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How much are stranding records affected by variation in reporting rates? A case study of small delphinids in the Bay of Biscay

Matthieu Authier · Hélène Peltier · Ghislain Dorémus · Willy Dabin · Olivier Van Canneyt · Vincent Ridoux

Abstract Marine vertebrate strandings offer an opportunistic sampling scheme that can provide abundant data over long periods. Because the stranding process involves biological, physical and sociological parameters, confounding complicates the interpretation of results. The statistical analysis of these data relies on generalized linear or additive models in order to infer long-term trends, but does not easily account for drift or variation in reporting rates. Here, we capitalized on county-level (administrative) variation following the passing of a law for compulsory reporting of stranded marine mammals in France to investigate how variation in reporting rates may affect the observed trend in stranded small delphinids in the Bay of Biscay. Using a time-series spanning more than 30 years across eight administrative counties, we built variance partitioning models for the analysis of count data. We discussed the choice of an appropriate likelihood to conclude the Negative Binomial useful and interpretable in the context of small delphinid strandings. We expanded the model with a recent methodology to detect structural breaks in the time series, focusing on overdispersion. We performed statistical robustness checks with respect to variations in reporting rates and discuss their causal interpretation in the context of observational data. Stranding frequencies increased on average 7-fold over 30 years. We conclude that reporting rates to the French stranding network have been stable since the early 1990s, and the average 3-fold increase in stranded small delphinids observed in the Bay of Biscay since 1990 is due to other factors, including bycatch. Codes and data are available to replicate the analysis to other national stranding networks.

Keywords Monitoring · Marine mammal · Strandings

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Introduction

The European Union issued a Marine Strategy Framework Directive (MSFD hereafter) to protect and restore the ecological integrity of marine ecosystems within member states. The ambitious goal of the MSFD is to achieve "Good Environmental Status" (GES hereafter) of marine ecosystems on a suite of 11 descriptors, including biodiversity. GES is defined as "the environmental status of marine waters where these provide ecologically diverse and dynamic oceans and seas [. . .], and the use of the marine environment is at a level that is sustainable [. . .]" (Article 3.5 of Directive 2008/56/EC of the European Parliament and of the Council of 17 June 2008). Among the threats looming on marine biodiversity, bycatch or the capture or entanglement of non-target species in fishing gear, is foremost (DeMaster et al. 2001; Reeves et al. 2013). Monitoring marine species is paramount to diagnose impediments or progress towards GES. Monitoring marine mammals is however challenging (Evans and Hammond 2004). While dedicated surveys are needed to obtain crucial parameters such as absolute abundances (Hammond et al. 2013), the low temporal frequency at which such surveys can be carried out results in low statistical power to detect declines (Taylor et al. 2007). Yet the MSFD aims at monitoring relative progress and diagnosing problems at a finer temporal resolution: complementary data are needed in order to implement conservation measures in a timely fashion.

Marine vertebrate strandings offer an opportunistic sampling scheme that is valuable to study abundant, rare and cryptic species. Dedicated at-sea surveys for such species are logistically difficult and costly (Evans and Hammond 2004; Thompson et al. 2012). Stranded cetaceans provide raw material for many scientific purposes: for example population genetics (Amaral et al. 2012; Bilgmann et al. 2011), reconstructing individual reproductive history (Dabin et al. 2008), foraging ecology (Spitz et al. 2012; Dunshea et al. 2013), documenting temporal trends (Fruet et al. 2012; Pikesley et al. 2012; Truchon et al. 2013; Williams et al. 2011); explaining extreme stranding events (Fernández et al. 2012; Jepson et al. 2013; Rubio-Guerri et al. 2013; Williams et al. 2011; Wright et al. 2013); or estimating at-sea mortality (de Boer et al. 2012; Koch et al. 2013; Peltier et al. 2013; Williams et al. 2011).

Stranding is the result of at-sea mortality, buoyancy, local drift and prevailing winds, shore substrate and detection probability (Peltier et al. 2012, 2013; Williams et al. 2011). Peltier et al. (2014) described stranding data as 3-dimensional: (1) a biological dimension which includes mortality rate and abundance; (2) a physical dimension linked to the drift process; and (3) a societal dimension encompassing detection and reporting of stranded carcasses by citizens. Interpreting stranding records is difficult as the outcome of interest, a standardized number of stranded carcasses, results from many processes interacting along these three dimensions (Peltier et al. 2012; Williams et al. 2011). In particular stranding probabilities are difficult to estimate *in situ*, but substantial progress has been made with drifter experiments (Koch et al. 2013) or physical modelling of drift and winds (Peltier et al. 2012, 2013, 2014).

In monitoring stranded cetaceans, interest also lies in elucidating the causes behind observed patterns. Causal inference usually follows from evidencing a statistically significant relationship over time. Implicit here is the view of causation as "robust dependence" (Goldthrope 2001). This view amounts to little more than statistics because no explicit reference to theory needs to be made (Goldthrope 2001). While monitoring may be of political value, it can be scientifically inefficient without the ability to manipulate (Yoccoz et al. 2001). The view that only manipulation legitimates causal inference falls under the view of "causation as consequential manipulation" (Goldthrope 2001). A causal

model goes beyond mere description: it provides means to predict how a response variable will change when one or more causal variables are manipulated (Rubin 2006). With stranding records, 'time' is not a variable that can be manipulated, nor is it usually a well-defined treatment (Cox 1992; Hölker et al. 2007). However, a limitation of this view of "causation as consequential manipulation" is its lack of reference to a generative process operating at a level below that of the observed pattern (Cox 1992; Goldthrope 2001). This realization invites for another view of causation: "causation as generative process" (Goldthrope 2001). Under this view, both theory (at a proximate and mechanistic level) and predictability (at a larger scale) are considered in tandem with robust statistical dependence to perform causal inference with observational data.

Establishing causation requires an interpretable model with good predictive ability, and that potential confounders are taken into account to obtain robust results. Because the number of stranded carcasses is the result of many underlying processes (Peltier et al. 2012), any detected trend in stranding records may be due, for example, to varying discovery and reporting rates (hereafter detection probability) of carcasses over time. Albeit direct manipulation is usually impossible, "quasi-experiments" may sometimes serendipitously arise in observational studies: any event unrelated to the outcome of interest that generates variation provides an opportunity to mimic an experimental situation. In particular geographical variation may provide opportunities to attempt causal inference with observational data. In large countries, the subnational organization of administrative territories offer means to investigate patterns of variations while still holding important factors, such as legislation, constant (Barr et al. 2012). We propose to analyze French stranding data at the administrative county level to capitalize on known differences in local conditions between counties. Eight French counties border the Bay of Biscay, with "Les Landes" county differing in one major respect: since 1991, monitoring has been institutionalized. In this county, local permanent staff is in charge of monitoring and cleaning beaches, for aesthetic reasons linked to tourism. We expect reporting rates of stranded cetaceans to have remained fairly constant since the 1990s there.

We built within a Bayesian framework statistical models for analyzing data collected over > 30 years of daily monitoring of stranded carcasses of Common dolphins (*Delphis delphis*) and Striped dolphins (*Stenella coeruleoalba*) along more than 3,000 km of shorelines in the Bay of Biscay (Fig. 1). Emphasis was first put on model predictive ability: we used statistical models and assess their ability to generate data similar to the observed data ("causation as generative process"). Secondly, we checked the robustness of our results to the inclusion of variables related to reporting rates. Throughout, we focused on modelling overdispersion. Finally, we discussed the biological interpretation of this parameter in the context of small delphinid strandings.

Materials and methods

Ethics statement

The study is entirely based on data collected from cetacean carcasses found stranded along the French coasts and did not involve observation or experimentation on captive animals by any means, nor did it rely on field observation of live animals.

