Supplementary Material to "Can modelling the drift of bycaught dolphin stranded carcasses help identify involved fisheries? An exploratory study" by Peltier et al.

October 17, 2019

This supplementary material provides further details on the analyses carried by Peltier *et. al*, including

1. a (pairwise Pearson) correlation plot of the covariates (fishery effort data); and
2. a comparison of two exploratory Generalized Additive Models (GAM), with and without a 'spatial effect' operationalized as a bivariate smooth terms of ($WGS84$) longitude and latitude.

Descriptive Statistics

Pearson's pairwise correlation

We carried out an exploratory analysis given the observational nature of our data, and the correlative nature of matching inferred at-sea mortality areas with coarse fisheries effort data. As such, our aims are not explanatory (see Leek & Peng (2015) or Shmuéli (2010) for a general and technical discussion of modelling purposes).

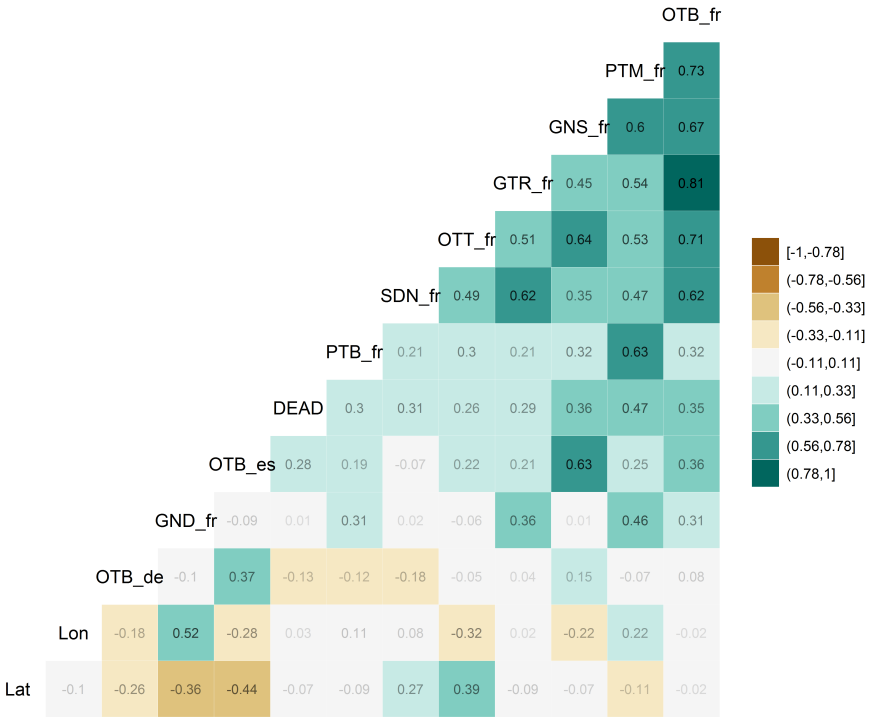


Figure 1: Correlation plot of all the variables (including the response variables `DEAD` considered in the exploratory analyses.

The largest pairwise correlation (in absolute value) was 0.81 between two fisheries (`GTR fr` and `OTB fr`): these two fisheries were operating in similar regions of the Bay of Biscay during winter 2017. This spatial overlap is a relevant piece of information, and one that should not be discarded on statistical grounds only. For explanatory purposes, it is best to include uncorrelated variables, but this is rarely possible with observational data. Instead, some hard threshold is usually applied (e.g. absolute pairwise correlation below 0.7). For other purposes than explanatory modelling, multicollinearity is less problematic (Shmuéli (2010), page 299). As our aims were to correlate fisheries effort with inferred at-sea mortality of common dolphins, we are not trying to isolate individual contribution of each fisheries, nor are we trying to explain per se. We aimed to identify candidate fisheries for further considerations with independent data of a less correlated nature, and thus decided to retain all fisheries that were deemed relevant on *a priori* grounds.

Moran's I statistics

Moran's I statistics for all variables included in the analyses are reported in Table 1 below. For our data (Figure 2), the null expected value of Moran's I was -0.019 ± 0.010.

