weak seasonality and constant pressures throughout seasons. The documented morbillivirus epizootics of 1990–1991, 2004, and 2007–2008 may explain

yearly variations in this species (Keck et al., 2010; Rubio-Guerri et al., 2013).

Our approach evaluates the impacts of extreme ASMEs by considering extreme stranding values (Davison & Huser, 2015). In our case, extreme ASMEs are defined as a large number of strandings over a 3-day period. Still, predicted return levels are only forecasts, suggesting possible outcomes over a given time period, not certain events. The risk associated to these events (Figure 5) enables us to compare species, and to anticipate an appropriate field response during months with higher risks. The species most at risk was the common dolphin, with risk peaking during the winter months. Harbor porpoises were most at risk during early spring, but the

associated risk is low compared to that of common dolphins (Figure 5).

This study focused on probabilistic forecasting of small cetacean ASMEs using stranding data and EVT modeling. Forecasting risk is essential to anticipate a timely and adequate field response to strandings in order to collect valuable information about mortality causes and pressures on populations. The EVT models had good predictive abilities for two species, common dolphins and striped dolphins, reflecting no change in pressures over the period 2013–2018. The selected model included a linear trend indicating an increase in ASME magnitude over time. Model predictions may be used in management directives to assess whether new pressures emerge or whether management actions alleviate known pressures. In the case of small cetaceans, this would translate to a change in the linear trend. Our model predictions provided expected numbers of deaths due to extreme events. These numbers are both an indicator of population status and of (negative) interaction intensity between small cetaceans and human activities in our study area. Our indicator cannot report the causes of mortality events but quantifies of the consequences of such events in terms of mortality. Collecting auxiliary data on causes of death remains paramount to identifying key pressures. This study illustrates the importance of long-term monitoring schemes (e.g., stranding networks) and the added value of stranding data within conservation frameworks like the MSFD to build a risk-based indicator to evaluate the environmental status. This indicator can be used to monitor the effects of pressures by comparing forecasts and observations, thereby drawing attention early when a mismatch occurs. This indicator will be compared to stranding data every 6 years, at the beginning of the following MSFD cycle, to monitor changes in pressures acting on small cetaceans and assess the "Good Environmental Status" of marine ecosystems. The outcome of such risk-based indicators should benefit the monitoring and the conservation of species impacted by extreme mortality events. This new conservation tool could allow stakeholders and policymakers to implement mitigation measures in order to reduce anthropogenic pressures affecting wildlife species.

ENDNOTE

[1] Directive 2008/56/EC of the European Parliament and of the Council of 17 June 2008 establishing a framework for community action in the field of environmental policy (Marine Strategy Framework Directive), OJ L 164, 25.06.2008.

ORCID

Colin Bouchard https://orcid.org/0000-0003-0845-9492

REFERENCES

Anonymous. (2017). Long-term relationships. *Nature Ecology and Evolution*, *1*, 1209–1210. https://doi.org/10.1038/s41559-017-0306-4

Authier, M., Peltier, H., Dorémus, G., Dabin, W., Van Canneyt, O., & Ridoux, V. (2014). How much are stranding records affected by variation in reporting rates? A case study of small delphinids in the Bay of Biscay. *Biodiversity and Conservation*, *23*(10), 2591–2612. https://doi.org/10.1007/s10531-014-0741-3

Barbraud, C., Delord, K., & Weimerskirch, H. (2015). Extreme ecological response of a seabird community to unprecedented sea ice cover. *Royal Society Open Science*, *2*(5), 140456–6. https://doi.org/10.1098/rsos.140456

Beven, K. (2016). Facets of uncertainty: Epistemic uncertainty, nonstationarity, likelihood, hypothesis testing, and communication. *Hydrological Sciences Journal*, *61*(9), 1652–1665. https://doi.org/10.1080/02626667.2015.1031761

Bossart, G. D. (2011). Marine mammals as sentinel species for oceans and human health. *Veterinary Pathology*, *48*(3), 676–690. https://doi.org/10.1177/0300985810388525

Burek, K. A., Gulland, F. M. D., & O'Hara, T. M. (2008). Effects of climate change on arctic marine mammal health. *Ecological Applications*, *18*(sp2), S126–S134. https://doi.org/10.1890/06-0553.1

Burgman, M., Franklin, J., Hayes, K. R., Hosack, G. R., Peters, G. W., & Sisson, S. A. (2012). Modeling extreme risks in ecology. *Risk Analysis*, *32*(11), 1956–1966. https://doi.org/10.1111/j.1539-6924.2012.01871.x

Chambert, T., Rotella, J. J., & Garrott, R. A. (2012). Environmental extremes versus ecological extremes: Impact of a massive iceberg on the population dynamics of a high-level Antarctic marine predator. *Proceedings of the Royal Society B: Biological Sciences*, *279*(1747), 4532–4541. https://doi.org/10.1098/rspb.2012.1733

Clark, J. S., Carpenter, S. R., Barber, M., Collins, S., Dobson, A., Foley, J. A., Lodge, D. M., … Wear, D. (2001). Ecological forecasts: An emerging imperative. *Science*, *293*, 657–660.

