# An empirical Bayesian hierarchical modelling of fleet and vessel-level bycatch rates in commercial fisheries: a prospective tool for managing risk through targeted intervention

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## Abstract

Assessing the risks of fishing-induced mortality on bycatch and protected species is a priority for fisheries managers, who require an accurate estimation of the fleet and individual vessel bycatch interaction rates. Standard estimation of individual vessel bycatch rates (number of interactions divided by total effort) can be biased, as it does not consider effort heterogeneity among the fleet and ignores prior knowledge of the fleet or fishery interaction rate. We develop an empirical Bayesian approach for estimating vessel bycatch rates that: (i) considers effort heterogeneity among vessels and; (ii) pools the data from similar vessels for more accurate estimation of interaction rates. The proposed average interaction rate of a vessel is, therefore, the weighted average pool rate and the standard interaction rate of the vessel. We apply this inference method to the estimation of seabird bycatch rates in the component of the Australian Eastern Tuna and Billfish Fishery targeting southern bluefin tuna to illustrate its capability to provide fishery managers with insights on fleet-wide bycatch mitigation performance and identification of disparate vessels for targeted compliance intervention. This method can also be used by fishery managers to develop fleet-wide performance criteria or quantitative evaluation standards for bycatch species, similar to that implemented for seabirds in Australia under the Threat Abatement Plan.

## Introduction

Bycatch in commercial wild-capture fisheries is an international issue of growing concern for fisheries managers (Diamond, 2004; Gilman et al., 2008). For the purposes of this study, bycatch is defined as the "portion of the catch that is discarded at sea dead, or injured to an extent that death is the result" (Hall et al., 2000). Species that have little or no economic value to fishers (e.g. due to their small size); prohibited species (e.g. those targeted in other fisheries); regulatory discards (e.g. species below the size limit); or protected species (e.g. marine turtles, seabirds etc.) are all various examples of bycatch species that may be subsequently discarded at-sea (Diamond, 2004).

While the 1982 United Nations Convention of the Law of the Sea (UNCLOS) under Article 61 requires signatories to determine the biological and ecological impacts of fishing on non-target (bycatch) species, this is made more difficult due to a lack of fishery-dependent data in most commercial fisheries. As reported by Tuck (2011), bycatch data are often limited due to inadequate and incomplete information on vessel characteristics, fishing effort and species composition. Many bycatch species are under or over reported, non-reported or misreported in fishery logbooks (Walsh et al., 2002; Walsh et al., 2005; Sampson, 2011; Mangi et al., 2016; Macbeth et al., 2018). For example, in an examination of catch rates for blue shark (Prionace glauca), Walsh et al. (2002) found that underreported catches in fishery logbooks were due to fishers being too busy to report incidental catches. In a similar study examining the catch rates for blue marlin (Makaira nigricans), Walsh et al. (2005) observed that fisher-reported logbooks tended to over-report catches due to fishers misidentifying striped marlin (Tetrapturus audax) and shortbill spearfish (Tetrapturus angustirostris) as blue marlin. The inadequacies of fishery logbook data have often led decision-makers to use at-sea observer data as an alternative to quantify bycatch taken by commercial fisheries. However at-sea observer data has its own suite of biases (Benoît and Allard, 2009; Faunce and Barbeaux, 2011; Wakefield et al., 2018) and any extrapolations of at-sea observer data at low-levels of coverage is likely to produce imprecise results when capture of species is a rare occurrence (Wakefield et al., 2018).

