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Estimating harvest and its uncertainty in heterogeneous recreational fisheries

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ABSTRACT

Although some stocks are being severely exploited by recreational fishing, estimating the biomass extracted (harvest, *H*) by recreational fisheries is difficult, especially for marine recreational fisheries. One way to estimate *H* by recreational fisheries is to combine the fishing effort (*E*) with catch-per-unit-of-effort (*CPUE*) data. However, naively ignoring heterogeneity in *E* and *CPUE* may result in biased and imprecise estimates of *H*. We propose a framework to address three relevant heterogeneity levels: the spatial and temporal heterogeneity of recreational *E*, environmental effects on recreational *CPUE*, and the variability in angler skills (between-angler heterogeneity). Specifically, we combine (i) space-time model predictions of *E* (number of boats per km^2) on the day scale (i.e., fishing trips), (ii) environmentally driven model predictions of daily catch (number of squid per fishing trip), and (iii) off- and on-site surveys to account for angler heterogeneity. The precision of the *H* estimates was assessed using bootstrap confidence intervals. This framework was applied to the recreational fishery for the squid *Loligo vulgaris* at Palma Bay (Mallorca Island, western Mediterranean). The estimated effort was 15,750 angler-fishing trips (95% CI: 13,086 to 18,569), which yielded an annual harvest of 20.6 tons (95% CI: 16.9–24.5). This harvest was estimated to represent 34% of the total commercial landings in Mallorca, which highlights the importance of recreational harvesting and the need to account for recreational fisheries to improve squid stock management. The framework proposed here provides a promising tool for estimating *H* in other heterogeneous recreational fisheries and may be the first step toward assessing the actual impact of recreational fisheries on squid populations.

1. Introduction

The amount of biomass captured by fisheries is a key parameter in estimating exploitation rates and is important for predicting and managing exploited stocks (Hilborn and Walters, 1992; Hsieh et al., 2006; Anderson et al., 2008; Neubauer et al., 2013). However, this remains elusive for many marine recreational fisheries (Arlinghaus et al., 2015). This is especially evident in the Mediterranean Sea, where monitoring and assessment of the catch by recreational fisheries are rarely conducted (Font and Lloret, 2014). Typically, only the harvests of commercial fleets are accounted for, with those of recreational fisheries being neglected (Cooke and Cowx, 2004). However, growing evidence suggests that recreational fisheries may play important roles in the declines of some exploited stocks (Coleman et al., 2004; Cooke and Cowx, 2004). Disregarding this component of mortality may result in overoptimistic views of the status of such stocks and promote management options that lead to overfishing (Post et al., 2002). Providing accurate and precise harvest estimates is therefore a pivotal issue when addressing the management of recreational fishing, which should be aimed at ensuring the sustainable exploitation of marine resources (Steffe et al., 2008; Hartill et al., 2012).

The recreational fishing harvest (*H*) could be easily estimated by the product of effort (*E*) and catch-per-unit-of-effort (*CPUE*). However, these two variables are typically spatially and/or temporally structured and are subject to different sources of variability, which makes the estimation of the harvest attributable to recreational fishing a major challenge. The heterogeneity and uncertainty of *E* for recreational fisheries are related to variability due to the large number of anglers in comparison with the relatively low number of

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commercial fishermen (Cooke and Cowx, 2004). In addition, commercial fishermen are typically subject to mandatory surveys (e.g., vessel monitoring systems or automatic identification systems) that may provide information regarding the spatial and temporal distributions of fishing effort (Mills et al., 2007; Gerritsen and Lordan, 2011; McCauley et al., 2016). Such data have improved knowledge of the spatial dimensions of some fisheries and have contributed to better estimates of management reference points (e.g., maximum sustainable yield) that are needed for proper stock management (Beare et al., 2005; Cotter and Pilling, 2007; Mesnil et al., 2009).

Unfortunately, spatial monitoring occurs in almost no recreational fisheries. Moreover, among those studies that consider the spatial dimension of effort, most focus on lake landscapes (Hunt et al., 2011; Post et al., 2012) and few address marine open water (Parnell et al., 2010; Alós et al., 2012; Fujitani et al., 2012; Hartill et al., 2016). Consequently, some recreational fishery collapses have been related to incorrect assumptions about the spatial distribution of fishers (Post et al., 2008).

Similar to the case for *E*, the reporting of *CPUE* is mandatory for most commercial fleets. However, for recreational fleets, obtaining catch data is even more challenging than obtaining effort data. Full censuses of all anglers are often unavailable (McCluskey and Lewison, 2008); however, the number of recreational anglers is often orders of magnitude greater than the number of commercial fishermen (Cooke and Cowx, 2004; Arlinghaus et al., 2015). Moreover, they are less accessible and more heterogeneous (Arlinghaus et al., 2013). There are many sources of heterogeneity in *CPUE* (e.g., differences attributable to fishing trip, access point, zone, fishing modality, angler expertise, angler motivation, etc.), which may result in large biases (Pollock et al., 1994, 1997; Hunt, 2005; National Research Council, 2006; McCluskey and Lewison, 2008). Creel surveys might provide reliable information about both *E* and *CPUE*, which can be combined to estimate *H* (Pollock et al., 1994; Hartill et al., 2012), but complex, stratified sampling designs are needed (Pollock et al., 1994, 1997; Griffiths et al., 2013; Rocklin et al., 2014), and proper error propagation (needed for estimating precision) requires sophisticated statistical methods (Lockwood, 1997; McCormick et al., 2013). Moreover, it is widely recognized that recreational *CPUE* can vary substantially as a function of environmental characteristics (e.g., Ortega-Garcia et al., 2008; Kuparinen et al., 2010; Cabanellas-Reboredo et al., 2012a).