Fishery	Flag	Code	February		March	
			Fresh	Slightly decomposed	Fresh	Slightly decomposed
Danish seines	French	SDN_fr	0.757	0.696	0.696	0.709
Drift nets	French	GND_fr	0.654	0.701	0.723	0.677
Set gillnets	French	GNS_fr	0.545	0.559	0.693	0.724
Trammel nets	French	GTR_fr	0.520	0.518	0.486	0.537
Otter twin trawls	French	OTT_fr	0.697	0.652	0.705	0.683
Pair trawls midwater	French	PTB_fr	0.671	0.573	0.641	0.640
Pair trawls bottom	French	PTM_fr	0.654	0.650	0.660	0.661
Otter trawls bottom	German	OTB_de	NA	NA	0.660	0.693
Otter trawls bottom	Spanish	OTB_es	0.783	0.805	0.769	0.764
Otter trawls bottom	French	OTB_fr	0.548	0.609	0.578	0.620
		bycaught dolphins	0.644	0.794	0.810	0.793

Table 1: Estimated Moran's I statistics for all variables.

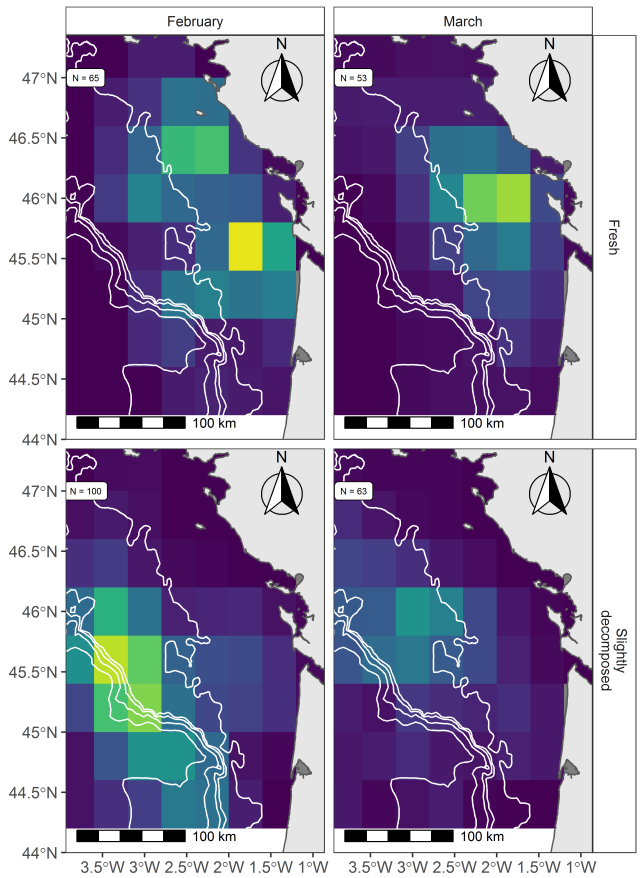


Figure 2: Estimated densities of bycaught dolphins during the peak events of winter 2017 in the Bay of Biscay.

Alternative Specification

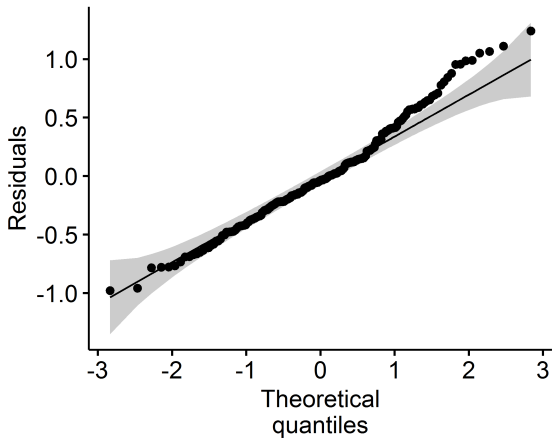
We first fitted a Generalized Additive Models (GAM) with Gaussian likelihood to the $\log(1 + y)$ transformed data (to ensure the positive constraint on both estimated densities of bycaught dolphins and fishery effort data). Our data are not count data but estimated densities. We used linear models, which require that the residuals, a latent variable, follow a normal distribution, not that the response (or dependent) variable follows a Gaussian distribution (see *inter alia* Lumley *et al.* (2002); Barker & Shaw (2015)).

