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1	Estimation of the spawning stock and recruitment
2	relationship of $Octopus \ vulgaris$ in Asturias (Bay of
3	Biscay) with generalized depletion models:
4	implications for the applicability of MSY
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34	Abstract
35	We developed a new type of generalized depletion model adapted to the rapid life
36	cycle of Octopus vulgaris and the data collection framework put in place in its co-
37	managed small-scale fishery (SSF) in Asturias, northwest Spain. The model uses
38	weekly data from 19 seasons to estimate annual recruitment and female spawners
39	emigration out of the vulnerable stock to attend to their broods. The matched
40	annual spawners-recruitment (SR) magnitudes are then used as observations in a
41	non-Bayesian hierarchical inference framework. The Shepherd SR model was se-
42	lected among three alternatives. The stock has a high degree of density-dependence,
43	leading to overcompensation. The estimated SR model has an unstable equilib-
44	rium point, driving the stock to deterministic cyclic fluctuations under small dis-
45	turbances. Under those conditions the maximum sustainable yield (MSY) is not
46	applicable, lending further credence to Sidney Holt's opposition to the MSY as a
47	basis for the elaboration of fishery management objectives, with potentially wide
48	relevance to the management of SSF and cephalopod fisheries. We argue that har-
49	vest rates based on mean latent productivity, a concept that includes the MSY as
50	a special case, are more adequate and sustainable for fluctuating stocks.
51	Keywords: stock-recruitment; cephalopod fisheries; small-scale fisheries; hierarchical models;
52	Asturias

⁵³ 1 Introduction

Holt (2020) summarized his opposition to maximum sustainable yield (MSY) as an ex-54 cessive target yield for fisheries mainly on the grounds of cost-benefit considerations for 55 fishers as economic agents, while also pointing out other benefits of a lower target yield 56 including less need for government subsidies, less by-catch and less harm to ecosystems 57 (Holt and Raicevich, 2018). He further doubted that stocks would produce a constant 58 surplus even at constant abundance because of changes in biological rates (Holt, 2011). 59 Related research in mathematical ecology shows that even stable biological rates under 60 constant environments may lead to widely varying abundance under certain conditions 61

(May, 1975). The MSY is the constant surplus that occurs when the stock is at the size 62 that maximizes the population growth rate. Fishing that removes the MSY would main-63 tain the stock stable at that level of abundance. Many large stocks may behave so because 64 of demographic inertia creating continuity, especially when they have several cohorts in 65 the age structure. Semelparous populations though, with their weakly-overlapping gener-66 ations, may behave differently because these populations approximate discrete dynamic 67 nonlinear systems. These may exhibit rich dynamics ranging from stable equilibrium 68 points, to which the MSY concept applies, to cyclic oscillations and chaotic regimes 69 (May, 1975), where the MSY does not apply because the population growth rate, and 70 therefore the yield, are not constant, fluctuating with oscillations in abundance. 71

MSY as a target yield or as a generator of reference points or proxies is commonly 72 invoked in the management of cephalopod stocks (Quetglas et al., 2015; Ren and Liu, 73 2020; Sauer et al., 2019; Roa-Ureta et al., 2020; Wang et al., 2020) and small-scale fisheries 74 (SSF) (Giron-Nava et al., 2018; Pomeroy et al., 2009; Gough et al., 2020; Roa-Ureta et al., 75 2020), although there is general scarcity of stock assessment studies in both cephalopods 76 (Quetglas et al., 2015) and SSF (Lleonart and Maynou, 2003) relative to fish and large-77 scale fisheries. Cephalopod fisheries and SSF present special challenges to management 78 and stock assessment because of life history traits, data-poor condition, large number 79 of small operators, diverse social and geographic attributes and multiple small stocks 80 (Berkes et al., 2001; Berkes, 2003; Hilborn and Hilborn, 2012; Maravelias et al., 2018). A 81 recent review of cephalopod stock assessment and management (Arkhipkin et al., 2020) 82 recommended innovative depletion models running at rapid time steps because these can 83 handle rapid life histories, short lifespans, and single-cohort population compositions, all 84 important aspects of cephalopod biology. Depletion models are also less data-demanding 85 because they do not require samples of the biological composition or fishery-independent 86 data and so are useful for small-scale data-poor fisheries (Roa-Ureta, 2015; Roa-Ureta et 87 al., 2015, 2019, 2020). 88

