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Original Article

An empirical Bayesian approach for estimating fleet- and vessel-level bycatch rates in fisheries with effort heterogeneity and limited data: a prospective tool for measuring bycatch mitigation performance

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Minimizing fishing-induced mortality on bycatch and endangered, threatened or protected species is a necessity for fisheries managers. Estimating individual vessel bycatch rates by dividing the amount of bycatch by effort (nominal rate) can be biased, as it does not consider effort heterogeneity within the fleet and ignores prior knowledge of fleet bycatch rates. We develop an empirical Bayesian approach for estimating individual vessel and fleet bycatch rates that: (i) considers effort heterogeneity among vessels and; (ii) pools data from similar vessels for more accurate estimation. The proposed standardized bycatch rate of a vessel is, therefore, the weighted average of the pool rate and nominal rate of the vessel; where the weights are functions of the vessel's fishing effort and a constant estimated from the model. We apply this inference method to the estimation of seabird bycatch rates in the component of the Australian Eastern Tuna and Billfish Fishery targeting yellowfin tuna. We illustrate the capability of the method for providing fishery managers with insights on fleet-wide bycatch mitigation performance and the identification of outperforming and underperforming vessels. This method can also be used by fishery managers to develop fleet-wide performance measures or quantitative evaluation standards.

Keywords: bycatch, catch rates, Eastern Tuna and Billfish Fishery, Poisson–gamma, protected species, seabirds, threat abatement plan

Introduction

Global fisheries bycatch in wild-capture fisheries is an issue of growing concern (Diamond, 2004; Gilman *et al.*, 2008). Species that have little or no economic value to fishers (e.g. due to their small size); prohibited species (e.g. those managed in other fisheries); regulatory discards (e.g. species below or above the size limit); or endangered, threatened or protected (ETP) species (e.g. marine turtles, seabirds) are all examples of bycatch species (Diamond, 2004). For this article, we refer hereafter to bycatch species as those species that are caught and subsequently discarded at sea, or in the case of ETP species, interacted with at sea.

While the 1982 United Nations Convention of the Law of the Sea under Article 61 requires signatories to determine the biological and ecological impacts of fishing on non-target (bycatch) species, this can be difficult for most commercial fisheries that lack fishery-dependent data. 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 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 fishers tended to over-report catches due to 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 have 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 are likely to produce imprecise and inaccurate results when capture of a species is a rare occurrence (Wakefield *et al.*, 2018).

Despite the issues associated with logbook data, it often remains the principal source of information on fishery catch and effort due to many management authorities requiring vessels to fill out their logbook as a condition of their licence or permit (Sampson, 2011). Access to fishery logbook data allows the nominal discard rate for bycatch species to be calculated at an individual vessel or fleet level. This is often done by dividing the amount of bycatch by the total effort for a given vessel. This is termed the "nominal" estimate. This vessel-level estimation could be unbiased if there are sufficient observations (i.e. adequate sample size), 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 bycatch rate of zero (0.0 bycatch per 1000 hooks), where vessel 1 expended a significantly greater amount of effort compared with vessel 2. Calculation of the nominal estimate would suggest that both vessels are performing identically; however, from the perspective of a fishery manager, vessel 1 is outperforming vessel 2 since there has been no bycatch recorded with a substantially greater exposure to risk (i.e. effort). Moreover, a fishery manager is more confident in the bycatch rate of vessel 1, simply due to the greater level of effort expended compared with vessel 2, whose zero-bycatch rate could simply be due to chance through limited exposure. The nominal estimate also only uses each vessel's information for estimating the rate and ignores other available information (e.g. effort data) from "similar" vessels in each fleet or fishery. Given these limitations, we propose a "standardized" estimate using an empirical Bayesian approach that considers effort heterogeneity among the fleet and pools data from "similar" vessels for rate estimation. Similar vessels are defined as those that share comparable fishing behaviour patterns [e.g. "fishing styles" after Boonstra and Hentati-Sundberg (2016) or "fishing tactics" after Pelletier and Ferraris (2000)] and can be pre-determined using variable quantitative or semi-quantitative methods based on the data from the commercial fishery or expert judgement, respectively.

Vessel-, fleet- and fishery-level estimations of bycatch rates are sources of information that assist fisheries managers with monitoring the performance of bycatch mitigation measures. Vessel-level estimation may provide insight (through a targeted investigation) on why a vessel is underperforming (higher bycatch rate) or outperforming (lower bycatch rate) the fleet average (e.g. due to fishing in an area with the high abundance of protected species or appropriately deploying mitigation devices, respectively). Comparing the vessel-level estimated bycatch rates to the fleet-level estimate ensures that individual vessels are accountable for their actions and allows managers to set quantifiable bycatch thresholds for the fishery. Quantifiable measures, standards or reference points that guide expected levels of performance can create incentives for industry to reduce their bycatch 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 market-based incentives or disincentives (carrots and sticks) 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 or 0.05 birds per 1000 hooks in various Australian Commonwealth fisheries (Commonwealth of Australia, 2018). Attached to this performance measure are criteria developed to guide the management response when the bycatch rate is exceeded, which may target individual vessels or the fleet and may have immediate economic costs (Commonwealth of Australia, 2018).