In commercial fisheries where logbook data can be verified and trusted as an accurate representation of fishing catch and effort, the nominal discard rate for bycatch or interaction rate for protected species can be calculated at a fishery or individual vessel level. This is often done by dividing the number of interactions by the total effort for a given vessel. This is termed the "standard estimation rate". This vessel-level estimation could be unbiased if there are enough observations and fishers have not changed their fishing practices over the time period assessed. However, this is often not the case as different vessels enter and exit the fishery through time and change their fishing practices, influencing catchability (Tuck, 2011). Furthermore, consider two longline vessels with the same standard seabird interaction rate of zero (0.0 interactions per 1,000 hooks), where vessel one expended a significantly greater amount of effort compared to vessel two. A standard estimation rate would suggest that both vessels are performing identically; however from the perspective of a fishery manager, vessel one is outperforming vessel two since there have been no interactions with a substantially greater exposure to risk (i.e. effort). Moreover, a fishery manager is more confident in the interaction rate of vessel one simply due to the greater level of effort expended compared to vessel two, whose zero interaction rate could simply be due to chance through limited exposure. The standard estimation also only uses each vessel's information for estimating the rate and ignores prior knowledge about the overall rate in a given fleet or a fishery. Given these limitations, we propose a "revised estimation rate" at a vessel level using an empirical Bayesian approach that considers effort heterogeneity among the fleet and pools data from "similar" vessels for rate estimation. Similar vessels being those that share comparable fishing behaviour patterns (i.e. "fishing styles" after Boonstra and Hentati-Sundberg (2016)) and are pre-determined using a machine learning clustering method (see, Parsa et al 2018, unpub. data for further information on the cluster analysis). The proposed revised estimation rate of a vessel is therefore the weighted average of the pool (fleet) rate and the standard estimation rate of the individual vessel.

We contend that a vessel-level estimation of bycatch rates is equally valuable as one at a fleet or fishery-level. A vessel-level estimation may provide insights on why a particular vessel is underperforming (higher interaction rate) or outperforming (lower interaction rate) the fleet average (e.g. due to fishing in an area with high abundance of protected species or appropriately deploying mitigation devices, respectively). Assessing individual vessel performance also ensures individuals are accountable for their actions and allows managers to seek further information or undertake targeted compliance action against vessels with poor performance. By comparing the vessel-level estimated bycatch or interaction rates to the fleet-level-estimate allows managers to set quantifiable bycatch targets for the fishery. Quantifiable targets, standards or reference points that guide expected levels of performance can create incentives for industry to reduce bycatch or interaction rates, through for example, altering fishing behaviour or adopting alternative bycatch mitigation technology (Diamond, 2004; Grafton et al., 2007; Kirby and Ward, 2014; Lent and Squires, 2017). When these performance standards create economic incentives or disincentives (carrot and stick) for industry, they have the potential to further improve fleet bycatch performance and reduce regulatory costs (Gjertsen et al., 2010; Pascoe et al., 2010). For example, in Australia, there is a Threat Abatement Plan (TAP) for seabirds, which sets a maximum permissible bycatch rate of 0.01 to 0.05 birds per 1,000 hooks in various Australian Commonwealth fisheries (Commonwealth of Australia, 2018). Attached to this performance standard are criteria developed to guide the management response when the bycatch rate is exceeded, which may target individual vessels or the fishery and may have immediate economic costs (Commonwealth of Australia, 2018).

In this paper, we outline an inference method for calculating a "revised estimation rate" and apply it to a case study of seabird interaction rates in the southern bluefin tuna (cluster) component of the Australian Eastern Tuna and Billfish Fishery (ETBF). We use the Australian ETBF as an example because we are confident that the fishery logbook data is an accurate representation of catch composition and interactions with protected species in the years subsequent to the introduction of EM technologies (Emery et al., 2019a). The results of the analysis are discussed in the context of (i) developing quantitative performance standards for bycatch and protected species; (ii) reducing the costs of fishery compliance and enforcement activities through targeted intervention and; (iii) making fishers individually accountability for their bycatch and interaction rates.

# Methodology

In our model, we assume that the average amount of bycatch or number of interactions (hereafter termed interactions) is proportional to the total units of effort. This assumption is valid and it is supported by both literature (Hatch, J. M. 2018)and our discussion with fishery managers (AFMA, pers. comm. 2018). We should emphasise that other factors could contribute to the interaction rate such as climate, food abundance and availability, as well as seasonality. While they are not considered in our study, in an effort to keep the model as simple as possible, they could be incorporated as covariates.