Observatoire PELAGIS (formerly "Centre de Recherche sur les Mammifères Marins") is the institution permanently in charge of coordinating the French marine mammal stranding network ("Réseau National d'Échouage", hereafter RNE) under the decree of
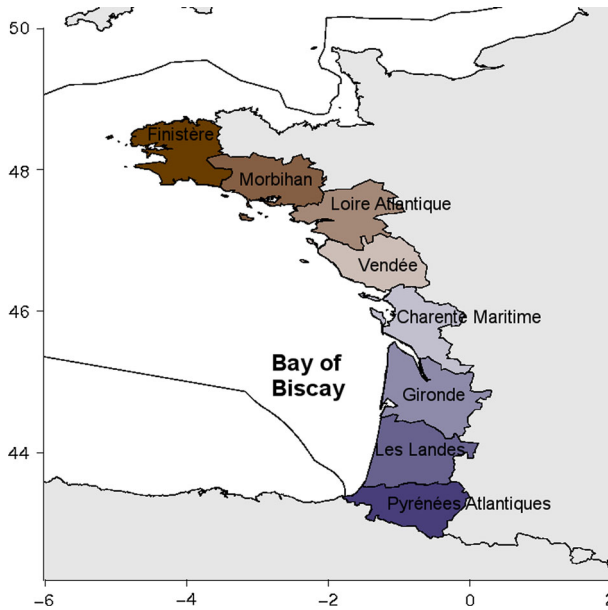
Fig. 1 Bay of Biscay. The eight French administrative counties ("Départements") bordering the Atlantic Ocean and included in the analysis are emphasized with *color*. On a South–North gradient, these counties are "Pyrénées Atlantiques", "Les Landes", "Gironde", "Charente Maritime", "Vendée", "Loire Atlantique", "Morbihan" and "Finistère". The French Exclusive Economic Zone extending in the Atlantic Ocean is delineated with a *black line*

November the tenth of 2010, jointly taken by the Ministery in charge of the Environment and the Ministery in charge of Fisheries, regarding the use of biological data and samples collected on stranded marine mammals for scientific research and monitoring purposes. All species of marine mammals occurring in waters under French juridiction are protected by the decree of July the first of 2011.[1] Since the early 2000s, the French Ministry of the Environment, Sustainable Development and Ecology mandates Observatoire PELAGIS (UMS 3462 du CNRS, Université de La Rochelle) to centralize information, biological samples and data on marine mammals in mainland France. It authorizes Observatoire PELAGIS staff and trained volunteers (that is, holders of a "Green Card" delivered upon completion of a training program dispensed by Observatoire PELAGIS) to manipulate and sample cetacean carcasses for scientific purposes. In the present study, sampling only involves species determination. This work was carried out following European regulations on the use of stranded dead cetaceans for scientific purposes.

Sample collection

The RNE is dedicated to the monitoring of marine mammal populations. Around 260 trained volunteers are currently taking an active part in the network. These volunteers make the complete coverage of French coastlines possible. Standardized training of volunteers by permanent Observatoire PELAGIS staff, which takes place twice a year, ensure the homogeneity, comparability and standardization of data collection procedures in the

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[1] http://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000024396902.

field. Data are further checked for consistency or errors before their incorporation in a national database managed by Observatoire PELAGIS. Each stranded animal corresponds to a datum in the database.

The RNE was established in the early 1970s, but its *modus operandi* is considered unchanged since the early 1980s. The mandatory reporting of cetacean strandings to RNE by town and village administrations (municipalities) was enforced by law in 1988. Among the > 36,000 French municipalities, 800 have a geographic access to the sea, and may report a stranded animal. We used data collected in the eight counties ("départements") bordering the Bay of Biscay (Fig. 1). These counties encompass approximatively 300 coastal municipalities, all of which have reported at least one stranded cetacean to RNE since its inception.

Local citizens dwelling in a coastal municipality may spot a stranded cetacean and either contact their local authorities or Observatoire PELAGIS directly, which will subsequently send a RNE volunteer to collect data on the stranded cetacean. Thus densely inhabited coastal towns may have higher detection rate of strandings. Demographic data on these municipalities have been collected by "Institut National de la Statistique et des Études Économiques" approximatively every ten year since the 1970s. We downloaded demographic data from http://www.insee.fr in order to incorporate this covariate as a statistical control in models (see Sect. 2.7).

Since 1998, Observatoire PELAGIS has set up an internet site with contact informations and what to do when a stranded cetacean is found. Data on French household access to internet at the nation level were taken from "Centre de Recherche pour l'Étude et l'Observation des Conditions de Vie"[2] in order to incorporate this covariate as a statistical control in models (see 2.7 below).

In this study, we aggregated the number of small delphinid strandings over a period of ten days at the county level. Thirty-three years of data from 1980 till 2012 were extracted for each county. Data are an array of three periods of 10 days times 12 months times 33 years times eight counties, that is a sample size of nearly 10,000 ($3 \times 12 \times 33 \times 8 = 9,504$). Small delphinids are meant to include both the Common dolphins *Delphis delphis* and Striped dolphins *Stenella coeruleoalba*. These two species are similar in size, and were pooled in this analysis because carcasses were sometimes too putrefied to allow unambiguous species identification. Pooling makes the assumption that stranded carcasses of these two very similar species would trigger the same response by casual observers.

Coastline lengths of sea-bordering counties were taken from the "Observatoire National de la Mer et du Littoral".[3] Coastline lengths of the eight French Atlantic counties varies by one order of magnitude ("Pyrénées Atlantiques" < 100 km and "Finistère" > 1,000 km), and were incorporated in every model to account for the positive relationship between stranding probability and seashore length.

Notations

$\mathbb{E}(x)$ and $\mathbb{V}(x)$ are respectively the mean and variance of the random variable x. $\mathscr{P}(\lambda)$ denotes the Poisson distribution of mean parameter λ. $\mathscr{N}\mathscr{B}(\text{overdispersion}, \lambda)$ denotes the Negative Binomial distribution of mean parameter λ and overdispersion parameter (Zheng et al. 2006). The usual parametrization of a Negative binomial (for example, Gelman et al. 2003 page 576) is $\mathscr{N}\mathscr{B}(\eta, \kappa)$ where $\lambda = \frac{\eta}{\kappa}$ and overdispersion $= 1 + \frac{1}{\kappa}$, but we chose to

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[2] http://www.credoc.fr/.

[3] http://www.onml.fr/accueil/.

follow the more convenient parametrization of Zheng et al. 2006. $\mathscr{U}(L, U)$ denotes the uniform distribution with lower bound L and upper bound U. $\mathscr{N}(\mu, \sigma)$ denotes the normal distribution of mean parameter μ and scale parameter σ. $\mathscr{C}(\mu, \sigma)$ denotes the Cauchy distribution of mean parameter μ and scale parameter σ. $\mathscr{S}(\mu, \sigma, v)$ denotes the Student distribution of mean parameter μ, scale parameter σ and v degrees of freedom. $\mathscr{G}(\text{shape}, \text{rate})$ denotes the Gamma distribution parametrized in terms of a shape and rate (or inverse-scale) parameters.

