How Observation Coverage Shapes Bycatch Metrics in the Tropical Tuna Purse Seine Fishery

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Abstract

Keywords

bycatch, pelagic species, spatiotemporal models, purse seine fleet, tunas

1 Introduction

Purse seine fishing is a technique that targets and catch entire fish schools in the surface by encircling them with a fishing net called "seine". In the tropical oceans, purse seine is employed to target tropical tunas such as skipjack (*Katsuwonus pelamis*), yellowfin (*Thunnus albacares*), and bigeye (*Thunnus obesus*). In addition to target species, tropical tuna fisheries catch non-target species collectively referred to as bycatch, which can be discarded at sea, retained to be sold on local markets, or consumed on board (Hall et al., 2017). The ratio of bycatch to target tuna catch in the purse seine fleet is considered relatively low in comparison to other fishing gears, such as longlines, that can result in substantial levels of bycatch (Amandè et al., 2010; Liu et al., 2008; Peatman et al., 2023). However, the impact on pelagic populations and ecosystems may be important, especially for vulnerable long-lived species with low reproductive rates (Dulvy et al., 2014). Therefore, it is essential to conduct studies on bycatch rates and their variability over space and time; however, they are often complicated by a lack of bycatch data recorded in fisheries logbooks, taxonomic identification of bycatch species, among other factors.

One of the most reliable sources of information to quantify the amount of bycatch is the use of on-board trained scientific data collectors (a.k.a. observers). When designing an observer sampling program, the level of coverage required will depend on the objectives of the observer program, which might vary from estimating bycatch of protected species, to improving bycatch and catch data for assessment of fish populations, to collecting biological data. In some cases, it may be necessary to have an exact count of the total incidental mortality of bycatch species, especially threatened or endangered species, so a 100% observer coverage may be needed. However, in most cases, a level of 100% observer coverage is not attainable, then the coverage level chosen must ensure that the total bycatch estimate is sufficiently accurate and precise. Then, assuming these observed units are representative of unobserved activity, design-based (e.g., ratio estimators, Cochran (1977)) or model-based (e.g., generalized linear models, Coelho et al. (2020)) approaches can be used to expand the observed bycatch to the remainder of the fishery. One of the main features of ratio estimators is that they do not incorporate a formal underlying statistical model (i.e. are free of any assumptions regarding data structure), and therefore are broadly used in fisheries worldwide, including tuna purse seine fisheries (Amandè et al., 2012; Amandè et al., 2010).

Despite their widespread use, there are a number of potential issues in applying ratio estimators to estimate bycatch. First, using observed catches of target species or any other measure of effort implicitly makes an assumption about a linear relationship between non-target and target catches (Amandè et al., 2012; Fonteneau and Richard, 2003). This may be unrealistic since the distribution of catches of non-target species is often zero-inflated or has a small number of observations containing extremely high values (Ortiz and Arocha, 2004), and the liner relationship may not hold (Stock et al., 2019). Second, the boundaries of strata used in a ratio estimator can be somewhat arbitrary whenever poststratified boundaries are used. For instance, Amandè et al. (2010) defined strata in the Atlantic Ocean based on ecological features for estimating bycatch of the tuna EU purse seine fishery, which may not be adequate for all bycatch species. Third, for rare-event bycatch species, it is common for zero bycatch events to be observed in a given year (ratio estimator is equal to 0), and when bycatch events are observed, the ratio estimator often delivers implausibly high estimates. Lastly, a final and related point is that within each stratum, bycatch rates are assumed to be uniform, while in reality they may vary by season, depth, or other factors.