One of the main strengths of our model is that it requires minimal data. We only need total effort and the total number of interactions for each vessel in the fleet/fishery in the timeframe of interest. To estimate the interaction rate of individual vessels, we develop a Poisson-Gamma (Carlin and Louis 2010) model considering two sources of uncertainties: (i) the uncertainties that are arising from lack of knowledge (e.g. the actual interaction rate is not known), termed as epistemic uncertainty and; (ii) uncertainty associated with natural variations in the sample, termed as aleatory uncertainties (e.g. same amount effort leads to a different number of interactions). Consequently, we use a gamma prior distribution to capture epistemic uncertainties within the pool of data to model the variation in interaction rates as we do not know the actual rates. That is, we assume that the interaction rate of vessel $i$ is a random variable with the gamma distribution of shape parameter $\alpha$ and scale parameter $\beta$. We denote it by $\lambda_i \sim Gamma(\alpha, \beta)$ and the gamma probability density function can be expressed as Equation (1). The mean of a gamma distribution is $\frac{\alpha}{\beta}$ .

$$\pi(\lambda_i) = \frac{\beta^{\alpha} {\lambda_i}^{\alpha-1} e^{-\beta\lambda_i}}{\Gamma(\alpha)}, \alpha > 0, \beta > 0, \lambda_i > 0. \tag{1}$$

We later update the prior for each vessel to estimate its interaction rate. The updating process can be done quickly as the posterior of gamma distribution remains in the gamma family, and we only need to update the shape and scale parameters. Assume we observed $n_0$ species interactions for $E_0$ units of effort. The Bayes Theorem implies that the posterior distribution is of the form of Equation (2).

$$\pi(\lambda | n_0, E_0) = \frac{(\beta + E_0)^{\alpha} \lambda^{\alpha+n_0-1} e^{-(\beta+E_0)\lambda}}{\Gamma(\alpha + n_0)}, \alpha, \beta, \lambda, E_0 > 0, n_0 = 0,1,2,3, \ldots \tag{2}$$

Assuming the actual interaction rate $\Lambda_i = \lambda_i$ for vessel $i$ and it is constant for given $E_i$ units of effort, then we can model the aleatory uncertainty in the interaction rate by a Poisson probability distribution expressed in Equation (3).

$$P(N_i = n_i | \Lambda_i = \lambda_i) = \frac{(\lambda_i E)^{n_i} e^{-\lambda_i E_i}}{n!}, E_i > 0, \lambda_i > 0, n_i = 0,1,2, \ldots \tag{3}$$

Since we do not know the true $\Lambda_i$ for vessel $i$, we average the Poisson distributions, weighted against the prior distribution as Equation (4). This provides the probability distribution of the number of bycatch interactions that will interact with vessel $i$, based only on our knowledge of the pool, i.e. the prior distribution.

$$P(N_i = n_i) = \int_0^{\infty} \frac{(\lambda_i E_i)^{n_i} e^{-\lambda_i E_i}}{n_i!} \frac{\beta^{\alpha} {\lambda_i}^{\alpha-1} e^{-\beta\lambda_i}}{\Gamma(\alpha)} d\lambda, \quad \alpha > 0,\ \beta > 0,\ n_i = 0,1,2, \ldots \tag{4}$$

Greenwood and Yule (2010) proved that the distribution of $N_i$ is Negative Binomial as shown in Equation (5).

$$P(N_i = n_i) = \frac{\Gamma(n_i + \alpha)}{\Gamma(\alpha) n_i!} \left(\frac{\beta}{\beta + E_i}\right)^{\alpha} \left(\frac{E_i}{\beta + E_i}\right)^{n_i}, \quad \alpha > 0,\ \beta > 0,\ n_i = 0,1,2, \dots \tag{5}$$

To estimate the parameters of prior $(\alpha, \beta)$, we can either use expert judgment or only the data. Our approach is to use the data (empirical approach). We pool all data and assume they are generated from the Negative Binomial distribution of Equation (5). We use the Maximum Likelihood Estimates (MLE) of pooled data as the parameters of prior. We can also construct a joint confidence region for the prior parameters using likelihood theory (Lawless, 2011). Let $\hat{\alpha}$ and $\hat{\beta}$ be the estimated values of prior parameters and vessel $i$ interacted with $n_i$ bycatch species when $E_i$ units of effort have been deployed. Then, we can estimate the average interaction rate of vessel $i$ as follows:

$$E(\lambda_i | N_i = n_i) = \int_0^{\infty} \lambda_i \, \pi(\lambda_i | N_i = n_i, \hat{\alpha}, \hat{\beta}) d\lambda_i = \frac{\hat{\alpha} + n_i}{\hat{\beta} + E_i} = \frac{\hat{\alpha}}{\hat{\beta}}(1 - z) + \frac{n_i}{E_i} z, \tag{6}$$

where $z = \frac{E_i}{\hat{\beta} + E_i}$.