Statistical analysis of raw counts of stranded Cetaceans

Strandings are count data, often analyzed with Generalized Linear Models or Generalized Additive Models with a Poisson likelihood (Pikesley et al. 2012; Fruet et al. 2012). The Poisson distribution is useful to model integer value variables (O'Hara and Kotze 2010), but it is restrictive because it assumes a variance equal to the mean (Berk and MacDonald 2007). Count data often exhibit two characteristics: (1) a variance larger than the mean, that is overdispersion (Berk and MacDonald 2007); and (2) an excess of zeros (Martin et al. 2005). The Negative Binomial distribution expands the Poisson distribution to account for over-dispersion (Berk and MacDonald 2007): the latter scales the variance with the mean ($\mathbb{V}(y) = \text{overdispersion} \times \mathbb{E}(y)$). The Poisson distribution assumes overdispersion = 1, while the Negative Binomial distribution assumes overdispersion ≥ 1. Overdispersion arises because observations are correlated (Berk and MacDonald 2007): in the case of marine mammals, the same process (for example epizootics (Carpenter 2013; Di Guardo 2012)) affecting a demographic unit may induce a multiple strandings event, thus violating the implicit assumption of independence between strandings under a Poisson likelihood.

Excess zeros in count data may result from imperfect detection (Martin et al. 2005; Péron et al. 2010). Given the observational nature of strandings, detection probability may be an issue. Zero-inflated models offers a solution to model imperfect detection. For data y modelled with a Poisson likelihood, the frequency ratio of zero and single events is $\frac{\Pr(y = 0)}{\Pr(y = 1)} = \frac{1}{\mathbb{E}(y)}$. For data y modelled with a Negative Binomial likelihood, this ratio becomes $\frac{\Pr(y = 0)}{\Pr(y = 1)} = \frac{\text{overdispersion}}{\mathbb{E}(y)}$. Because the overdispersion parameter is at least 1, a negative binomial distribution induces an excess of zeros compared to a Poisson distribution.

The issue of choosing the appropriate likelihood is important to avoid overfitting (see Electronic Supplementary Materials). Overfitting is capitalizing on chance, and can happen when a statistical model is learning noise from a peculiar dataset rather than a meaningful signal that may be found in independent data (Babyak 2004). Overfitting can result in misleading inferences.

Model building

Let y_{ijkt} denotes the ith datum corresponding the number of stranded carcasses to wash ashore during ten of days of month j and year t on the coastline of the kth county. Month and year effects were always included in the variance components models we built. Month effects (α_j) were assumed exchangeable and drawn from a normal distribution with common variance σ_{month}^2. Likewise year effects (β_t) were assumed exchangeable and drawn from a normal distribution with common variance σ_{year}^2. To account for local

conditions at the county level, county effects (θ_k) were assumed exchangeable and drawn from a normal distribution with common variance σ^2_{county}.

Our simplest model accounting for the data structure is a cross-classified random intercept model (Browne et al. 2007), with month, year and county modelled as random effects. We were interested in assessing any temporal trend in the data. This trend may be slightly different for each county because of local factors not explicitly accounted for in the model. We thus included a county-level random slope, that is we modelled slope parameters as exchangeable. This assumption is important: it is known *a priori* that "Les Landes" county differs from all the others owing to its institutionalized monitoring of beaches, and constant detection probability, since the 1990s. Violation of the exchangeability assumption of counties would betray non-constant detection probabilities in the other counties. The different parametric models we entertained are summarized in Table 1.

$M1$ may be viewed as a default model:

$$y_{ijkt} \sim \mathscr{P}(\text{Coast}_k \times \lambda_{jkt}) \tag{1}$$

where the mean number (per 10 days and per unit of littoral length) of stranded carcasses in month j of year t found in county k is:

$$\log(\lambda_{jkt}) = \theta_{k,1} + \theta_{k,2} \times t + \alpha_j + \beta_t \tag{2}$$

$M2$ expands $M1$ to account for an excess of zeros. The likelihood for the data is a mixture of a degenerate mass at zero and a Poisson distribution. The model for the mixing proportion is also a cross-classified random intercept model as described above. $M2$ has approximately twice as many parameters as $M1$. $M3$ is a generalization of $M1$ and includes an overdispersion parameter common across all years. $M4$ further generalizes $M3$: the overdispersion parameters are year-specific. $M5$ is an elaboration of $M4$ described below (see Sect. 2.6). Models $M1-2$ assumed a Poisson likelihood for the data, while models $M3-5$ assumed a Negative Binomial distribution. In all models, a logarithmic link function was used. In zero-inflated models, the mixing proportion was modelled with a logit link.

Structuring overdispersion

Overdispersion is usually treated as a nuisance parameter, or a parameter not of primary interest itself, but that must be taken into account for correct inferences. Yet, overdispersion may capture interesting information (Zheng et al. 2006). Our large dataset enables us to estimate a year-specific overdispersion parameter (Model $M4$, see Tables 1 and 2). In $M4$, overdispersion parameters are unstructured: we can obtain a time-series of overdispersion parameters over the study period. The statistical problem becomes to identify 'surprising' points. Fúquene et al. (2014) proposed a method to identify outliers and structural breaks in time-series. Let $\kappa_t = \dfrac{1}{\text{overdispersion}_t - 1}$, so that $\kappa_t > 0$. The $\kappa_{t>1}$ are modelled with a random walk, on a logarithmic scale to ensure positive values:

$$\text{for} \quad t \geq 1, \log(\kappa_{t+1}) = \begin{cases} \log(\kappa_t) + \varepsilon_t \\ \log(\kappa_1) + \sum_{i=1}^{t} \varepsilon_i \end{cases} \tag{3}$$

The next value of a given $\log(\kappa_{t+1})$ is the previous value $\log(\kappa_t)$ plus a small deviation ε_t. Large deviations in magnitude may betray outliers. Fúquene et al. (2014) proposed to

assume a heavy-tailed distribution, the Student t, for the ε_t. The Student t distribution can be represented as a scale mixture of normal (Gaussian) distributions (Andrews and Mallows 1974): let z_t be a random variable with a normal distribution, $z_t \sim \mathcal{N}(0, \sigma_\varepsilon)$; and ω_t an independent, positive, random variable. The random variable $\varepsilon_t = \dfrac{z_t}{\sqrt{\omega_t}}$ is a scale mixture of normals. The conditional distribution of ε_t given ω_t is $\mathcal{N}(0, \dfrac{\sigma_\varepsilon}{\sqrt{\omega_t}})$. If $\omega_t \sim \mathcal{G}(\frac{v}{2}, \frac{v}{2})$, the marginal distribution of ε_t is Student t with v degree of freedom. This representation of the Student t as a mixture of normals with different variances is useful: the parameter ω_t has mean 1, the conditional distribution of ε_t is normal with scale σ_ε. When $\omega_t < 1$, $\dfrac{1}{\sqrt{\omega_t}} > 1$ allows for a greater variance than usual: the deviation ε_t may have a larger than usual magnitude. Thus a value of $\omega_t < 1$ will betray an outlier in the time-series. The parameter v for degrees of freedom controls tail-heaviness (or how far the tail extends from the mean value): for large values of v ($v \geq 30$), the Student t distribution is similar to a normal distribution, while small values of v authorized outliers. We fixed $v = 4$ as in Fúquene et al. (2014). Fúquene et al. (2014) further proposed a weakly-informative Beta2 prior for the scale parameter σ_ε. We embedded Eq. 3 in model $M4$ (Table 1) to detect outliers in the time-series of overdispersion coefficients. This model is labeled $M5$ (Table 1).