The octopus fishery in Asturias is an SSF that has been managed through a participa-89 tory, co-management approach since 2001 (Fernández-Rueda and García-Flórez, 2007). 90 This is a form of governance incorporating local community participation (Basurto *et al.*, 91 2017; FAO, 2015; Courtney et al., 2020; Roa-Ureta et al., 2020). In Asturias, the result-92 ing management framework was adapted to the fishers' needs, leading to an orderly and 93 agreed upon system of operation and data collection. In 2016, this fishery became the 94 first octopus fishery certified by the Marine Stewardship Council (MSC), which led to in-95 creased fishers income (Fernández Sánchez et al., 2020). However, its certification status 96 was conditional on completing studies of octopus abundance, productivity and exploita-97 tion status for the implementation of harvest control rules, since these were not available 98 at the time of certification. One aspect of the participatory approach was comprehen-99 sive sharing of fishing operational data at the finest time resolution by fishers as willing 100

participators in co-management. These high temporal resolution data offer a source of 101 information on stock status that depletion models can harvest efficiently, offsetting the 102 lack of biological composition and fishing-independent data typical of data-poor and data-103 limited SSF to a certain extent. In addition to sharing data, management determined a 104 season of operation that included both a recruitment pulse and the brooding emigration 105 of female spawners (Fernández-Rueda and García-Flórez, 2007). Some versions of gen-106 eralized depletion models, those applied to eel elver fisheries, include immigration and 107 emigration pulses (Lin et al., 2017; Lin and Tzeng, 2018; Lin and Jessop, 2020). Thus the 108 fishery for octopus in Asturias provides an opportunity to develop new depletion models 109 that estimate both recruitment and female spawners abundance. 110

The spawning abundance and recruitment (SR) relationship is a cornerstone of marine 111 population dynamics and stock assessment. In semelparous species such as O. vulgaris, 112 the SR relationship plays a conceptually analogous role to surplus production models, 113 with production of recruits replacing productivity and spawners' abundance replacing 114 biomass (Quinn and Deriso, 1999, p. 122). From an SR relationship, MSY (in numbers) 115 occurs at the maximum vertical distance between the replacement line and the SR curve 116 (Quinn and Deriso, 1999, Fig. 3.19). Unfortunately, in addition to the difficulty in deter-117 mining the SR relationship for stock assessment in general (Hilborn and Walters, 1992, 118 p. 241) cephalopods in particular have weak SR relationships and are strongly impacted 119 by environmental conditions (Arkhipkin et al., 2020). Agnew et al. (2000) observed evi-120 dence of density-dependence in the SR relationship of the Patagonian squid fished in the 121 Falkland Islands though a re-analysis with different estimates for the same stock obtained 122 a noisy linear trend instead (Roa-Ureta, 2012). Otero et al. (2008) provided indirect ev-123 idence for density-dependent effects in O. vulgaris inhabiting the northern boundary of 124 the Canary-Iberian upwelling system. Here we use the results of the new depletion models 125 fitted to 19 seasons of the O. vulgaris SSF in Asturias to estimate the SR relationship, 126 providing direct evidence of substantial density-dependence. 127

These findings have implications for the use of the MSY as a reference point for 128 sustainable fishing rates in cephalopod fisheries and SSF more generally. In ICES (2020, 129 section 2.3) we proposed the mean latent productivity, a concept that includes the MSY 130 as a special case, as a more adequate reference point for determining harvest rates from 131 the O. vulgaris stock in Asturias. Here we discuss these implications in the context 132 of Sidney Holt's long-held opposition to the MSY, suggesting a further reason why the 133 MSY may not be adequate in general: many stocks may tend to undergo deterministic 134 fluctuations under fishing removals. 135

¹³⁶ 2 Materials and Methods

¹³⁷ 2.1 The fishery and data collection

A description of the co-management system, in place since 2000-2001, and results of 138 biological analyses, are presented in Fernández-Rueda and García-Flórez (2007). The 139 most important management measures during this period are: limiting entry to licensed 140 boats from any of eight legally-recognized fishers' associations, seasonal closures, gear 141 and boat regulations, minimum landing octopus weight, and a maximum catch per boat-142 season. This SSF is a single-species fishery operated by a varying number of authorized 143 boats, currently around 40. Fishing is conducted with baited traps during a season 144 that since 2004-2005 extends between December and July, and previously it started in 145 November (2004-2005), January (2003, 2004) or December and ended in May (2004-146 2005), August (2000-2001, 2001-2002) or July. Most boats operate with 2 fishers (65%) 147 of all fishing trips as average over the last three seasons) though some had a single fisher 148 (9%) and others carry three fishers (25%). On any given fishing trip, a maximum of 149 125 traps are lifted per fisher in 1-fisher and 2-fishers boats while a total maximum of 150 350 lifts per boat applies to boats with three fishers. These traps usually stay at sea, 151 are lifted in the morning of a fishing day, and in good days fishers may lift the traps a 152 second time. For these fishers, good days are days with good catch and good weather, 153 since weather is a major factor for small boats. The total area of operation covers the 154 western half of the coast of Asturias and has been estimated in the range of 228 to 397 155 km², with the lower bound coming from geographic data of radio-tagged boats and the 156 upper bound from the total area between the coast line and the 50 m isobath. This 157 area is divided into dozens of fishing grounds with varying extension, located between 158 the coastline and 50-m depth isobath in south-western Bay of Biscay (Fig. 1). Although 159 the magnitude of by-catch by other fleets has not been evaluated, sales data that can 160 be traced to specific boats reveal that boats operating with gears other than the traps 161 land very little octopus. A minimum landing weight of 1 kg per individual octopus has 162 also been agreed upon in the co-management system regulations. When traps capture 163 smaller octopuses they are returned to sea alive and in good conditions, as witnessed by 164 scientific observers. In other trap fisheries, discarded octopus have also been observed 165 returning to sea in good condition (Conners and Levine, 2016; Conrath and Sisson, 2018). 166 Furthermore, the biological sampling program yielding weight data supports the notion 167 that fishers are in general complying with the minimum landing weight regulation (Fig. 168 2) although under-sized octopus in the landings have been observed occasionally. 169