In this article, we outline an inference method for calculating a model-estimated (standardized) bycatch rate for each vessel, which is the weighted average of the pool (fleet) rate and the nominal estimation rate of the individual vessel. Using an empirical Bayesian approach for the analysis of rare-event data is not new (Myers *et al.*, 2002; Quigley *et al.*, 2011) and has been shown to produce less biased and more consistent estimates of the probabilities of rare events compared with conventional statistical methods (Khakzad *et al.*, 2014). We apply this method to a case study of seabird bycatch rates in the yellowfin tuna 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 are the accurate representation of catch composition and bycatch of protected species in the years subsequent to the introduction of electronic monitoring technologies (Emery *et al.*, 2019a). The results of the analysis are discussed in the context of (i) developing quantitative performance standards for bycatch species; (ii) reducing the transaction costs of management decision-making through a risk-based approach; and (iii) making fishers individually accountabile for their bycatch rates.

Methodology

Poisson–gamma model to estimate bycatch rates

In our model, we assume that the amount of bycatch is approximately proportional to the total units of effort. This assumption is valid and is supported by the existing literature (Hatch, 2018) and the results of our study (see below). To estimate the standardized (seabird bycatch) rate of individual vessels, we develop a Poisson–gamma (Carlin and Louis, 2009) model considering two sources of uncertainties: (i) the uncertainties that arise from the lack of knowledge (e.g. the actual bycatch rate is not known), termed epistemic uncertainty, and (ii) uncertainty associated with natural variations in the sample (e.g. same amount of effort leads to a different amount of bycatch), termed aleatory uncertainties. Consequently, we use a gamma prior distribution to capture epistemic uncertainties within the pool of data to allow us to model the variation in true bycatch (actual seabird bycatch) rates, which are currently unknown. That is, we assume that the true bycatch rate of vessel i is a random variable with the gamma distribution of shape parameter α and scale parameter β. We denote it by $\lambda_i \sim \text{gamma}(\alpha, \beta)$, and the gamma probability density function can be expressed as the following equation. The mean of a gamma distribution is $\frac{\alpha}{\beta}$, and here, we refer it as the pool rate.

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

We later update the prior for each vessel to estimate the standardized bycatch rate. The updating process can be done quickly as the posterior of the gamma distribution remains in the gamma family, and we only need to update the shape and scale parameters. If we assume that n_0 bycatch species were observed for E_0 units of effort, Bayes' theorem implies that the posterior distribution is of the form of the following equation:

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

Assuming that the true bycatch rate $\Lambda_i = \lambda_i$ for vessel i is constant for given E_i units of effort, we can then model the aleatory uncertainty in the bycatch rate through a Poisson probability distribution expressed in the following equation:

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

Since we do not know the true bycatch rate Λ_i for vessel i, we average the Poisson distributions, weighted against the prior distribution in the following equation:

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

Greenwood and Yule (1920) proved that the distribution of N_i is Negative Binomial as shown in the following equation:

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

To estimate the parameters of the prior distribution, α, β, we use a genetic algorithm optimization method (implemented in MATLAB Global Optimization Toolbox) to maximize the natural logarithm of the marginal likelihood (LML) functions assuming that (pooled) data are generated from the Negative Binomial distribution of (5). Our choice of algorithm was informed by as follows: (i) there being no closed-form solution for finding maximum values of LML functions and (ii) the LML functions being highly nonlinear and nonconvex.

Several methods have been proposed to construct a joint confidence region to address the uncertainty associated with the estimated prior parameters, such as the bootstrap method (Carlin and Gelfand, 1991), and using likelihood theory by assuming the negative of two times the natural logarithm of the relative marginal likelihood function has a chi-square distribution with two degrees of freedom (Basu and Rigdon, 1986). In this study, we used the second approach to construct a joint confidence interval for the maximum likelihood estimates and consequently the posterior mean (standardized) bycatch rate of each vessel.