Confounding variables

A confounder is a variable known to be causally related to the response variable, and whose omission in an analysis would generate a spurious relationship between the latter and a third variable of interest. We distinguished between confounding and lurking variables which are respectively known and unknown to the modeller. Known confounders in our case are (1) demographic evolution at the county level, (2) household internet access and (3) law enforcement. The more populous a county, the more likely a stranded carcasses may be reported. A 1988 law enforced mandatory reporting of cetacean strandings to Observatoire PELAGIS and RNE by town and village administrations. The passing of this law may have triggered an increase in reporting rates from local authorities. In 1998, Observatoire PELAGIS set up an internet site with information on whom to contact and what to do after the discovery of a stranded animal. Reporting rates from citizens may consequently have increased with household internet access. Upon selecting a model with an appropriate likelihood, we included these variables in Eq. 2:

$$\log(\lambda_{jkt}) = \theta_{k,1} + \theta_{k,2} \times t + \theta_{k,3} \times \text{law}_t + \theta_{k,4} \times \text{internet}_t + \theta_{k,5} \times \text{pop size}_{k,t} + \alpha_j + \beta_t$$

$$(4)$$

where $\text{law}_t = 0$ if $t < 1989$ and 1 otherwise; internet_t denotes the percent of household with internet access from 1998 onwards; and $\text{pop size}_{k,t}$ is the population size of county k in year t (see Sect. 2.2). Positive effects of all three covariates are expected if they are true confounders, in which case we also expect the regression coefficient for time t to attenuate or zero-out. Finally, we also compared the fit (via the EarthMover distance, see Sect. 2.8) of a model in which the parameters $\theta_{k,2}$, that is the regression coefficients for time, are set to zero in Eq. 4 to the fit of our parametric model $M4$ (Table 1).

Model checking, selection and testing

For each model, we used 3,000 draws from the posterior to predict each datum, and computed the average histogram of predictions ("posterior predictive checks", Gelman et al. 1996). This histogram was compared to the histogram of observed data, and model fit was visually assessed (see Fig. 3 in Minami et al. 2007 for a similar exercise). To numerically quantify model fit, we used the EarthMover distance which has an intuitive interpretation for the comparison of two histograms: each histogram may be viewed a pile of dirt and the EarthMover distance reflects the amount of dirt times the distance needed to turn one pile into the other. Each datum is like a sand grain, and the aim is to quantify how many sand grains and how far do we need to move them to transform the histogram of predictions into the empirical histogram of observed values. For inference, we selected the model with the smallest EarthMover distance, that is the model which was able to generate a histogram of predictions the most similar to observations.

Model fitting and priors

We favored a Bayesian framework. Bayesian estimation of random effects with a small number of levels (12 months, eight counties) is adequate (Stegmueller 2013). We used STAN (Stan Development Team 2013) called from R (R Development Core Team 2013) with the package rstan (http://mc-stan.org/). Weakly informative priors were used (Gelman 2006; Gelman et al. 2008). For variance parameters, we used a half-Cauchy prior: $\sigma \sim \mathscr{C}^+(0,1)$. For intercept parameters, we used a Student t: intercept $\sim \mathscr{S}(0,10,7)$. For slope parameters, we used a Student t: slope $\sim \mathscr{S}(0,2.5,7)$. For overdispersion parameters in models $M3-4$, we used uniform priors: overdispersion $\sim \mathscr{U}(1,100)$. Three chains were initialized with different starting values. After appropriate burn-in (1,000 iterations) and thinning of the chains (1 value every two iterations stored), convergence was assessed using the Gelman-Rubin convergence diagnostic (Cowles and Carlin 1996). Unless stated otherwise, posterior means are reported with 95 % Highest Probability Density intervals ($_{2.5\%}$Mean$_{97.5\%}$) (Louis and Zeger 2009). Inferences are based on a posterior sample of 3,000 iterations. Covariates were standardized following (Gelman 2008). STAN and R codes are available as supplementary materials.

Results

The mean number of stranded small-sized delphinids per 10 days over the study period was $\mathbb{E}(y_{obs}) = 1$ and the variance was $\mathbb{V}(y_{obs}) = 34$. Seventy-three percent (73 %) of the data were zeros. All models converged ($\hat{r} < 1.1$). Models with a Poisson likelihood did not fit the data well: these models failed to predict enough zeros and predicted too many observations between 1 and 10 strandings (Fig. 2a). Changing the likelihood for a Zero-Inflated Poisson fixed the problem for the excess zeros, at the cost of twice as many parameters; but the models still overpredicted frequencies of strandings of 1–10 individuals (Fig. 2b). Using a Negative Binomial likelihood however resulted in a more acceptable fit (Fig. 2c, d). This ranking is similar to that of Minami et al. (2007) with shark bycatch data. Poisson and Zero-Inflated Poisson models were unable to predict events of more than 50 stranded dead dolphins. Negative binomial models were able to predict events of up to 80 stranded dead dolphins. No models could satisfactorily take into account the handfull of
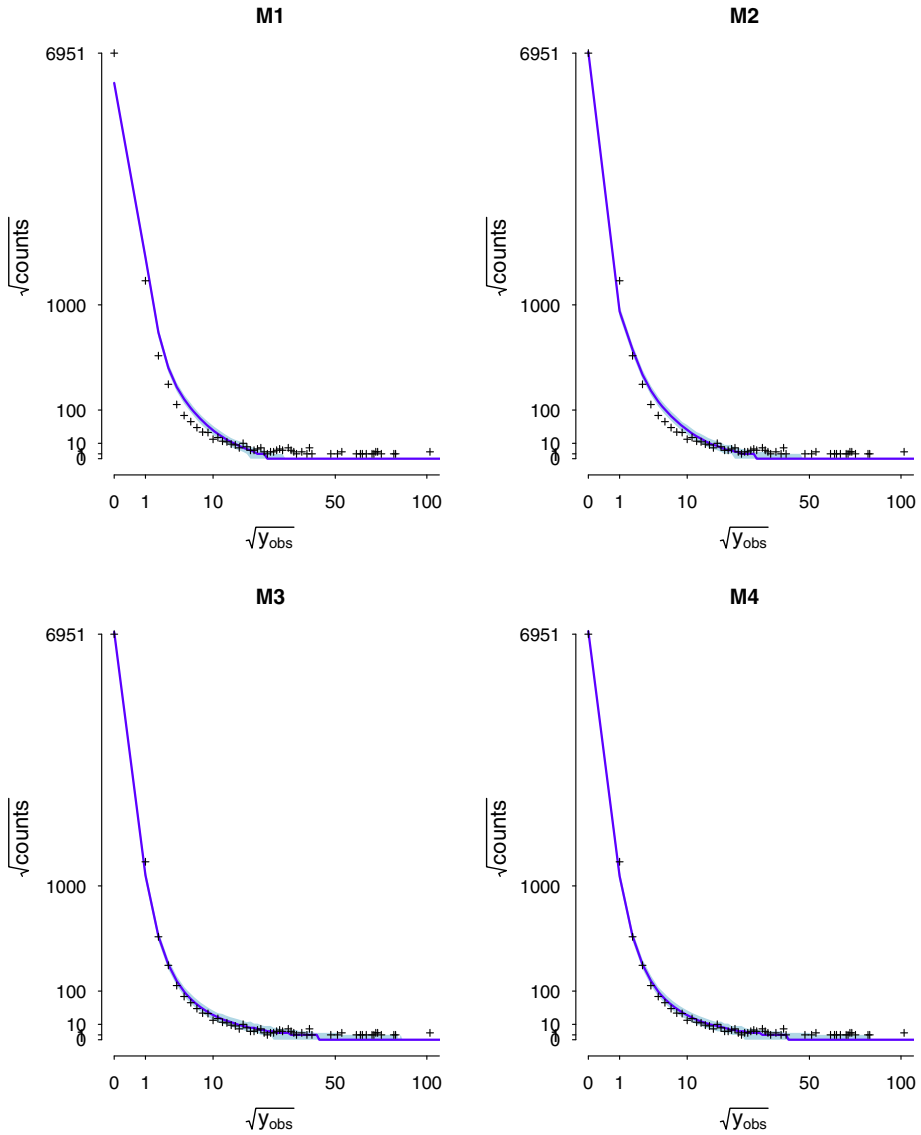
Fig. 2 Parametric model fit. After model fitting, the posterior distribution of estimated parameters was used to generate replications of the data. For each replicate, the empirical histogram of predictions was computed. The mean predicted histogram were finally compared to the target histogram of observed data to assess whether estimated parameters were able to predict similar data sets to the one the model was calibrated with. Both x- and y-axes are on a square-root scale for ease-of-read purposes. Histograms are truncated at 100 (only five events, among 9,504, of more than 100 stranded carcasses over 10 days during the study period)