Spatiotemporal models are increasingly adopted in multiple fisheries applications (Ducharme-Barth et al., 2022; Grüss et al., 2023; Thorson, 2019), including undertaking bycatch analyses (e.g., Yan et al. (2022)). These models can provide detailed predictions for any location based on spatial autocorrelation in the observations. However, they are also complicated and require more data to generate robust predictions, which make it unsuitable for data-poor fisheries. In the majority of cases, spatially explicit model-based estimators have increased precision relative to simpler estimators that assign observations to strata (Thorson et al., 2015; Thorson and Ward, 2013). There are a number of additional advantages of spatial models, including the ability to better quantify shifts in distribution (Thorson et al., 2016) and improved ability to identify fine-scale hotspots of high bycatch (Cosandey-Godin et al., 2015). For tuna fisheries, spatiotemporal models like generalized additive models (GAMs) have recently been used to obtain annual estimates of the most important bycatch species (Dumont et al., 2024; Peatman et al., 2023).

In this study, we implemented a simulation experiment to evaluate the impacts of different levels of sampling coverage on the annual bycatch estimates derived from design-based and model-based estimators. Our hypothesis is that model-based estimators may provide more accurate bycatch estimates under low sampling coverage scenarios. We used data from the Spanish purse seine tuna fishery operating in the Atlantic Ocean as study case. We performed our analyses differentiating by set type: operating on free schools (FSC) or floating objects (FOB), since they have different bycatch dynamics (Peatman et al., 2023). Our simulation experiment may be extended to other fisheries with fine-scale bycatch information and support the implementation of sampling programmes across tuna RFMOs.

2 Methods

In the following sections, we describe the data used in our analyses, the design and model-based estimators, and the simulation framework.

2.1 Data

We used two data sources in our study: observers and effort data.

Observers data: cover the activity of Spanish purse seiners sourced from different public scientific programmes, notably the Data Collection Framework, as well as the activity of vessels from different nations registered with OPAGAC-AGAC under flag states, coastal states or the Code of Good Practices observer programme in the tropical Atlantic Ocean between the 2015 and 2023. The observer programmes referred to above collect various types of information, including details on fishing activities, such as the location of fishing sets, the type of set or the fishing mode (FSC or FOB); the amount of target catch and bycatch that is retained and discarded by species, and the condition at release of the fish that are discarded. Observers identify specimens at the lowest possible taxonomic level, which is generally the species level.

Effort data: describe

2.2 Species composition standardization

Describe

2.3 Model fitting

We use the *sdmTMB* geostatistical spatiotemporal model (Anderson et al., 2024) to fit taxon-specific bycatch per set (in weight) in the observers data. Geostatistical spatiotemporal models have become widely used in fisheries over the last decade (Anderson et al., 2024; Thorson, 2019), and are used when georeferenced data (e.g. each has a corresponding latitude and longitude) with an underlying spatial process is available. *sdmTMB* is written in Template Model Builder (TMB, Kristensen et al. (2016)) and R (Team, 2025) for a friendly user interface, and can be viewed as an extension of generalized linear mixed models (GLMMs), but with additional spatial and spatiotemporal components, which are approximated as random effects.

Mathematically, the model structure can be expressed as:

$$u_{s=1:S,t} = f^{-1}(Xb + \omega + \epsilon_t)$$

where˘ represents the bycatch predictions at locations $s = 1 : S$ for a given year t, $f^{-1}()$ is the inverse link function, X represents the design matrix of fixed effects, b is the vector of estimated parameters, ω are the estimated latent spatial effects, and ϵ_t represents year-to-year latent spatiotemporal effects. ω represents a spatial intercept that is constant with time while ϵ_t represents spatial deviations over time, and both are modelled as Gaussian random fields (GRFs):

$$\omega \sim MVN(0, \Sigma_\omega)$$
$$\epsilon \sim MVN(0, \Sigma_\epsilon)$$

where MVN is the multivariate normal distribution, and the covariance matrix Σ is modelled with Matérn covariance (Lindgren et al., 2011; Matérn, 1986), which defines the rate at which spatial covariance decays with distance.

We used the Tweedie distribution $Tweedie(\mu, \phi^2, p)$, where $1 < p < 2$, and a log link function (Tweedie, 1984). For fixed effects, we incorporated the year and quarter effects as factors, and the target tuna catch (the sum of skipjack, yellowfin, and bigeye tunas) as a continuous covariate.

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4 Tables