Biological Conservation 243 (2020) 108488

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

Letter to the editor

Design issues adumbrate conclusions on LED-mediated bycatch risk reduction of cetaceans and turtles in fishing nets: A comment on Bielli et al. (2020)

ARTICLE INFO

Keywords:
Causal analysis
Design of experiments
Bycatch
Marine megafauna
Covariate overlap

Worldwide, bycatch is one of the biggest threat to the long-term viability of cetaceans and turtles (Reeves et al., 2013; Wallace et al., 2013), or marine megafauna in general (Lewison et al., 2004). Reducing marine megafauna bycatch is urgent: Bielli et al. (2020) reported a decreased risk of bycatch for cetaceans and turtles by small-scale fisheries targeting elasmobranchs in Peruvian waters when green visible spectrum light emitting diodes (LEDs) were added on fishing nets. To estimate the causal effect of LEDs on bycatch, some nets had LEDs (treatment) and some nets had none (control). Due to intrinsic difficulties of collecting relevant data in realistic settings while not overburdening fishermen with additional constraints, nets with LEDs were, on average, shorter than nets without. The ratio of effort (in km of net soaked per day) in treatment versus control amounts to 40%. Because of this systematic difference between treatment and control in the experimental design, less bycatch (in absolute numbers) is expected in treatment than in control conditions. This may be taken into account in the statistical analysis of data. However, such a design results in treatment and effort being intrinsically confounded: estimating the causal effect of LEDs on bycatch with these data is problematic as any estimated effect will be model-dependent (Rubin, 2008).

Two main modelling choices are possible for analysing these data with generalized linear mixed models. Either use a Bernoulli likelihood (0: no bycatch; 1: at least one individual bycaught) with effort as a covariate to account for the systematic difference between control and treatment; or use a Poisson likelihood with effort as an offset. The two choices are reasonable (since the Poisson distribution can approximate a Bernoulli when the probability parameter is small), but can lead to different conclusions depending on the experimental design for data collection. Simulations can illustrate this point: Poisson-distributed bycatch data were generated in two conditions (treatment versus control) assuming a rate of 0.05 event per unit effort for both. Hence, the treatment effect was always nil in these simulations. This bycatch rate implies a probability of no bycatch (for a unit effort) of Pr (Bycatch = 0) = $e^{-0.05} \approx 0.951$ and a probability of bycatch Pr (Bycatch = 1) = $1 - e^{-0.05} \approx 0.049$. Effort was assumed to follow a lognormal distribution of mean 1 and coefficient of variation 0.5 (computed from Table S1 in Bielli et al., 2020). 10, 000 datasets with 850 observations in control and treatment conditions each were simulated. Crucially, the ratio of effort between treatment and control conditions was allowed to vary from 0.1 to 1.0 by increment of 0.05. For each ratio, the simulated datasets were analysed with generalized linear models, assuming a Bernoulli or a Poisson likelihood (Fig. 1).

Both the Bernoulli and Poisson models were able to reach the correct conclusions (in the simulations) of no treatment effect when effort was comparable across treatment and control (ratio close to 1). As less effort was allocated to treatment compared to control, the Bernoulli model gave negatively biased estimates of treatment effect, which suggested a decreased risk with the treatment. In contrast, the Poisson model did not suggest any effect. These results illustrate how a design imbalance and a lack of covariate overlap (here effort) prevents an unambiguous assessment of treatment effect (Rubin, 2008). When treatment is confounded with effort, results can be heavily model-dependent because the data do not allow to statistically disentangle a treatment effect from the systematic difference in effort.

Because effort was systematically lower for treatment compared to control, the estimated efficacy of LEDs on bycatch may be very model-dependent: little or no imbalance in effort is required for a clear assessment of the causal effect of LEDs on cetacean and turtle bycatch. Currently, the effect of LEDs on cetacean and turtle bycatch in fishing nets may have been overestimated. Bycatch mitigation is urgent in many fisheries and requires unambiguous evidence to gain acceptance and maintain trust between scientists and fishermen.

Declaration of competing interest

None.

https://doi.org/10.1016/j.biocon.2020.108488
Received 22 January 2020; Accepted 22 February 2020
Available online 07 March 2020

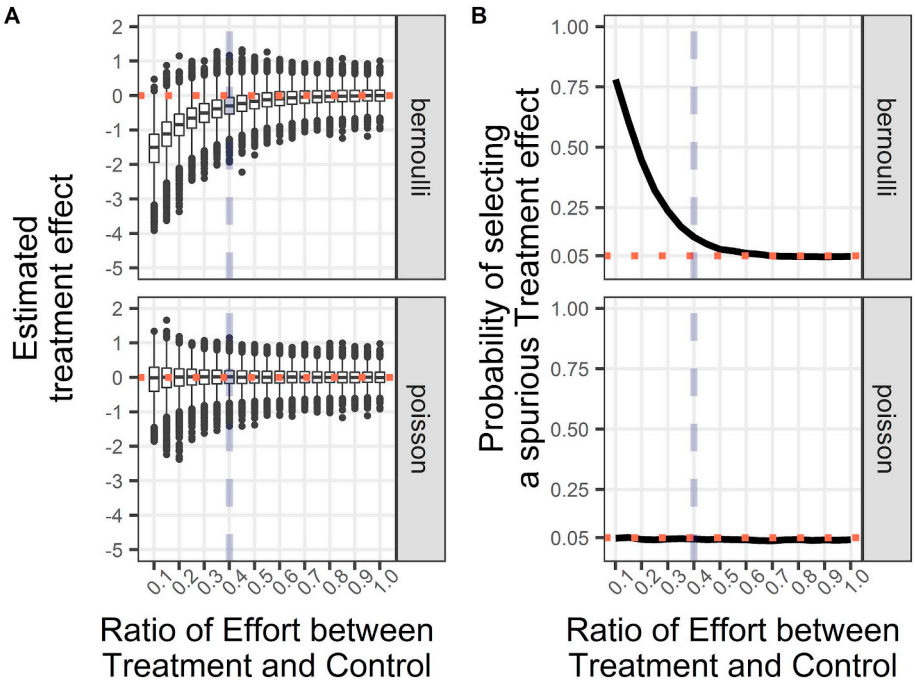

Fig. 1. A – Bias in estimated treatment effect when assuming a Bernoulli likelihood for bycatch data (upper panel). Data were simulated assuming no difference in bycatch between control and treatment conditions, but with a difference in effort due to study design. The bias disappears when the data are analysed with a Poisson likelihood (lower panel). Boxplots represent 10,000 estimated regression coefficients from a generalized linear model that includes both effort (as an offset with a Poisson likelihood) and treatment effects. The dotted red line shows the true effect size for treatment, and the blue dashed line the ratio of effort reported in Bielli et al. (2020). B – Probability of selecting with Akaike Information Criterion (AIC) a spurious treatment effect: models with and without treatment effects were compared and the model with the lowest AIC was kept for inference ($\Delta_{AIC} > 2$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Acknowledgements

MA thanks the French Ministry of Ecology ("Ministère de la Transition Ecologique et Solidaire") for financial support. MA and FC thank Jérôme Spitz for contructive comments.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2020.108488.

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