extreme events: five events of > 100 stranded carcasses, including one with 349 animals. Model fit is numerically summarized in Table 2. The best model was $M4$: a Negative Binomial likelihood provided an aquedate fit to these data. The large sample size of our
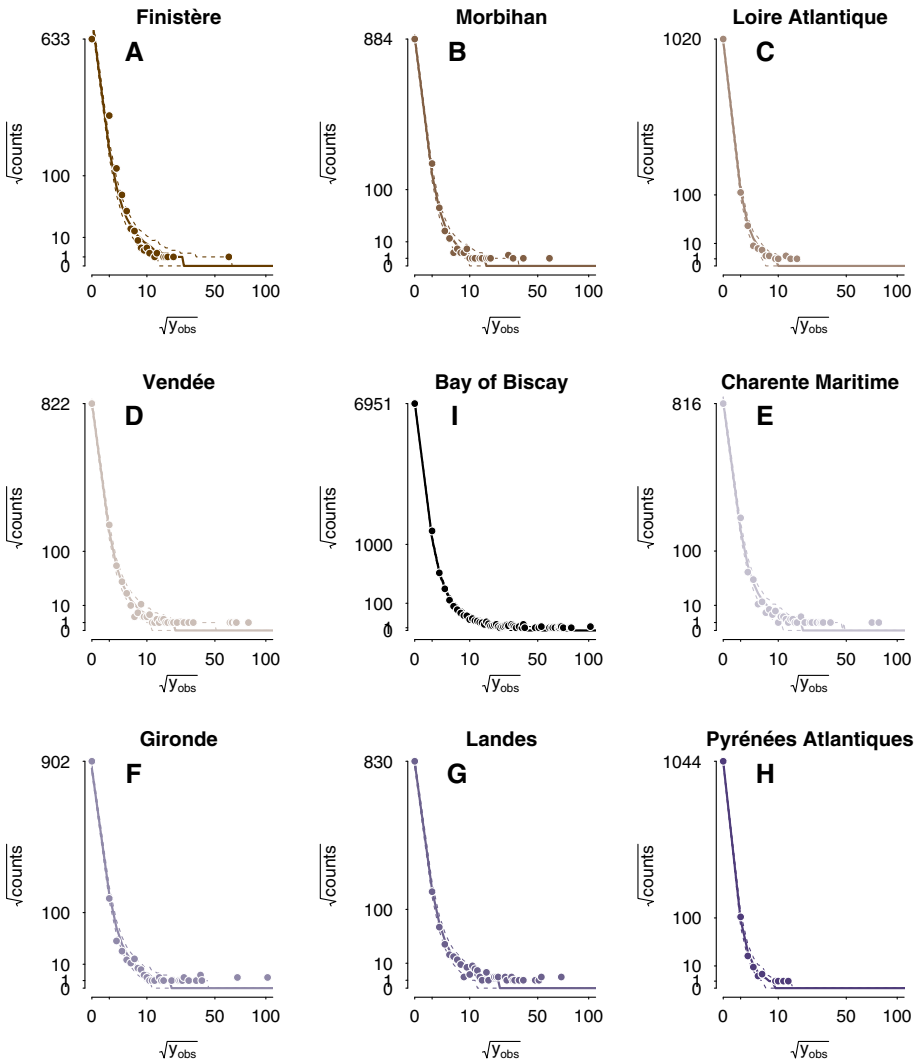
Fig. 3 Model fit at the level of individual counties. We compared within each county predicted and observed histograms. The mean prediction is depicted in solid line, and a 95 % HPD interval as dashed lines. Both x- and y-axes are on a square-root scale for ease-of-read purposes. Histograms are truncated at 100 (only five events, among 9,504, of more than 100 stranded carcasses over 10 days during the study period)

data allowed us to estimate a year specific overdispersion parameter, which also slightly improved model fit (Table 2). Model fit at the county level was also adequate (Fig. 3).

Figure 4a shows the ranking of each factor (month, year or county) in relative importance: monthly variation were the most pronounced in magnitude, followed by county-level variations, and lastly by year-level variations. These results are in line with those of Peltier et al. (2014) who used a different modelling approach with a subset of the data we used. Estimated parameters can be interpreted as multiplicative factors (Fig. 4b, c): the number of reported stranded carcasses of small delphinids increased 5-fold in February compared to an average month like May or December, or a 10-fold increase compared to a
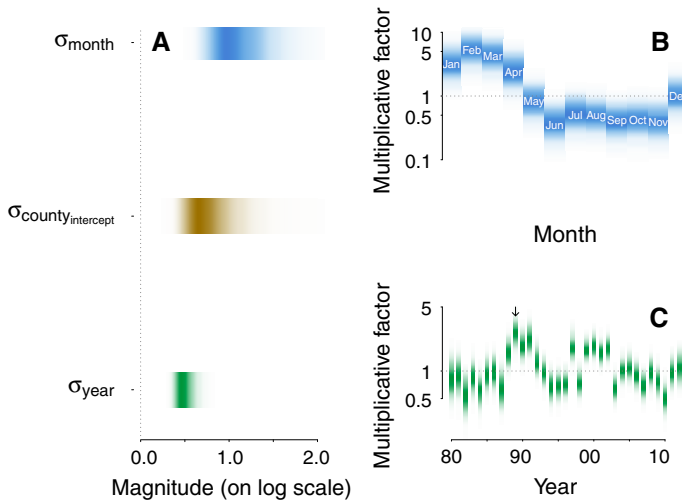
Fig. 4 Visualizing results. **a** Ranking of sources of variation in terms of importance and magnitude. Seasonal and yearly variations were most and least pronounced respectively. **b** Estimated multiplicative factors for monthly variations. **c** Estimated multiplicative factors for yearly variations. The year of law enforcement for mandatory stranding reporting is indicated with an *arrow*. Estimation uncertainty is displayed with shading using the R package `denstrip` (Jackson 2008)

summer month like July or August (Fig. 4b). Strandings were less frequent during the summer and autumn month but increased dramatically during winter and spring months (Fig. 4b, Peltier et al. 2012). Yearly variations were present but less pronounced, except for a spike in the late 1980s. This spike happened the same year a law for mandatory reporting of stranded animals was enforced.

Between 1980 and 2012, the mean number of strandings increased $_{2.3}7.0_{12.3}$ fold over the Bay of Biscay coastal areas (Fig. 5i). This overall trend did not mask county-level peculiarities: small delphinid strandings increased in all the 8 French counties bordering the Atlantic Ocean (Fig. 5a–h). Using $M1$, a model that did not fit the data (see Table 2), would have resulted in different inferences regarding trends (see Supplementary Fig. S1). The model we selected included overdispersion parameters (Fig. 6). Overdispersion, that is a variance inflating factor relative to a Poisson distribution, decreased over the 33 studied years (Fig. 6a). We further applied the method described in Fúquene et al. (2014) to identify structural breaks in this time-series (Fig. 6b, c). The years 1992 and 1998 were outliers, both because overdispersion decreased sharply compared to the rest of the series.