Coles, S. (2001). *An introduction to statistical modeling of extreme values*. London, England: Springer.

Coles, S., & Pericchi, L. (2003). Anticipating catastrophes through extreme value modelling. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *52*(4), 405–416. https://doi.org/10.1111/1467-9876.00413

Cook, C. N., Inayatullah, S., Burgman, M. A., Sutherland, W. J., & Wintle, B. A. (2014). Strategic foresight: How planning for the unpredictable can improve environmental decision-making. *Trends in Ecology & Evolution*, *29*(9), 531–541. https://doi.org/10.1016/j.tree.2014.07.005

Davison, A. C., & Huser, R. (2015). Statistics of extremes. *Annual Review of Statistics and Its Application*, 2(1), 203–235. https://doi.org/10.1146/annurev-statistics-010814-020133

Denny, M. W., Hunt, L. J. H., Miller, L. P., & Harley, C. D. G. (2009). On the prediction of extreme ecological events. *Ecological Monographs*, 79(3), 397–421. https://doi.org/10.1890/08-0579.1

Dietze, M. C., Fox, A., Beck-Johnson, L. M., Betancourt, J. L., Hooten, M. B., Jarnevich, C. S., Keitt, T. H. et al. (2018). "Iterative near-term ecological forecasting: Needs, opportunities, and challenges." *Proceedings of the National Academy of Sciences of the United States of America*, 115(7), 1424–1432. https://doi.org/10.1073/pnas.1710231115

Dolman, S., Baulch, S., Evans, P. G. H., Read, F., & Ritter, F. (2016). "Towards an EU action plan on Cetacean Bycatch." *Marine Policy*, 72, 67–75. https://doi.org/10.1016/j.marpol.2016.06.020

Fey, S. B., Siepielski, A. M., Nusslé, S., Cervantes-Yoshida, K., Hwan, J. L., Huber, E. R., … Carlson, S. M. (2015). "Recent shifts in the occurrence, cause, and magnitude of animal mass mortality events." *Proceedings of the National Academy of Sciences of the United States of America*, 112(4), 1083–1086. Retrieved from http://www.pnas.org/content/early/2015/01/08/1414894112.short

Gibbs, M. T., & Browman, H. I. (2015). Risk assessment and risk management: A primer for marine scientists. *ICES Journal of Marine Science*, 72(3), 992–996. https://doi.org/10.1093/icesjms/fsu232

Gross, K. L., Mittelbach, G. G., & Reynolds, H. L. (2005). Grassland invasibility and diversity: Responses to nutrients, seed input, and disturbance. *Ecology*, 86(2), 476–486. Retrieved from http://www.esajournals.org/doi/abs/10.1890/04-0122

Guillou, A., Naveau, P., Diebolt, J., & Ribereau, P. (2009). Return level bounds for discrete and continuous random variables. *TEST*, 18(3), 584–604. https://doi.org/10.1007/s11749-008-0125-7

Gulland, F. M. D., & Hall, A. J. (2007). Is marine mammal health deteriorating? Trends in the global reporting of marine mammal disease. *EcoHealth*, 4(2), 135–150. https://doi.org/10.1007/s10393-007-0097-1

Gutschick, V. P., & BassiriRad, H. (2010). Biological extreme events: A research framework. *Eos, Transactions American Geophysical Union*, 91(9), 85–86. Retrieved from http://onlinelibrary.wiley.com/doi/10.1029/2010EO090001/abstract

Hammond, P. S., Macleod, K., Berggren, P., Borchers, D. L., Burt, L., Cañadas, A., Desportes, G. et al. (2013). Cetacean abundance and distribution in European Atlantic shelf waters to inform conservation and management. *Biological Conservation*, 164, 107–122. https://doi.org/10.1016/j.biocon.2013.04.010

Hohn, A. A., Rotstein, D. S., & Byrd, B. L. (2013). Unusual mortality events of harbor porpoise strandings in North Carolina, 1997–2009. *Journal of Marine Biology*, 2013, 1–13. https://doi.org/10.1155/2013/289892

Jewell, R., Thomas, L., Harris, C. M., Kaschner, K., Wiff, R., Hammond, P. S., & Quick, N. J. (2012). Global analysis of cetacean line-transect surveys: Detecting trends in cetacean density. *Marine Ecology Progress Series*, 453, 227–240. https://doi.org/10.3354/meps09636

Keck, N., Kwiatek, O., Dhermain, F., Dupraz, F., Boulet, H., Danes, C., Laprie, C., … Libeau, G. (2010). Resurgence of morbil-livirus infection in Mediterranean dolphins off the French coast. *Veterinary Record*, 166(21), 654–655. https://doi.org/10.1136/vr.b4837

Kuiken, T. (1994). Review of the criteria for the diagnosis of by-catch in cetaceans. *European Cetacean Society Newsletter*, 26, 38–43.