The estimated rate can be interpreted as a weighted average of the pool mean ($\hat{\alpha} / \hat{\beta}$) and the standard rate ($n_i / E_i$). Equation (6) also implies that when we have more experience with a vessel (higher E), more weight will be allocated to the standard rate, while for a vessel with less effort, more weight will be allocated to the pool mean.

## Australian seabird interaction case study

We apply this method to vessels in the SBT sub-fishery of the Australian Eastern Tuna and Billfish Fishery (ETBF) to illustrate how the method can provide fishery managers with insights on fleet-wide bycatch mitigation performance and identify non-performing vessels for targeted compliance intervention. The ETBF is a pelagic longline fishery that operates within the Australian Exclusive Economic Zone (EEZ) and adjacent high seas waters targeting yellowfin tuna (Thunnus albacares), bigeye tuna (Thunnus obesus), albacore tuna (Thunnus alulunga), broadbill swordfish (Xiphias gladius) and striped marlin (Tetrapturus audux). The ETBF operates from Cape York, east and south to the Victorian – South Australian border, including waters around Tasmania and the high seas of the Pacific Ocean. In 2017, there were a total of 39 longline and two minor line vessels active in the ETBF (Patterson et al., 2018). In the ETBF, vessels that have fished more than 30 days in the previous or current fishing season must have operational EM technology installed. For the purposes of our study, the SBT sub-fishery comprises all sets where SBT was the dominant catch (see Parsa et al, unpub. data). Consequently, the SBT sub-fishery is defined as the collection of all SBT sets in the fishery. We limit our analysis of the SBT sub-fishery to the years 2016 and 2017 when EM technologies were installed on full-time ETBF vessels because recent studies have indicated that fishers have improved their logbook reporting of bycatch and protected species, and there is high congruence between logbook and EM analyst reported seabird interactions (Larcombe et al., 2016; Emery et al., 2019a; Emery et al., 2019b).

## Results

There was high heterogeneity in the effort data for the 17 ETBF vessels operating in the SBT sub-fishery from 2016 and 2017, with one vessel setting nearly 150,000 hooks and another less than 10,000 hooks (Figure 1). Furthermore, the number of interactions with seabirds varied among vessels with similar effort. For example, Vessel_ID 2, and 8 expended a similar amount of effort (30-40,000 hooks) in the sub-fishery during 2016 and 2017 but the number of recorded seabird interactions was different. The difference could be due to efficient implementation of seabird mitigation strategies.

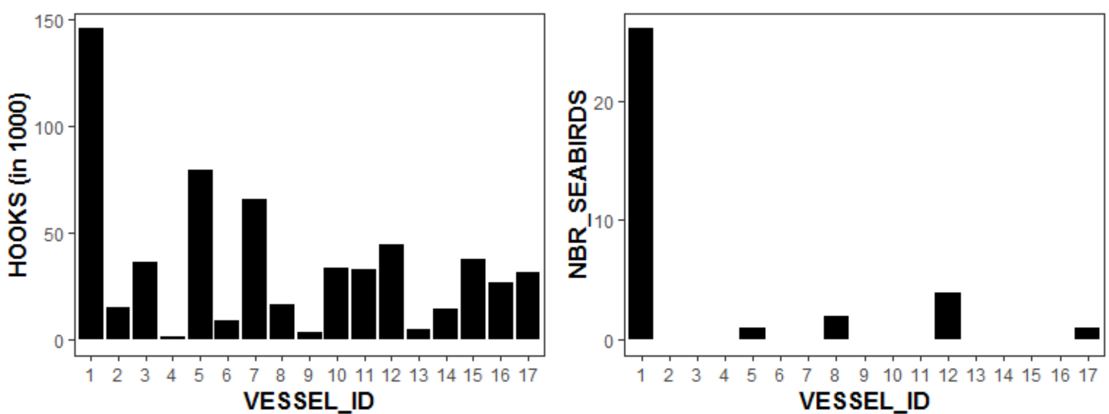


***Figure 1: Total seabird interaction and total effort of 17 vessels in SBT sub-fishery of ETBF for the years 2016-2017.***

Further exploration of the large amount of effort by Vessel_ID 1 in 2016 and 2017 revealed significant annual and seasonal variation in fishing effort (Figure 2). For example, the vessel was not active in the fishery during January to March 2016 and the effort in April to June 2016 is less than half of the effort from the same season in 2017. Moreover, even with a similar amount of effort in October to December in both years, the number of seabird interactions are different (aleatory uncertainty).