During the peer review process, a reviewer critically raised a concern about spatial autocorrelation in the residuals, and suggested to include a spatial smooth term to assess the robustness of results. We present below the results of this suggestion, and contrast it with the results reported in the main manuscript.

```
M0 <-                    gam(DEAD ~ 1 +
                 s(event, bs = "re") +

         s(SDN_fr, k = 4, bs = "tp") +
         s(GND_fr, k = 4, bs = "tp") +
         s(GNS_fr, k = 4, bs = "tp") +
         s(GTR_fr, k = 4, bs = "tp") +
         s(OTT_fr, k = 4, bs = "tp") +
         s(PTB_fr, k = 4, bs = "tp") +
         s(PTM_fr, k = 4, bs = "tp") +
         s(OTB_de, k = 4, bs = "tp") +
         s(OTB_es, k = 4, bs = "tp") +
         s(OTB_fr, k = 4, bs = "tp") +
           data = X, family = gaussian
                                      )
```

```
M1 <-                    gam(DEAD ~ 1 +
                 s(event, bs = "re") +
        s(Lon, Lat, k = 4, bs = "tp")
         s(SDN_fr, k = 4, bs = "tp") +
         s(GND_fr, k = 4, bs = "tp") +
         s(GNS_fr, k = 4, bs = "tp") +
         s(GTR_fr, k = 4, bs = "tp") +
         s(OTT_fr, k = 4, bs = "tp") +
         s(PTB_fr, k = 4, bs = "tp") +
         s(PTM_fr, k = 4, bs = "tp") +
         s(OTB_de, k = 4, bs = "tp") +
         s(OTB_es, k = 4, bs = "tp") +
         s(OTB_fr, k = 4, bs = "tp") +
           data = X, family = gaussian
                                      )
```



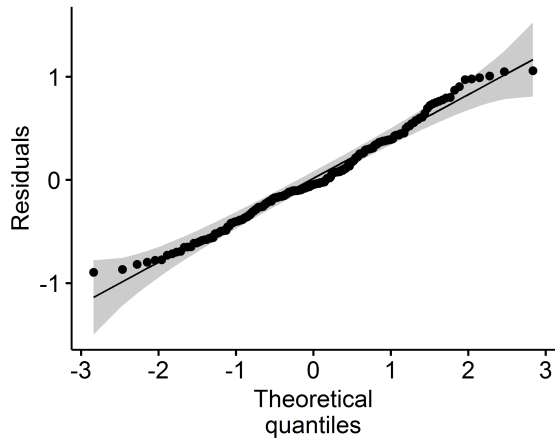


Table 2: Model specifications and Quantiles-Quantiles plots.

Convergence was reached for both models. In both cases, a Kolmogorov-Smirnov test rejected the null hypothesis of normality for the residuals (at the 5% significance level), although QQplots appeared satisfactory, especially for the spatial model (see Figure in lower cells of Table 2).

The critical assumption for linear regression is not normality of the residuals but homoscedasticity, that is constant variance of the latent residuals (Lumley *et al.*, 2002). To assess this assumption, we fitted models, both spatial and non-spatial, to our data and then binned the response variable with respect to its empirical quintiles, and computed the empirical standard deviation of residuals for each bin. Results are summarized in Table 3 below and suggest no substantial violation of this critical assumption.

Bin	model `M0`	model `M1`
1	0.225	0.246
2	0.280	0.303
3	0.270	0.288
4	0.313	0.298
5	0.337	0.318

Table 3: Checking the homoskedasticity assumption.

Including a smoothing term of longitude and latitude (keeping the basis complexity set to 4) second model attenuated some effects as can be seen in the figures in Table 4 below.