We propose an alternative framework to address the spatial and temporal variability in *E* and the environmentally driven variability in *CPUE*. Moreover, we consider between-angler heterogeneity by categorizing the anglers into types, and propose a bootstrap-based framework for combining these three sources of uncertainty. This framework was applied to the recreational fishery for the European squid *Loligo vulgaris* Lamarck (1798). Specifically, the proposed framework combines (i) model-based estimates of *E* (varying in space and time; Cabanellas-Reboredo et al., 2014a,b), (ii) model-based estimates of *CPUE* (varying in time; Cabanellas-Reboredo et al., 2012a) and (iii) between-angler differences to estimate *H* for a given year.

2. Materials and methods

2.1. Case study and sampling units

The analytical strategy we propose is aimed at estimating *H* as a function of *E* and *CPUE* in spatially and temporally structured marine recreational fisheries while accounting for different sources of uncertainty and evaluating the effect of angler heterogeneity in *CPUE* in relation to angler skills. We applied this strategy to the recreational fishery for squid at Palma Bay (Mallorca Island, NW Mediterranean; Fig. 1) and used 2010 as the model year. A detailed description of this recreational fishery is provided by Cabanellas-Reboredo et al. (2014b).

The study region was divided into spatial units of 1 km^2, and the temporal unit was day (fishing trips). Such a space-time scale results from a trade-off between maximizing the spatial-temporal resolution when predicting *E* and CPUE and minimizing the problems related to between-unit dependencies (i.e., avoiding spatial and temporal autocorrelation; Cabanellas-Reboredo et al., 2012a, 2014a,b; Fig. 1). Consequently, Palma Bay was divided into 173 cells (Cabanellas-Reboredo et al., 2014a,b), which resulted in a total of 63,145 units (i.e., 173 cells multiplied by 365 days in a year).

2.2. Harvest estimation ignoring angler heterogeneity

2.2.1. Bootstrapping fishing effort (E)

All of the bootstrapping procedures described in Sections 2.2 and 2.3 were compiled into a single, custom script (Supplementary material) using R (http://www.r-project.org/). E_{ij} (i.e., the number of anglers on day *i* in cell *j*) was estimated from the number of boats fishing in a given cell:

$$E_{ij} = \sum_{b=1}^{B_{ij}} F_{ijb}, \tag{1}$$

where B_{ij} is the predicted number of boats (*B*) on day *i* in cell *j*, and F_{ijb} is the number of anglers on each boat (*b*) at a given day (*i*) and cell (*j*). Model-based estimates of B_{ij} were obtained from the Bayesian space- and time-explicit model described by Cabanellas-Reboredo et al. (2014a). This model was fitted to the data (i.e., the number of boats per cell) obtained from 63 visual censuses covering the full area considered (Palma Bay) to obtain the positions of any recreational squid boats (Cabanellas-Reboredo et al., 2014a,b; Fig. 1). This spatially- and temporally-explicit model allowed the expected number of boats in any cell on any day during the model year (2010) to be estimated. The explanatory variables of the model are aimed at relating *E* to the main motivations of anglers (fishing quality, costs, facility development, environmental quality, interactions among anglers, and regulations; Hunt, 2005).

To obtain not only point estimates but also reliable confidence intervals (CI) for each value of B_{ij}, we produced *N* random bootstrap samples (*N* = 1000), taking into account not only the uncertainty in the model parameters but also the three levels of stochastic variation considered in the model (cell, day and unstructured residual variation; Cabanellas-Reboredo et al., 2014a,b). In this approach, a given bootstrap sample results from combining the same random sample from each of the posterior distributions of the model parameters (i.e., accounting for the correlation patterns between such parameters) with a given combination of values for the corresponding explanatory variables (i.e., the specific values of the variables corresponding to day *i* and cell *j*) plus a random sample of each of the three stochastic error levels mentioned above. Thus, *N* bootstrap samples for the expected number of boats were produced for each of the statistical units (173 cells multiplied by 365 days).

We next addressed the number of anglers. The number of anglers per boat (F_b) from the 1,271 boats surveyed in the 63 censuses was available (Cabanellas-Reboredo et al., 2014a,b). Therefore, we first explored the existence of between-season differences in F_b by fitting the observed data to a positive Poisson model (implemented with the *vglm* function of the *VGAM* package; Yee, 2015). The significance of the results was tested using a likelihood ratio test against the null model (i.e., a model ignoring season). Accordingly, *N* bootstrap samples from the empirical data (i.e., the observed distribution of F_b) corresponding to day *i* (i.e.,