There was a strong positive linear correlation (Pearson's r = 0.82) between the number of seabird interactions and the effort for each vessel (Figure 3). This suggests that considering the number of interactions proportional to the amount of effort in SBT sub-fishery of the ETBF is a valid assumption.

To estimate the seabird interaction rates in the SBT sub-fishery of the ETBF, we assume that the interaction rate of each vessel is constant during 2016 and 2017 but we expect some variations in the number of interactions with a similar amount of effort (aleatory uncertainty). As suggested in the model, we calculated the pool estimates $(\hat{\alpha}, \hat{\beta})$ in Equation (5) using MLE method as $\hat{\alpha} = 0.31$ and $\hat{\beta}$= 9773. We use the estimates to calculate the fishery mean interaction rate (0.31/9773*1000 = 0.031) as well as each vessel mean interaction rate using Equation (6) As model suggested we observed that the estimated revised interaction rates of vessels with low fishing effort are closer to the average of the sub-fishery while these revised interaction rates are similar to standard rates for vessels with high fishing effort (see Figure 4).

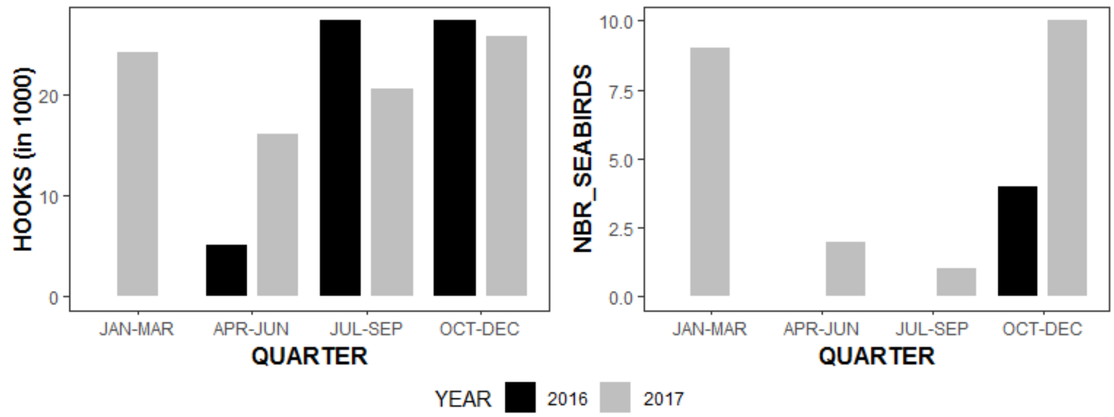


***Figure 2 Total effort and total seabird interactions of vessel 1 during 2016-2017 across different seasons.***

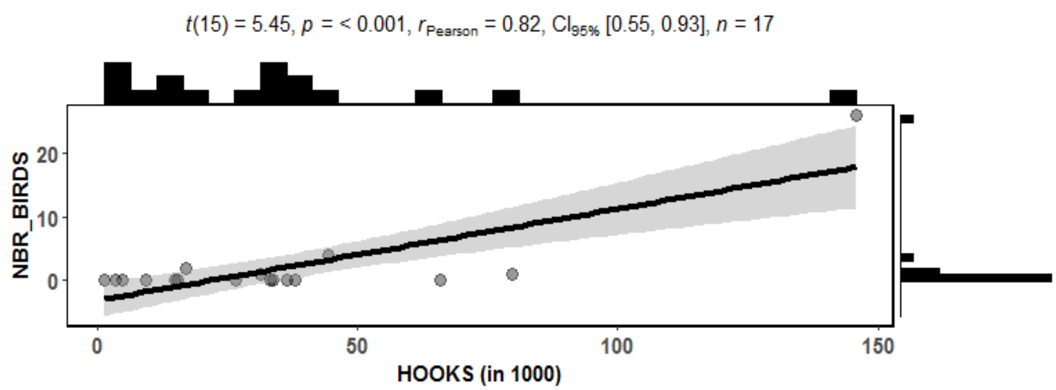


***Figure 3 The number of seabird interactions against the total effort of 17 vessels in SBT. The black line is the trend line.***