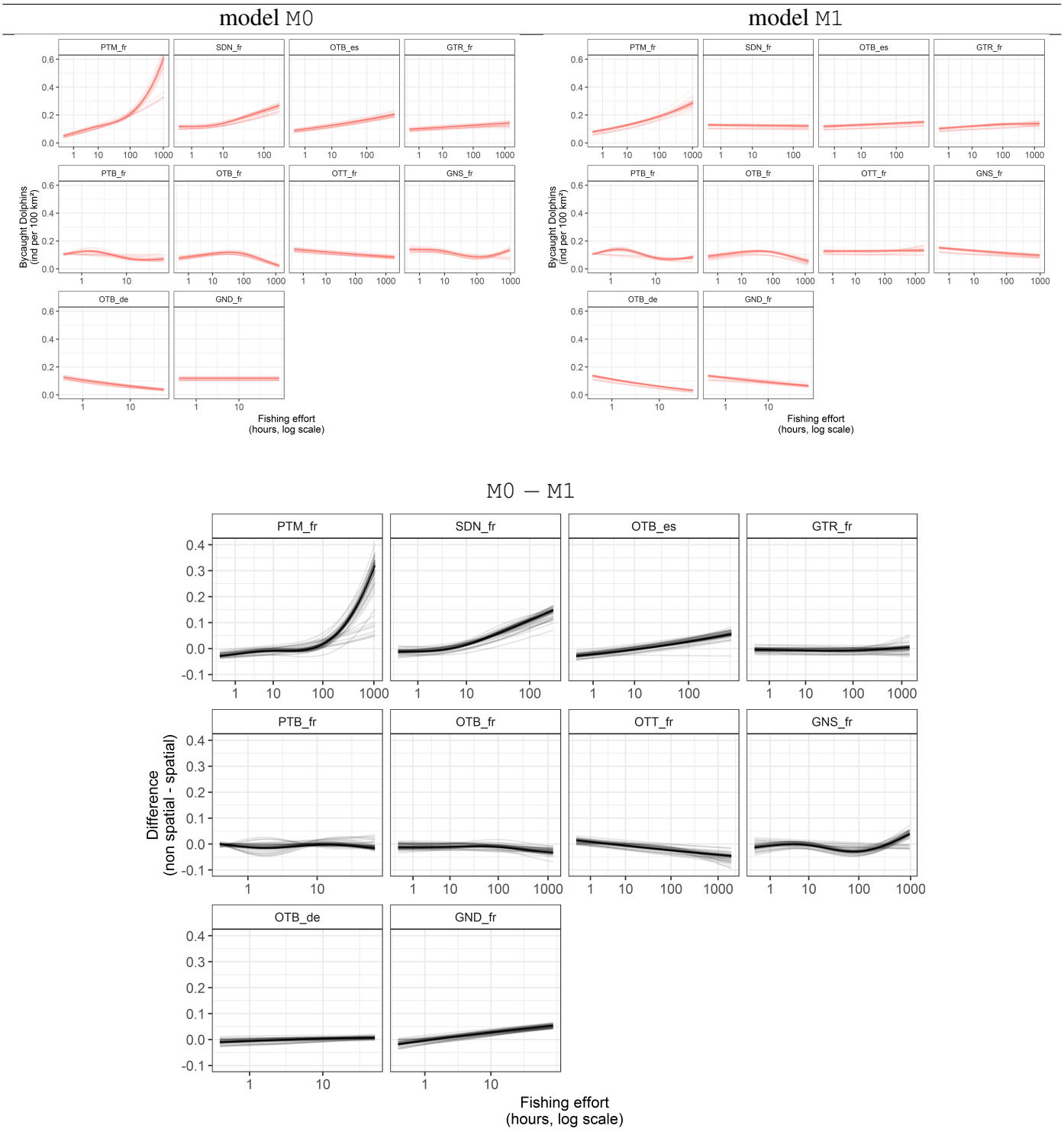


Table 4: Estimated relationships with GAMs. The thick line is estimated from the complete data. Thin lines are jack-knifed estimates (with one cell removed) to assess the robustness of results.

Attenuated relationships involved `PTM_fr`, `OTB_es` and `SDN_fr`. For the latter, the spatial model `M1` suggested no relationship with estimated densities of bycaught dolphins (see upper right cell of Table 4), which is also consistent with no reported dolphin bycatch from on-board observers on this fishery as discussed in the main manuscript. Although the spatial model was favoured by `AIC` (271 for `M1` vs 283 for `M0`), the associated gain in R^2, a measure of data variance accounted for by the model, was minor (42% for `M1` vs 39% for `M0`).

Failing to account for spatio-temporal correlation in the residuals may result in inflated p-values, and in general, over-confident inference (e.g. too narrow confidence intervals or bands). However, there are also many problems with conditioning on significance (see for example Wasserstein & Lazar (2016); Amrhein *et al.* (2019)). Our aims here were to generate candidate fisheries, from a limited data set focus on one extreme event for further investigation. Because our aims was to investigate and identify candidate fisheries in need of greater scrutiny, and given the high levels of bycatch, the costs associated with a type-I error are greater than the those of a type-II error (see Noss (1994) or Buhl-Mortensen (1996)). Thus we retained and presented results from the non-spatial model in the main manuscript, with the explicit caveat that our study is exploratory, and aims at identify candidate fisheries which need to be confirmed by ancillary data and non-correlative methods (*e.g.* onboard observers, cameras etc.).

References

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