We let $\hat{\alpha}$ and $\hat{\beta}$ are the estimated values of prior parameters and let vessel i interacts with n_i bycatch species when E_i units of effort have been deployed. We estimate the standardized bycatch rate of vessel i, which is the posterior mean of λ_i as follows:

$$E(\lambda_i | N_i = n_i) = \int_0^{\infty} \lambda_i \pi\left(\lambda_i | N_i = n_i, \hat{\alpha}, \hat{\beta}\right) d\lambda_i = \frac{\hat{\alpha} + n_i}{\hat{\beta} + E_i}$$

$$= \frac{\hat{\alpha}}{\hat{\beta}}(1 - z) + \frac{n_i}{E_i} z, \quad (6)$$

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

The standardized bycatch rate can be interpreted as a weighted average of the pool (i.e. fleet) mean bycatch rate $(\hat{\alpha}/\hat{\beta})$ and the nominal bycatch rate of the vessel (n_i/E_i) where the weight is the function of a vessel's fishing effort and a scale parameter of the posterior gamma distribution. Equation (6) also implies that when we have more experience (i.e. fishing effort) with a vessel (higher E), more weight will be allocated to the nominal rate, while for a vessel with less experience, more weight will be allocated to the pool rate.

Application of the Poisson–gamma model to the Australian yellowfin tuna sub-fishery

We apply this method to vessels in the yellowfin tuna sub-fishery of the Australian 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 intervention. The ETBF is a pelagic longline fishery that operates within the Australian Exclusive Economic Zone and adjacent high sea waters targeting yellowfin tuna (*Thunnus albacares*), bigeye tuna (*Thunnus obesus*), albacore tuna (*Thunnus alulunga*), broadbill swordfish (*Xiphias gladius*), and striped marlin (*T. audax*). 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 (Figure 1a). In 2018, there were a total of 40 longline vessels active in the ETBF (Patterson *et al.*, 2018). In the ETBF, vessels that have fished >30 days in the previous or current fishing season must have operational electronic monitoring technology installed.

The yellowfin tuna sub-fishery of the Australian ETBF was differentiated from other sub-fisheries using a non-hierarchical clustering method, partitioning around medoids as similarly employed by Duarte *et al.* (2009) that identified structures within the data to quantitatively categorize individual fishing events to a particular métier (for more information on métier analysis, see Pelletier and Ferraris, 2000; Holley and Marchal, 2004). While the primary target species of the yellowfin tuna sub-fishery is yellowfin tuna, there is also a high proportion of oilfish (*Ruvettus pretiosus*) and striped marlin caught as by-products. The yellowfin tuna sub-fishery is a year-round fishery with most sets occurring between 7 and 9 a.m. off the New South Wales and Victorian State coastlines (Figure 1b). Typical gear characteristics include shallow setting with limited light stick use. In undertaking this analysis, we limit our study to the years 2016–2018 when electronic monitoring technologies were installed on all full-time ETBF vessels.