Discussion

We analyzed our data at the county level to capitalize on known differences between counties. In particular, monitoring has been institutionalized since 1989 in "Les Landes" county. Local permanent staff is in charge of monitoring and cleaning the beaches that borders the Bay of Biscay for aesthetic reasons linked to tourism. We can reasonably expect reporting rates of stranded cetaceans to have remained fairly constant since the 1990s there. Yet, the overall shape of the trend in "Les Landes" county does not differ from the other counties (Figs. 5, 7). "Les Landes" county has an overall higher number of
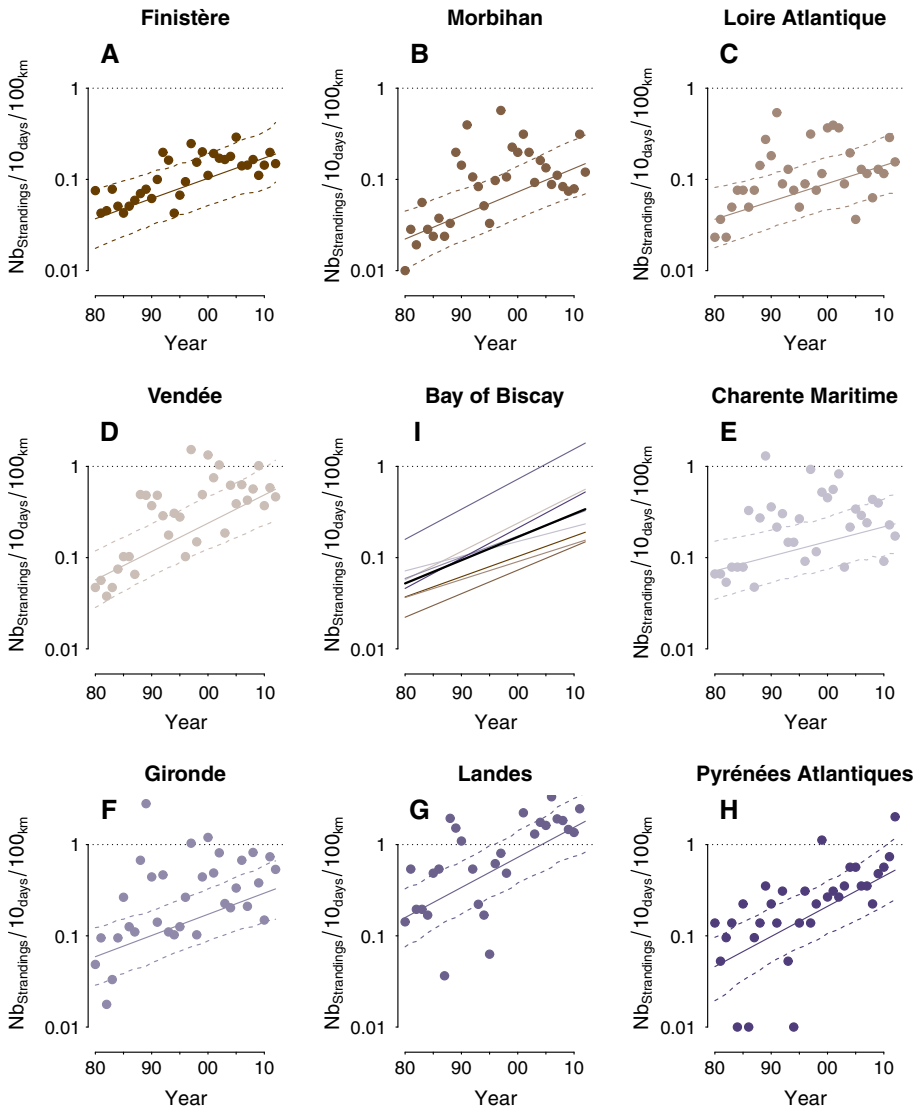
Fig. 5 Temporal trends in small delphinid strandings. Estimated trends from model $M4$ are depicted for each county (**a–h**), and the Bay of Biscay as a whole (**i**). The y-axis (on a logarithmic scale) represents the estimated mean number (per 10 days and per 100 km of coastline) of stranded carcasses, that is $\log(\lambda_{kt}) = \theta_{k,1} + \theta_{k,2} \times t$ plotted for each county k. *Dots* are the raw data, *solid line* is the posterior mean, and *dashed lines* represent a 95 % HPD interval around the mean (without taking into account the year random effects β_t, see Eq. 2 and Fig. 4c). In each of the county bordering the Bay of Biscay, the trend is that of an increased number of stranded small delphinids. Although counties have different intercepts, slopes over the study period are similar, suggesting no major difference in the processes behind these trends between the different counties. This pattern suggests that reporting rates, which are known to have been constant in "Les Landes" (**g**) since the 1990s, have also remained constant in the seven other counties

Fig. 6 Detecting outliers. **a** Time series of estimated overdispersion parameters from semi-parametric model $M4$. the inverse of overdispersion is plotted to constrain values in the unit interval [0:1], and avoid visual distortions because overdispersion coefficients are bounded between 1 and $+\infty$. *Dots* represent the mean, and *arrows* a 95 % HPD interval. **b** Time-series of year-specific deviations (see Sect. 2.6). The *solid line* represents the mean, and *dashed lines* a 95 % HPD interval. **c** Identifying outliers and structural breaks when the parameter $\omega_t < 1$ (see Sect. 2.6). *Dots* represent the mean, and *arrows* a 80 % HPD interval
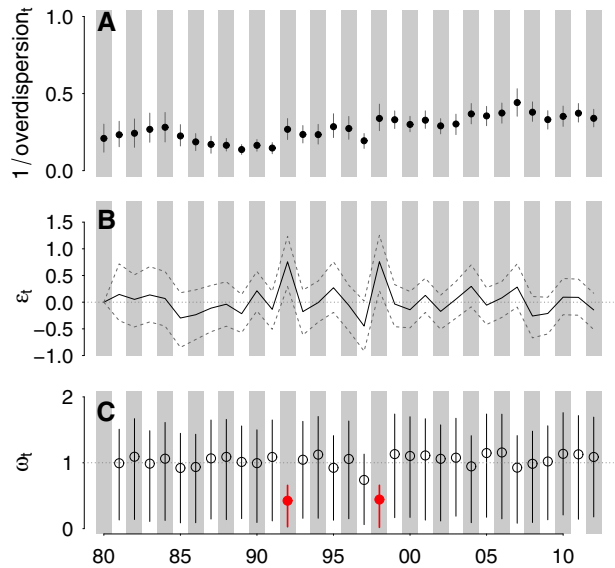
strandings (Fig. 7). This results from a favorable substrate and geography, 105 km of gentle-sloped sand beaches, which makes it a popular domestic touristic destination; and the absence of a major estuary. "Gironde", "Charente Maritime", and "Loire-Atlantique" counties take their name from large rivers that flow into the Bay of Biscay. "Pyrénées Atlantiques", "Morbihan" and "Finistère" counties have rocky and cliffy seashores, which lower the probability that a cetacean will strand and be detected. However, the estimated slope for "Les Landes" counties was comparable to that of two other counties ("Vendée" and "Pyrénées Atlantiques"), which vindicated the exchangeability assumption. By analyzing our data at the county level, we were interested in comparing "Les Landes" to the other counties, and in particular to the "Gironde" county with which it shares many features (same substrate, tourism, geographical proximity). These two counties have similar trends over the study period, which further suggests that detection probability is not sufficient to explain away the observed increase in stranding numbers.