Mannocci, L., Dabin, W., Augeraud-Véron, E., Dupuy, J.-F., Barbraud, C., & Ridoux, V. (2012). Assessing the impact of bycatch on dolphin populations: The case of the common dolphin in the eastern North Atlantic. *PLoS One*, 7(2), e32615. https://doi.org/10.1371/journal.pone.0032615

Maxwell, S. L., Fuller, R. A., Brooks, T. M., & Watson, J. E. M. (2016). Biodiversity: The ravages of guns, nets and bulldozers. *Nature News*, 536(7615), 143. https://doi.org/10.1038/536143a

Parsons, E. C. M., Favaro, B., Aguirre, A. A., Bauer, A. L., Blight, L. K., Cigliano, J. A., Coleman, M. A., … Sutherland, W. J. (2014). Seventy-one important questions for the conservation of marine biodiversity. *Conservation Biology*, 28(5), 1206–1214. https://doi.org/10.1111/cobi.12303

Peltier, H., Authier, M., Deaville, R., Dabin, W., Jepson, P. D., van Canneyt, O., … Ridoux, V. (2016). Small cetacean bycatch as estimated from stranding schemes: The common dolphin case in the Northeast Atlantic. *Environmental Science & Policy*, 63, 7–18. https://doi.org/10.1016/j.envsci.2016.05.004

Pierce, G. J., Santos, M. B., Murphy, S., Learmonth, J. A., Zuur, A. F., Rogan, E., Bustamante, P., … Boon, J. P. (2008). Bioaccumulation of persistent organic pollutants in female common dolphins (*Delphinus delphis*) and harbour porpoises (*Phocoena phocoena*) from western European seas: Geographical trends, causal factors and effects on reproduction and mortality. *Environmental Pollution*, 153(2), 401–415. https://doi.org/10.1016/j.envpol.2007.08.019

Read, A. J., Drinker, P., & Northridge, S. (2006). Bycatch of Marine Mammals in U.S. and Global Fisheries: Bycatch of Marine Mammals. *Conservation Biology*, 20(1), 163–169. https://doi.org/10.1111/j.1523-1739.2006.00338.x

Reeves, R. R., McClellan, K., & Werner, T. B. (2013). Marine mammal bycatch in gillnet and other entangling net fisheries, 1990 to 2011. *Endangered Species Research*, 20(1), 71–97. https://doi.org/10.3354/esr00481

Rubio-Guerri, C., Melero, M., Esperón, F., Bellière, E. N., Arbelo, M., Crespo, J. L., … Sánchez-Vizcaíno, J. M. (2013). Unusual striped dolphin mass mortality episode related to cetacean morbillivirus in the Spanish Mediterranean Sea. *BMC Veterinary Research*, 9(1), 106. Retrieved from http://www.biomedcentral.com/1746-6148/9/106/

Sergio, F., Caro, T., Brown, D., Clucas, B., Hunter, J., Ketchum, J., … Hiraldo, F. (2008). Top predators as conservation tools: Ecological rationale, assumptions, and efficacy." *Annual Review of Ecology, Evolution and Systematics*, 39, 1–19. https://doi.org/10.1146/annurev.ecolsys.39.110707.173545

Solow, A. R. (2017). On detecting ecological impacts of extreme climate events and why it matters. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 372(1723), 20160136. https://doi.org/10.1098/rstb.2016.0136

Steffen, W., Broadgate, W., Deutsch, L., Gaffney, O., & Ludwig, C. (2015). The trajectory of the Anthropocene: The great acceleration.

The Anthropocene Review, 2053019614564785. Retrieved from http://anr.sagepub.com/content/early/2015/01/08/205301961456478 5.abstract

Taylor, B. L., Rojas-Bracho, L., Moore, J., Jaramillo-Legorreta, A., Ver Hoef, J. M., Cardenas-Hinojosa, G., Nieto-Garcia, E., … Hammond, P. S. (2017). Extinction is imminent for Mexico's endemic porpoise unless fishery bycatch is eliminated. *Conservation Letters*, *10*(5), 588–595. https://doi.org/10.1111/conl.12331

Ummenhofer, C. C., & Meehl, G. A. (2017). Extreme weather and climate events with ecological relevance: A review. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *372*(1723), 20160135. https://doi.org/10.1098/rstb.2016.0135

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.