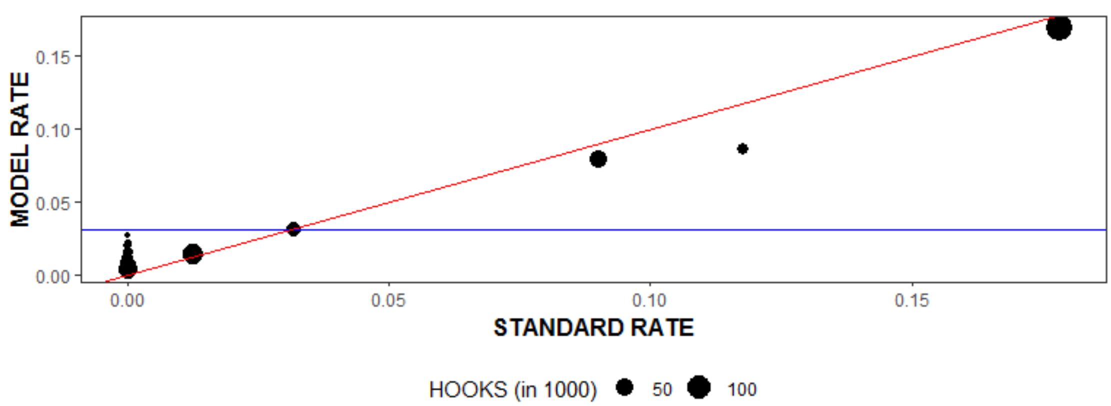


***Figure 4 Estimated interaction rates against standard interaction rate of vessels. The size of each point represents total effort of each vessel in 1000 hooks. The red line is the identity line and the blue line is fishery average rate.***

We can then construct the posterior distribution of the average seabird interaction rate of each vessel. For example, as illustrated in Figure 5, Vessel_ID6 has the greatest number of interaction rates below 0.02 while Vessel_ID 17 has the greatest number above 0.03. This suggests that considering uncertainties the Vessel_ID 6 outperforms Vessel_ID 17. The mean model estimated interaction rate of Vessel_ID 17 is closer to the fishery average but with a tighter distribution.

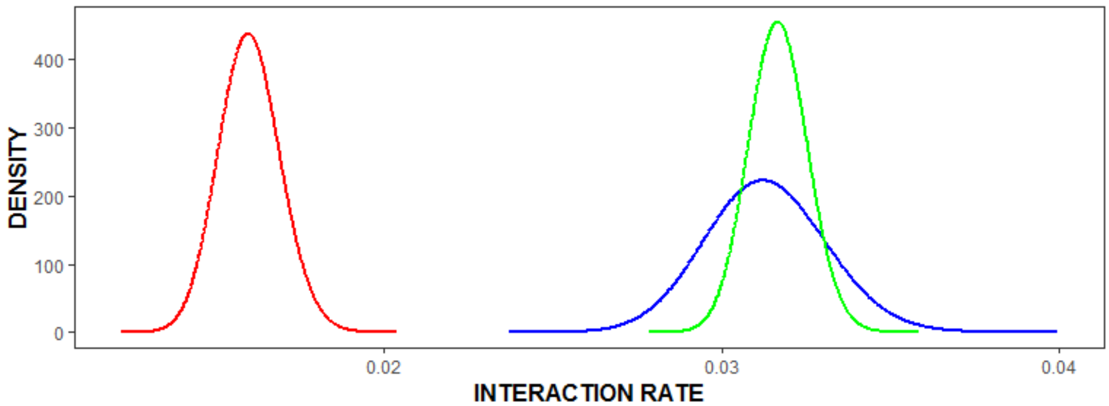


***Figure 5 Posterior distributions for the Vessel_ID 6 (red) and Vessel_ID 17 (green) on their mean interaction rates and distribution of fishery average interaction rate (blue).***

Finally, we present the summary of estimated interaction rates of 17 vessels in the SBT sub-fishery of the ETBF and the associated uncertainty with each estimation, which shows that the SBT sub-fishery average interaction rate is below the maximum permissible bycatch rate of 0.05 recommended in the Australian Seabird Threat Abatement Plan (TAP) (Commonwealth of Australia, 2018). (Figure 5).