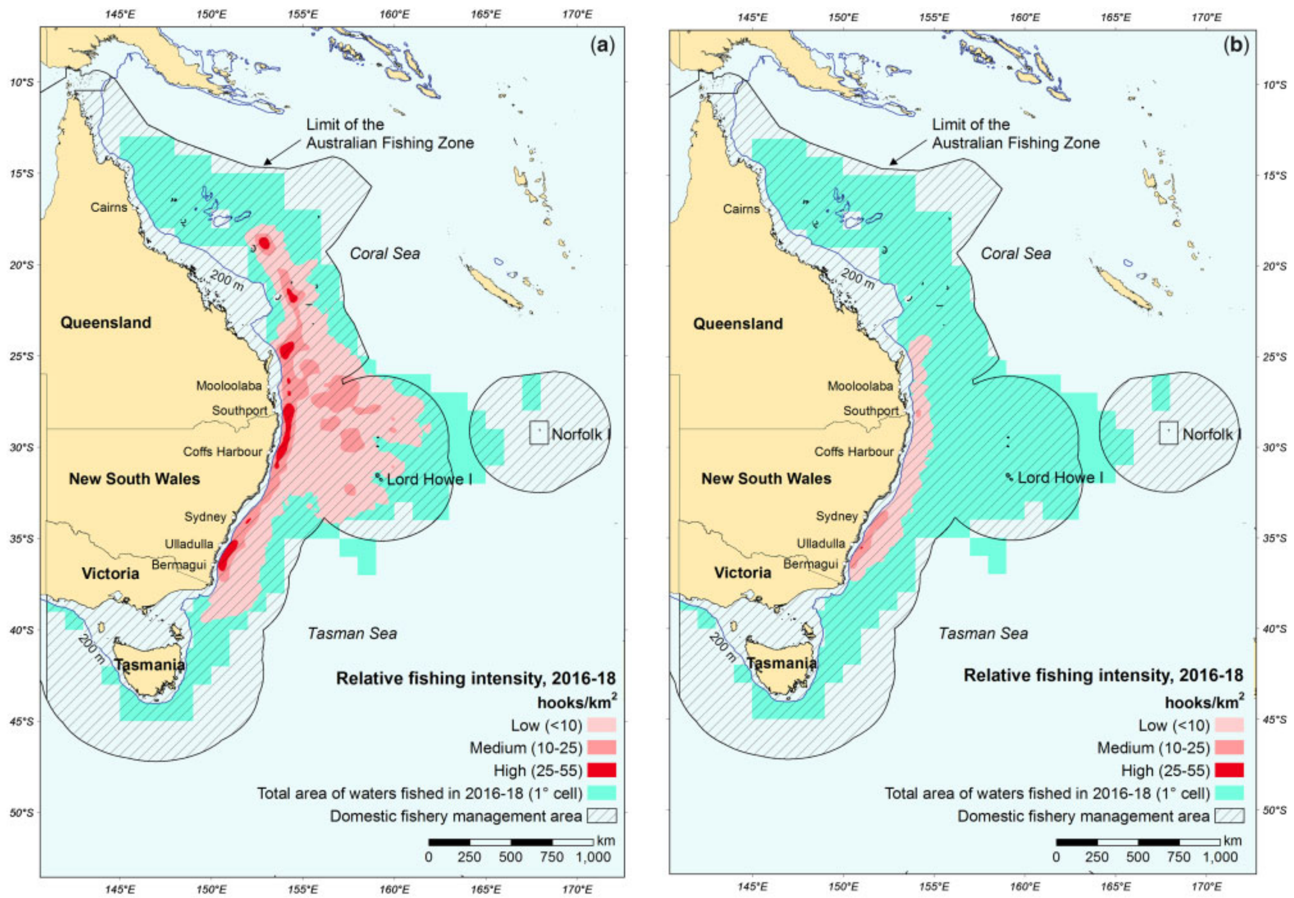

Figure 1. Area and relative fishing intensity in the (a) eastern tuna and billfish fishery and (b) yellowfin tuna component of the eastern tuna and billfish fishery in 2016–2018 calendar years.

This decision was based on recently published studies indicating that fishers have improved their logbook reporting of bycatch and protected species in these years, and there is high congruence between logbook and electronic monitoring analyst-reported seabird bycatch rates (Larcombe *et al.*, 2016; Emery *et al.*, 2019a, b). In 2016–2018, there were a total of 23, 29 and 26 longline vessels active, respectively, in this sub-fishery.

Results

Fishing effort in the yellowfin tuna sub-fishery

There was high heterogeneity in the effort data for the 34 ETBF vessels operating in the yellowfin tuna sub-fishery during 2016–2018, with *vessel_id 15* setting 216 000 hooks and *vessel_id 6* and *21* just 1000 hooks, for example (Figure 2a). Furthermore, the amount of seabird bycatch varied among vessels with similar effort levels (Figure 2b). For example, *vessel_id 16* and *vessel_id 28* expended a similar amount of effort (160–180 000 hooks) in the yellowfin tuna sub-fishery between 2016 and 2018, but the number of recorded seabirds was different (six and one, respectively) (Figure 2b). Nevertheless, there was a positive linear correlation (Pearson's $r = 0.59$, $p = 0.00028$) between the number of seabirds and the effort for each vessel. This result supports the assumption of proportionality between the amount of seabird bycatch and the amount of effort in the yellowfin tuna sub-fishery of the ETBF.

Assessing seabird bycatch rates in the yellowfin tuna sub-fishery

The mean seabird bycatch rate was 0.019 for the yellowfin tuna sub-fishery (i.e. average pool rate) based on (5), which was used in association with the nominal bycatch rate of the vessel in (6) to generate the standardized bycatch rate for each vessel. The standardized bycatch rate of a vessel with low levels of fishing effort was closer to the average pool rate, while the standardized bycatch rate of a vessel with high levels of fishing effort was closer to their nominal bycatch rate (Figure 3).

The fit of the estimated predictive distribution model to the empirical data was robust (Figure 4). There was a good fit to the data in both the centre and right-hand tails of the distribution, while there was a slight overestimation and underestimation of the zero and one occurrences, respectively, on the left-hand tail of the distribution (Figure 4). The good fit to the upper right-hand tail of the distribution is very important since this has greater consequences for seabird populations if the true bycatch rate of a vessel is relatively high.