Potential confounders

The number of stranded carcasses is the result of many underlying processes (Peltier et al. 2012): a change in any component may trigger a trend while other components remain unchanged. The observational nature of stranding data limits the scope for causal inference. In particular, detection probability of stranded carcasses is an obvious confounder. To account for this, we incorporated several confounders in our final model (Table 3). In the final model with no covariate but 'time', the slope coefficient was estimated at $_{0.66}1.44_{2.23}$. This coefficient decreased to $_{-0.23}0.96_{2.24}$ when confounders were included, suggesting that the increasing trend may partly result from an increase in detection. However, the sign of the coefficients for household internet access and county population size have the wrong sign (Table 3). For the latter, the negative sign implied that more populous county had fewer reported strandings, which does not make sense if detection probability is related to the number of inhabitants; unless this is also correlated with other cultural changes by which the lay public would pay less attention to natural events. The
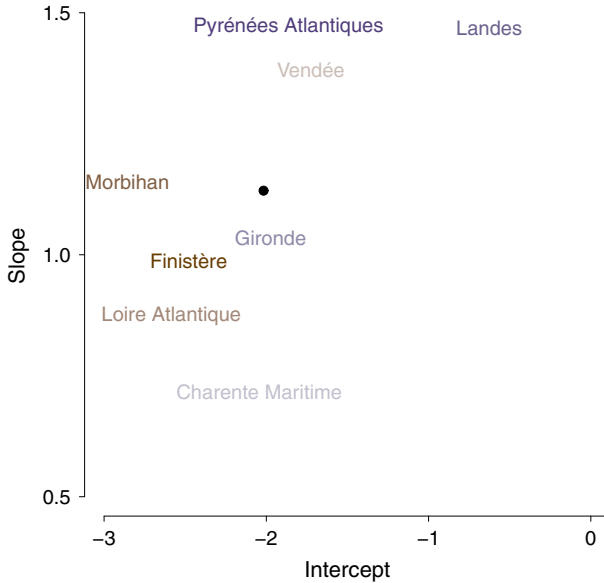
Fig. 7 Estimated county-level intercept ($\theta_{k,1}$) and slope ($\theta_{k,2}$) from model $M4$. The x-axis represents the county-specific intercept, and the y-axis the county-specific slope (for 'time'). "Les Landes" county has a larger intercept, that is a higher number of strandings than any other other county. Its slope coefficient for 'time' is however comparable to other counties. The *black dot* symbolizes the grand mean for the Bay of Biscay

Table 1 Parametric models: five models of varying complexity were considered; see Sect. 2.5

Name	Likelihood	Mean function	Overdispersion
$M1$	Poisson	$\log(\lambda_{jkt}) = \theta_{k,1} + \theta_{k,2} \times t + \alpha_j + \beta_t$	1
$M2$	Zero-Inflated Poisson	$\lambda_{jkt} = \pi_{jkt} \times 0 +$ $(1 - \pi_{jkt}) \times \exp(\theta_{k,1} + \theta_{k,2} \times t + \alpha_{j,1} + \beta_{t,1})$ where $\pi_{jkt} = \text{logit}^{-1}(\theta_{k,3} + \alpha_{j,2} + \beta_{t,2})$	1
$M3$	Negative Binomial	$\log(\lambda_{jkt}) = \theta_{k,1} + \theta_{k,2} \times t + \alpha_j + \beta_t$	overdispersion
$M4$	Negative Binomial	$\log(\lambda_{jkt}) = \theta_{k,1} + \theta_{k,2} \times t + \alpha_j + \beta_t$	overdispersion$_t$
$M5$	Negative Binomial	$\log(\lambda_{jkt}) = \theta_{k,1} + \theta_{k,2} \times t + \alpha_j + \beta_t$	overdispersion$_t = 1 + \dfrac{1}{\kappa_t}$ $\kappa_1 > 0$ for $t \geq 1$, $\log(\kappa_{t+1}) = \log(\kappa_t) + \varepsilon_t$

negative sign of the regression coefficient for household internet access is likewise surprising. In the era of omnipresent new technologies, it is paradoxical that a greater access to internet access should result in less reporting assuming that outdoor recreation habits of citizens have not changed. How can we explained the negative regression coefficient then? Household internet access is strongly correlated with 'time' over the study period, as can be seen from the large negative correlation between the regression coefficients for these

Table 2 Model selection with the EarthMover distance: the model which was able to make predictions most similar to observed data was selected

Model	EarthMover distance
M1	0.443
M2	0.384
M3	0.203
M4	**0.198**

The most richly parametrized model, $M2$, was not the one that provided the best fit because the likelihood was inappropriate for the small delphinid stranding data in the Bay of Biscay. Models with a Negative Binomial likelihood were clearly superior

Table 3 Estimating the effect of potential confounders: estimated regression coefficients of potential confounders affecting detection probability are reported on the diagonal

Covariate	Time			Law			internet			Pop size		
time	−0.23	0.96	2.24		−0.80			−0.86			−0.10	
law				−0.14	0.64	1.36		0.63			0.01	
internet							−2.04	−0.40	1.10		0.03	
pop size										−2.37	−0.92	0.37

Off diagonal figures correspond to empirical posterior correlations between parameters, and indicate collinearity between 'time' and household internet access

two covariates (Table 3): any increase in the regression coefficient for 'time' goes hand in hand with a similar decrease in the regression coefficient for household internet access. One solution to resolve this collinearity problem is to delete one of the covariates. When the regression coefficient for time was set to 0 in Eq. 4, model fit was slightly worse (EarthMover distance = 0.208 versus 0.198 for a model with just 'time'). In this case, the sign of the regression coefficient for household internet access became positive ($_{0.06}0.75_{1.57}$), that of law enforcement remained positive ($_{0.69}1.13_{1.59}$) and that of population size remained negative ($_{-2.32} - 0.84_{0.44}$).

Law enforcement in 1988 probably had a causal impact and increased detection probability: we observed a positive regression coefficient for this indicator variable. We detected a structural break in the time-series of overdispersion parameters corresponding to the year 1992 (Fig. 6c): overdispersion decreased in that year. Passing the law for mandatory reporting of stranded carcasses by local French administrations triggered an increase in the mean number of reported stranding (Fig. 4c), but compliance may have been partial for the first couples of years after law enforcement. A period of partial compliance could reflect the time needed for local authorities to adapt and implement routine procedures when a stranded carcass is discovered. By 1992 however, full compliance was probably achieved, which may account for the observed decrease in variability. Another, non-mutually exclusive factor, may be a greater public awareness of dolphin strandings following the Mediterranean morbilivirus epizootics of the early 1990s (Aguilar and Raga 1993), which was prominently covered by both local and national media.

Evidence for an effect of household internet access on reporting a stranded animal to Observatoire PELAGIS is less clear. During the early 1990s, less than 5 % of French household had an internet access and Observatoire PELAGIS had no website with instructions to follow in case of discovery of a stranded carcass. Yet, the overall and local trends were

all one of increase during the 1990s (Fig. 5). If internet access had a causal impact of reporting rate, it would manifest itself from the 2000s onwards, but this period corresponds to reduced rate of increase compared to the preceding decade. The internet covariate is 0 or very small for most of the 1990s. It thus appears unlikely that access to new technologies had an effect on detection in the 1990s which was nevertheless a period of increase in strandings. This can explain why the fit of model without 'time' is slighly worse than one with 'time'. Finally, although population size on the French Atlantic coast increased over the study period, the sign of the estimated coefficient for this confounding variable is not coherent with a causal effect on detection probability. This in turn suggests a preponderant role of local administrations and their staff (*e.g.* earthmovers) in reporting stranded carcasses, over that of the lay public.

Public awareness of cetacean conservation issues has likely increased over the study period. Were the lay public the only channel through which strandings were reported to Observatoire PELAGIS, population size would have increased reporting rates in all counties but "Les Landes". The reason why this does not show up in the data is probably linked to the effectiveness of the 1988 law. Most reportings are done through the "official channel" of municipalities calling directly Observatoire PELAGIS. Although Observatoire PELAGIS does get more calls from the lay public, these calls are largely redundant with those of municipal staff. This might be the reason why reporting rates may have remained more or less constant since the 1990s. Population size may also be too crude a proxy: more relevant information could be changes in leisure activities, either rural or urban. The former is more in favor of higher reporting rates than the latter, yet the French population is currently more urban than ever before.