The results of the model can be communicated in risk language. Here we propose a simple risk ranking framework using the outcome of the model. We also propose some examples of management intervention actions based on different levels of risk. We can define three risk levels based on the estimated interaction rates, uncertainty associated with estimation and management goals. Group one (high-risk elements) includes elements (e.g. vessel/fleet/fishery) with high interaction rates and tight confidence intervals for the estimated rates. A high interaction rate can either be defined relative to the target interaction rate of the fishery (e.g. TAP reference point) or the average interaction rate of the fishery. For example, Vessel_ID 1 and Vessel_ID 12 can be labelled as high-risk vessels since their interaction rates are above the fishery average and also TAP reference point (Figure 6.). Group two (low-risk elements) contains elements with low interaction rates and tight confidence intervals for the interaction rates. Vessel_ID 3 and Vessel_ID 5 can be considered as low-risk elements (Figure 6). Group three (uncertain-risk elements) comprises elements where there is high uncertainty associated with the estimated rates. For example, Vessel_ID 4 can be considered as an uncertain-risk element since the confidence interval for the average estimated rate is relativity large even though the estimated interaction rate is close to the fishery average. Fishery managers can intervene by defining trigger actions based on different levels of risk. For example, the low-risk elements can be promoted as the best practices in the fishery, while the high-risk items might be considered for immediate corrective actions. For uncertain-risk elements, managers may consider different actions such as a wait and see strategy to monitor the longer-term performance of the element or invest in buying down the uncertainty by allocating more resources in terms of observer coverage or reviewing the substantial proportion of recorded videos of sets when electronic monitoring is in place.

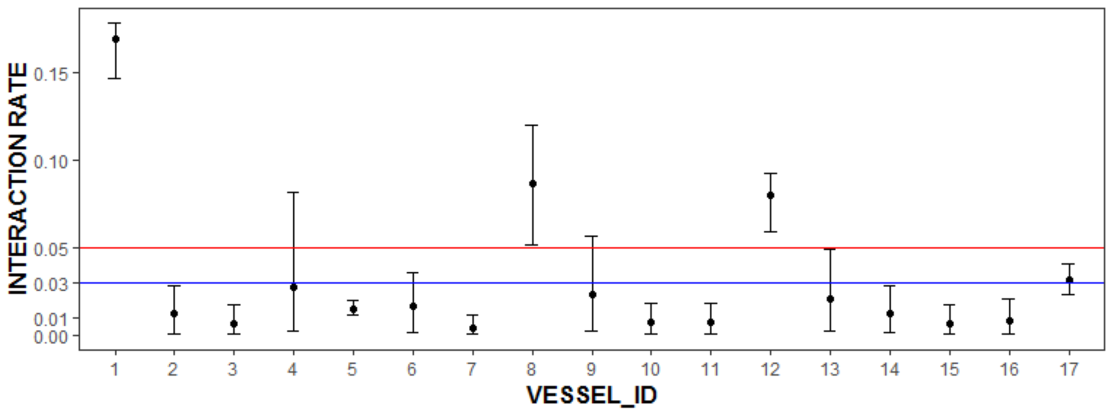


***Figure 6 Seabird interaction rates of 17 SBT vessels. The red line represents TAP recommended reference point, and the blue line represents SBT average interaction rate.***

# Conclusion

We developed a method to estimate the interaction rate at a vessel/fleet level to overcome some of the shortcomings of standard rate estimation. The model has strengths, including that it requires minimal data and the results can be immediately translated into management actions to manage bycatch. The average interaction rates of the fleet/fishery estimated by the model can be used to define the fishery bycatch management target or bycatch quota per vessel when there is no bycatch target reference point, similar to the seabird TAP reference point, for the species of interest in the fleet/fishery.

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