It is evident that between 2016 and 2018 the average pool rate (red line in Figure 5) in the yellowfin tuna sub-fishery was below the maximum permissible bycatch rate of 0.05 seabird per 1000 hooks (blue line) recommended in the Australian Seabird TAP (Commonwealth of Australia, 2018) (Figure 5). However, there was a large variation among the 34 individual vessels, with some vessels having high standardized bycatch rates above the TAP

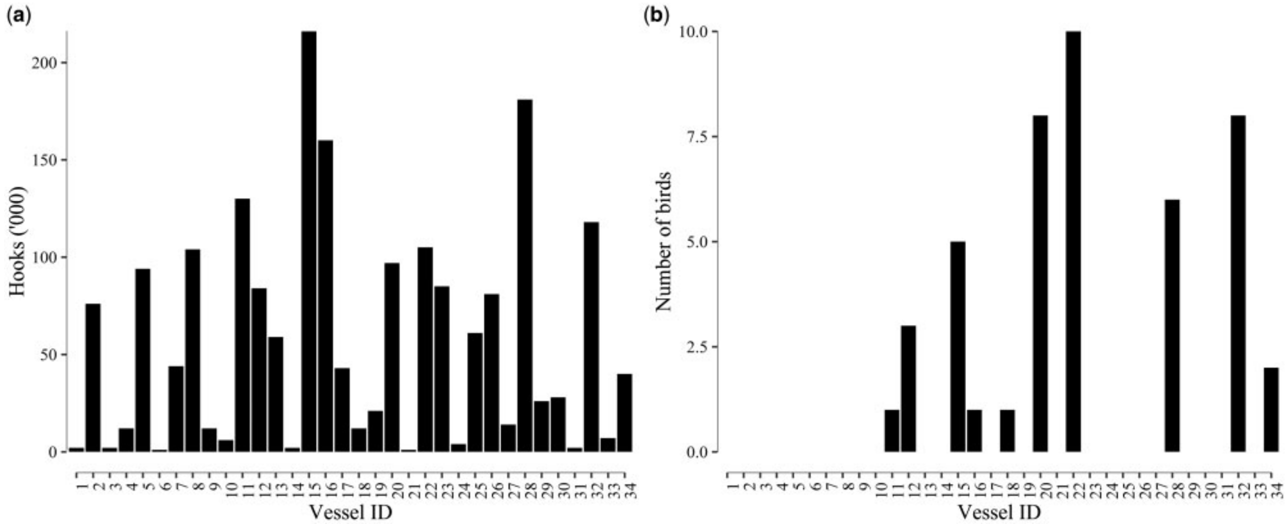

Figure 2. Total fishing effort (a) and amount of seabird bycatch (b) for a total of 34 vessels operating in the yellowfin tuna sub-fishery for the years 2016–2018.