Causal inference with observational data is inherently more difficult and tentative than with experimental data (Goldthrope 2001): without experimental control, an unknown confounder may still be lurking. Here, we focused on whether observed trends could have arisen from variations in reporting rates alone. We concluded that this may have been the case in the 1980s, but unlikely afterwards.

What happened in the 1990s?

A major threat to marine mammal populations worldwide is bycatch by fisheries targeting commercial fish species (Morizur et al. 1999; DeMaster et al. 2001; ICES 2005; Read et al. 2006; Moore and Read 2008; Reeves et al. 2013; Thompson et al. 2013). The Bay of Biscay corresponds to ICES Ecoregion G, subdivisions VIIIa and VIIIb. In the 1980s, the number of pair trawlers operating in the whole ICES Ecoregion G Subdivision VIII increased from less than 50 boats to more than 150 in the early 1990s and down to 100 in the early 2000s (Villalobos Hortiz 2008). The number of purse seiners remained more or less the same (between ≈25 and ≈40) during the 1990s but doubled in the early 2000s (Villalobos Hortiz 2008). Dolphin bycatch by pair trawlers or purse seiners is documented (Read et al. 2006; de Boer et al. 2012; Thompson et al. 2013), and a represent a serious threat to common dolphin population viability on the Bay of Biscay (Mannocci et al. 2012). In particular, common dolphins are at risk with the sea bass trawl fishery operating the Bay of Biscay because of the dietary overlap between sea bass (*Dicentrarchus labrax*) and common dolphins (Spitz et al. 2013). Because of high energy requirements (Spitz et al. 2012), small delphinids target preferentially prey of high energy contents such as European anchovies (*Engraulis encrasicolus*) and sardines (*Sardina pilchardus*) (Meynier et al. 2008; Spitz and Jouma'a 2013), on which European sea bass also feeds. A byproduct of dietary overlap may be increased interactions between dolphins and commercial pair trawlers, and eventually dolphin bycatch (Mannocci et al. 2012; Spitz et al. 2013).

We acknowledge that inferring the causes behind the trend observed in our data is a difficult endeavour, and ruling out potential confounders (as in Jepson et al. 2013 or Wright et al. 2013) is certainly a more realistic goal than finding the unique causal mechanism behind the observed pattern. Yet, there is ample independent data on the threats that bycatch poses to marine mammals (Morizur et al. 1999; DeMaster et al. 2001; ICES 2005; Read et al. 2006; Moore and Read 2008; Reeves et al. 2013; Thompson et al. 2013) to argue for at least a partial role of the later in the average 7-fold increase in stranding numbers of small delphinids we observed in the Bay of Biscay over 30 years (Fig. 5). Excluding data from the 1980s, the average increase over the whole Bay of Biscay is $_{2.0}3.8_{5.7}$-fold. Using an explicit physical drift model to account for stranding probabilities of dead dolphins, Peltier et al. (2014) demonstrated that the continental shelf of the Bay of Biscay is a mortality hotspot for common dolphins. Peltier et al. (2014) further estimated that a 2-fold increase in stranded common dolphins between winter and summer was due to drifting conditions alone. Here, we esti-mated a 10-fold increase (Fig. 4b), that is a 5-fold increased compared to what would be expected with seasonal drift conditions alone, which is again similar to what Peltier et al. (2014) found using a different approach that accounts explicitly for drift.

We discussed earlier a structural break we identified in 1992, but set aside the other one identified in 1998. Close inspection of Fig. 6 and data suggest that the outlier is rather the year 1997, in which overdispersion increased sharply compared to the surrounding years. This increase was due to the occurrence of six extreme events of more than 50 strandings per 10 days in mid-February 1997 in five counties. Examination of individual cases by querying our database revealed that a majority of the animals showed lesions either characteristic or suggestive of interactions with fishing gear (Kuiken 1994). Although our selected model did not cope well with predicting extreme stranding events, in this case the mean trend was unaffected (Fig. 5), and the overdispersion parameter acted as a buffer against these outlying observations. This, in turn, shed light on why a Negative Binomial likelihood is adequate for small delphinids data: multiple stranding events can stem from bycatch of a large number of animals that were interacting with a commercial fishery. The stranding events are no longer independent, but are correlated through a common cause of accidental death. Our study thus suggests using overdispersion as an indicator of years of unusual mortality. Yet, the precise identification of underlying causes behind unusual events is not something our models can elucidate with certainty, and ancillary information will be needed. In other words, overdispersion as an indicator has a low specificity, but this is unsurprising given the phenomenological nature of the model. In fact, the year 1997 is also an outlier in that several winter storms resulted in favorable drift conditions, which may partly explained the surge in observed strandings. However, Peltier et al. (2014) also found that 1997 was the first year with anomalously high strandings even after accounting for drift conditions. In our case, in spite of drift being a potential confounder, it does not alter how a large proportion of stranded small delphinids in the beginning of 1997 showed lesions characteristic of bycatch. The merit of model $M5$ is to allow robust (with respect to noise) inference on the mean trend, to provide a parameter that can be linked to a common cause of mortality (bycatch, epizootics), and to suggest in a principled way what are surprising observations in the time-series of these parameters.

Conclusion

We have provided an in-depth analysis and description of small delphinid strandings in the Bay of Biscay, capitalizing on county-level specificities to critically assess the consistency

and quality of data collected by the French stranding network RNE since 1980. With no claims of novelty (for example, see Minami et al. 2007), we suggested to use variance component models to take into account some peculiarities of count data, and proposed biological interpretation of parameters of interest. A good fit with the observed data was obtained with relatively simple models including seasonal and yearly variations and a trend over time. The model allowed to rank sources of variations in importance (Fig. 4a), and to reduce a large data set of nearly 10,000 points to less than 100 interpretable parameters. The number of stranded small delphinids have increased seven-fold since the 1980s. We discussed causal inference with observational data and investigated potential confounders related to detection of stranded carcasses. We inferred that the French stranding records appear most homogeneous in effort since the 1990s, with the corollary that the observed increased in strandings in due to other factors than an increase in reporting rates.

Although we adopted a narrow focus on the Bay of Biscay and RNE in order to provide a documented, context specific, analysis of observational data, we feel that our models may be of interest to other national stranding networks for monitoring purposes. Moreover, the graphical representation of results is relatively new and illuminating for applied research (Gelman 2005; Hector et al. 2011). Recent research also suggests that traditional reporting of results by means of F-statistics may create an illusion of predictability, even for experts (Soyer and Hogarth 2012).

We discussed the choice of an appropriate likelihood for the data, which seems an overlooked issue in the marine mammal stranding literature, and found the Negative Binomial useful and interpretable in the context of small delphinid strandings. This need not be the case with other taxa, especially species which are less abundant (baleen whales for example), but we suggest it should be tested along with the more common Poisson model to avoid overfitting (see Online Appendix). Finally, we did not consider modelling drift explicitly as in Peltier et al. 2013, 2014. The latter is to be preferred since any signal can be more meaningfully interpreted as freed from the confounding influence of drift. However, our aims here were to analyze strandings data in a general setting (see Peltier and Ridoux 2013 for setting the scene of stranding data analyses with a drift model). A future extension is to merge this work with explicit drift modelling (Peltier et al. 2013, 2014) for assessing and monitoring Good Environmental Status with respect to marine mammals within the EU Marine Strategy Framework Directive.

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