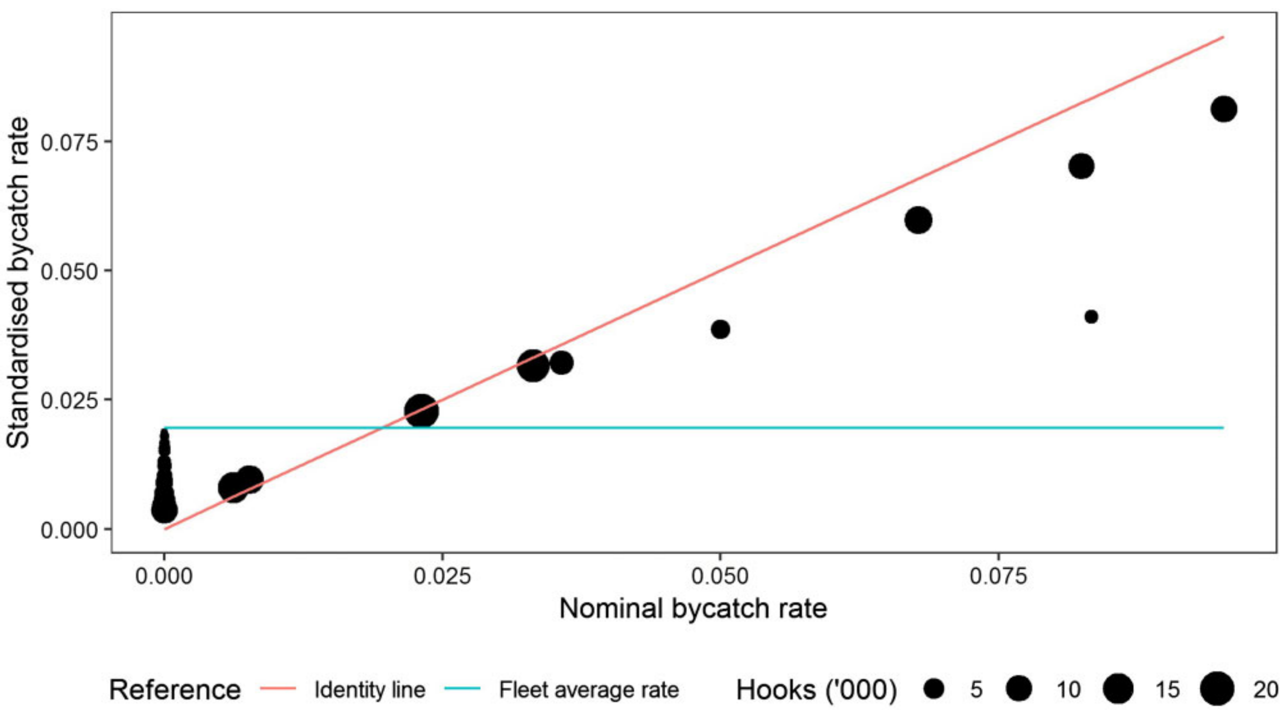

Figure 3. Standardized seabird bycatch rates for all 34 vessels in the yellowfin tuna sub-fishery for the years 2016–2018 plotted against their nominal bycatch rate. The size of each point represents the total effort of each vessel in '000s hooks. The red line is the identity line (1:1), and the blue line is the mean estimated bycatch rate for the fleet (i.e. average pool rate).

(e.g. *vessel_id 20*, *22*, and *32*) and others having lower standardized bycatch rates (e.g. *vessel_id 2, 5* and *8*). The level of uncertainty in the estimated bycatch rates also varied substantially at the individual vessel level (Figure 5).

Discussion

Attaining robust estimates of bycatch rates in fisheries is a significant challenge due to their low (often rare in the case of ETP species) frequency of occurrence, leading to uncertainty in rate estimation, which can be a significant barrier to the development of effective mitigation strategies (Komoroske and Lewison, 2015; Martin *et al.*, 2015; Suuronen and Gilman, 2019). Despite these challenges, fisheries managers are often required to make inferences about bycatch rates to inform their decision-making. This can lead to biased, imprecise estimates when using nominal estimation (dividing the total amount of bycatch by total effort) to determine the rate (Martin *et al.*, 2015). By considering effort heterogeneity among vessels and pooling the data from homogenous vessels (vessels that share comparable fishing behavioural patterns), our model-estimated (standardized) bycatch rate overcomes some of the shortcomings of nominal estimation (Bishop *et al.*, 2008). It also requires minimal data: only the total effort and amount of bycatch for each homogenous vessel within the timeframe of interest. This makes it more accessible to use in data-limited fisheries and easier for decision-makers to update and review regularly. Furthermore, by using Bayesian methods, which are well suited to the analysis of rare-event bycatch data, we can more fully integrate uncertainty, produce less volatile bycatch rate estimates, and enable evaluation of these estimates relative to existing performance measures (Gardner *et al.*, 2008; Martin *et al.*, 2015). We should emphasize that while other factors contribute to the bycatch rate, such as climate, location, food availability, and seasonality (Martin *et al.*, 2015; Cortés *et al.*, 2017), they were not considered in our model to ensure simplicity but could be incorporated as covariates in future modifications of this approach. Moreover, while we used a machine-learning clustering method to pre-determine homogenous vessels within the yellowfin tuna sub-fishery of the ETBF, expert opinion can likewise be used to identify vessels that share comparable fishing behavioural patterns.

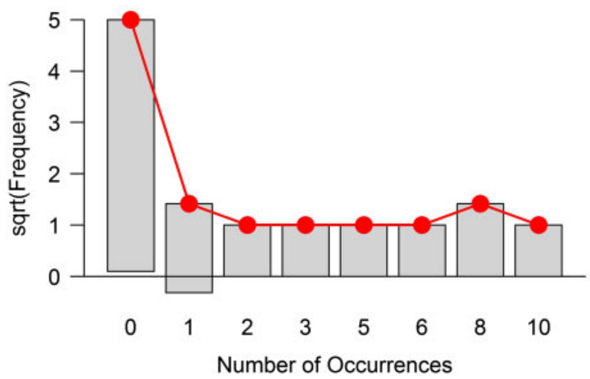

Figure 4. Hanging rootogram of the Poisson–gamma model fitted to seabird bycatch data for all 34 vessels in the yellowfin tuna sub-fishery for the years 2016–2018. The red line shows the expected amount of seabird bycatch estimated by the model, while the observed amount of seabird bycatch is shown as bars hanging from the red lines. The *x*-axis shows bins representing the nominal amount of seabird bycatch, while the *y*-axis shows the square root of the expected or observed amount of seabird bycatch. When the bar does not touch the *x*-axis (e.g. zero occurrences), it means that the amount of bycatch predicted by the model is higher than in the empirical data, while when the bar does touch the *y*-axis (e.g. one occurrence), it means that the amount of bycatch predicted by the model is lower than in the empirical data.

There are several important applications that will benefit from the empirical inference method we have developed. For instance, there is a need to evaluate the performance of individual fishing vessels and fleets against quantifiable targets such as bycatch performance measures or reference points, to inform management decision-making (Grafton *et al.*, 2007; Gjertsen *et al.*, 2010; Kirby and Ward, 2014). Our standardized bycatch rate can be used as a key indicator to measure the performance of an individual vessel/fleet relative to quantifiable targets (while also accounting for uncertainty) to identify outperforming and underperforming vessels for further investigation or corrective action. In our case study, it has allowed fishery managers to compare seabird bycatch rates of individual vessels and the fleet relative to the Australian TAP maximum permissible bycatch rate of 0.05 birds per 1000 hooks and quantitatively measure how individual vessels are performing relative to the fleet average. This can also be updated regularly to ensure responsiveness to changes in the status of bycatch species or reference points.

Our inference method also allows a hierarchy of the homogenous fleet to be developed in a risk management context to

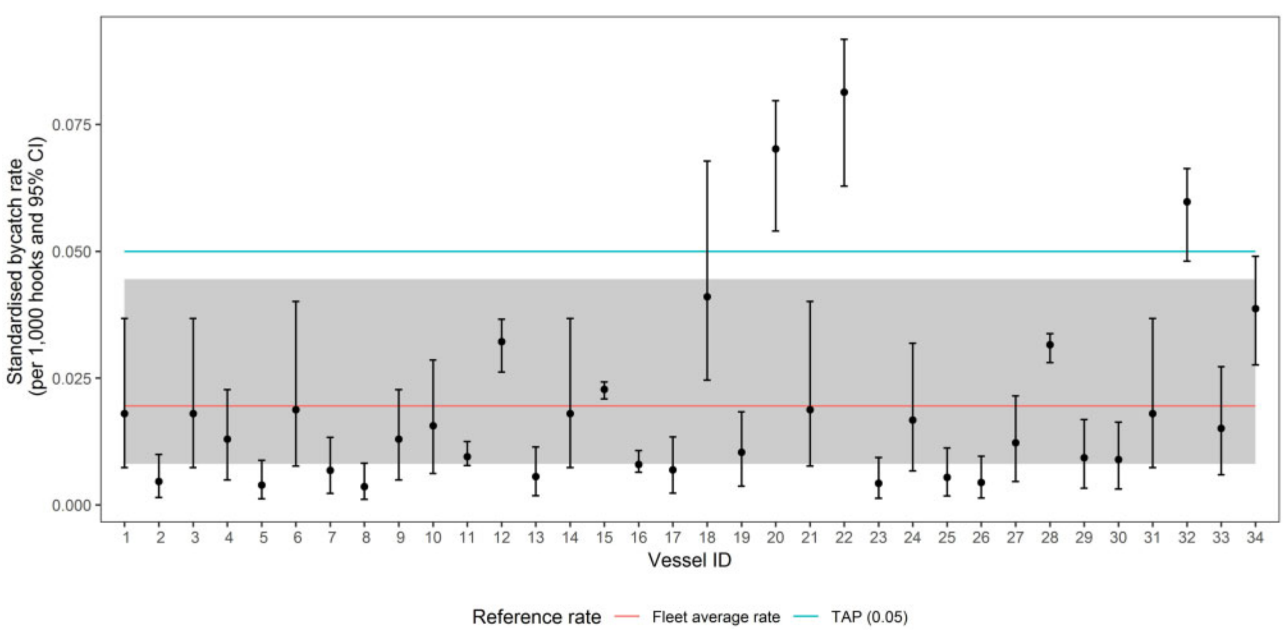

Figure 5. Standardized seabird bycatch rates for the 34 vessels in the yellowfin tuna sub-fishery for the years 2016–2018. The blue line represents the TAP recommended reference point (0.05 seabirds per 1000 hooks), and the red line represents the average pool rate. The grey shaded area represents the confidence interval for the estimated average pool rate.

prioritize resourcing and inform management decision-making. Decision rules can then be formulated based on each level of the hierarchy if considered prudent. We define three hierarchical levels based on the standardized bycatch rates (i.e. risk to seabirds), uncertainty and pre-existing management objectives (e.g. TAP: 0.05 seabirds per 1000 hooks). The "low-risk element" (i.e. those vessels with standardized bycatch rates and confidence intervals below the pre-existing limit reference point) would be considered best practice in the fishery and outperforming vessels, from which further information could be sought to determine their success in deploying mitigation measures and reducing bycatch. The "high-risk element" (i.e. those vessels with standardized bycatch rates and confidence intervals above the pre-existing limit reference point) would be considered poor-performing and prioritized for the investigation to determine what corrective action or mitigation measures are required to improve performance. The "uncertain risk element" (i.e. those vessels standardized bycatch rates above or below the pre-existing limit reference point but with confidence intervals that encompass the pre-existing limit reference point) is prioritized for further analysis to identify if their fishing operations share practices that reflect vessels in the "high-risk element". If similar practices are identified, corrective actions can be implemented. If the analysis remains inconclusive, these vessels may be prioritized for more intensive monitoring to rapidly acquire informative data before any decision could be made about their performance.

In the absence of a pre-defined bycatch performance measure, the standardized bycatch rate of the fleet could contribute to the formation of an appropriate performance measure (e.g. limit reference point) for an individual bycatch species. Conventionally, a limit reference point is defined as the level at which the risk of recruitment impairment is regarded as unacceptably high, or the minimum acceptable level of bycatch at which the measures being adopted are likely to be having the desired conservation effect (Tuck, 2011; Moore *et al.*, 2013; DAWR, 2018). When set as a performance measure (e.g. the Australian TAP for seabirds), it provides guidance on expected levels of performance for industry and provides the means for decision-makers to evaluate and improve bycatch mitigation (Grafton *et al.*, 2007). It also represents a uniform control limit for vessels that will drive adaptation and facilitate the robust assessment of mitigation technologies (Komoroske and Lewison, 2015). In the absence of information to determine population abundance using conventional assessments, this type of analysis can allow different stakeholders or interest groups to discuss appropriate limit reference points, which could be readily adjusted upon application or if new information on population abundance becomes available. Moreover, it can be applied in the context of "continuous improvement" until a limit reference point is defined with the objective of continually lowering the standardized bycatch rate of the fleet.

The ability to use a standardized bycatch rate to measure annually the individual and fleet performance against the limit reference point can create incentives for industry to be more individually accountable of their bycatch. This can be achieved by decision-makers introducing penalties (and/or rewards) for vessels that exceed (or maintain their bycatch below) the limit reference point (Diamond, 2004; Pascoe *et al.*, 2010). These market-based incentives could be in the form of restricting access to certain fishing areas, temporary loss of right of access and/or fines, creating a cost for sub-standard performance that would induce fishers to make choices that reduce bycatch (Diamond, 2004; Pascoe *et al.*, 2010). This is not too dissimilar from the system of dolphin mortality limits established to manage dolphin bycatch in the purse-seine tuna fisheries of the eastern Pacific Ocean managed under the *Agreement on the International Dolphin Conservation Programme* (Anon, 1999; Gjertsen *et al.*, 2010). Under this programme, a total annual limit of 5000 dolphins is set for the fishery in the Agreement Area and an equal share of this limit assigned to each applicable vessel (Anon, 1999). If at any time a vessel exceeds their dolphin mortality limit, they must cease fishing for tuna in association with dolphins, creating an incentive for improved bycatch mitigation. There is also a similar programme for the management of New Zealand sea lion (*Phocarctos hookeri*) mortalities in the New Zealand squid fishery, with a fishing-related mortality limit derived from a Bayesian model (Breen *et al.*, 2003) set annually (Chilvers, 2008). Once the limit is reached within a season, the fishery is then closed, creating an incentive for fishers to reduce their bycatch (Robertson and Chilvers, 2011).

While our standardized bycatch rate cannot be used to measure current population status (initial or current abundance), it can be used to monitor the performance of individual vessels and the fleet relative to the performance measure for an individual species. Of course, this assumes that decision-makers have access to data at a species taxonomic level that can be trusted. Fisher-reported logbook data have often been found to be inaccurate and inconsistent with at-sea observer data from the same trip, due to fishers either misreporting, under-reporting, over reporting, or non-reporting their bycatch (Sampson, 2011; Mangi *et al.*, 2016; Macbeth *et al.*, 2018). While in this case study we used logbook data that have been verified (using an electronic monitoring programme) (Emery *et al.*, 2019a, b), our model is not constrained to fisheries with verifiable logbook data. It can easily be applied to fisheries with unverified logbook data or extrapolated at-sea observer data (assuming coverage is sufficient) but noting the issues and caveats with precision remain the same as if an alternative model was run using that data (Wakefield *et al.*, 2018).

We developed a model to estimate standardized individual vessel and fleet bycatch rates that can be widely applied, is simple and accessible for fisheries with limited data, can deal with uncertainty in rate estimation, and can be easily interpreted in a risk context. Risk-based approaches or frameworks are useful for decision-makers to prioritize scarce resources (both in terms of further investigation or corrective action). Our model can also be readily updated to determine whether a vessel's bycatch rate changes over time or following intervention and has the potential to include additional information such as location and seasonality as covariates. Lastly, this approach could be tailored to each bycatch issue or situation and combined with additional risk-based models, such as fisheries compliance risk assessments (e.g. AFMA, 2017), to provide a more comprehensive risk framework for the fishery.

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