During the period of co-management (2000-2001 to 2018-2019), the data collection system included a census of daily catch in weight and fishing effort measured as the number of boats operating on any single day. The number of fishers per boat has just

become available in the last three fishing seasons so we could not use the number of fishers 173 or number of trap lifts per day as fishing effort. In addition to these census data, biological 174 samples are taken on some days of the season. For the purposes of this work, biological 175 samples provide data of mean individual weight in the catch to transform catch in weight 176 to catch in numbers. Considering the extension of the season (normally 7 months) and 177 the sparsity of biological sampling, we grouped the raw data into weekly time steps to fit 178 intra-annual generalized depletion models to each season's data. Fishing effort was the 179 total number of fishing days by all boats operating in any given week. The complete raw 180 data available for modelling are shown in Fig. 2. During the first few years (2000-2001 181 to 2007-2008), total annual landings averaged 180 tons and total annual effort normally 182 exceeded 3000 days of fishing, but later (2008-2009 to 2018-2019) landings decreased, 183 averaging 102 tons, and effort decreased as well to less than 2000 days (Supplementary 184 Fig. SM1). 185

¹⁸⁶ 2.2 Weekly mean weight model

One important shortcoming of the data was that the biological sampling of mean weight 187 did not occur in all weeks of the 19 seasons and yet individual weight data are necessary 188 to transform from catch in weight to catch in numbers in all weeks (Supplementary Table 189 SM1). As in previous cases with missing biological sampling (Roa-Ureta, 2015; Roa-Ureta 190 et al., 2019, 2020) the missing mean individual weight was replaced with predictions from 191 an accessory model fit with the available data. First, we fitted a simple model of mean 192 weight change through the weeks of the year with a cubic spline smoother, function 193 loess in R 3.6.1 (R Core Team, 2019). Little inter-annual variability was observed in 194 the seasonal pattern of the mean individual weight (Fig. 2) and this pattern was similar 195 to results presented in Fernández-Rueda and García-Flórez (2007). Thus we used the 196 pooled data from all 19 seasons to estimate the weekly mean weight model (n=275). 197 In the fit of this accessory model we created a predictor variable spanning the range of 198 week numbers in a year (1 to 53), then we used the data to fit the smoother with a span 199 parameter equal to 1 (equivalent to using the data from all weeks to predict the model 200 at each week), and finally to predict the expected mean weight and its standard error for 201 all weeks within a season (Supplementary Fig. SM2). Secondly, we predicted the mean 202 weight for each week in each season from a truncated normal distribution defined by the 203 predicted weekly mean weight ± 2 standard errors using R package Runuran (Leydold 204 and Hörmann, 2019) (Supplementary Fig. SM2). In this manner we obtained a complete 205 vector of mean weight matching the catch and effort data while introducing noise due to 206 sampling variation in the biological data. 207

²⁰⁸ 2.3 Generalized depletion model with spawning emigration

During the fishing season, two main events occur in the fishing dynamics of the Asturian 209 octopus that affect the stock abundance that is vulnerable to fishers. Firstly, a cohort of 210 young octopuses experiencing rapid growth become vulnerable to fishing by reaching the 211 minimum size (1 kg) that the fishers can retain. This is a recruitment pulse, i.e. a positive 212 pulse of abundance. Secondly, at a later time, females that have mated and spawned 213 become no longer vulnerable to fishing because they stop searching for food to spend 214 all their time caring for their eggs in dens (Garci et al., 2015). Although traps continue 215 to be deployed in areas where spawning females are searching for dens, these females 216 almost never lay their eggs in traps because they are unstable, being hauled every day 217 by fishers. Some other traps that remain at sea untouched for longer times occasionally 218 catch females with eggs, but this type of gear is not used in Asturias. Therefore, from the 219 point of view of the fishing dynamics, female spawners constitute emigration, a negative 220 pulse of abundance whose magnitude is the size of the female spawning stock. This latter 221 negative pulse is apparent in Fernández-Rueda and García-Flórez (2007, Tables 1, 2), 222 who showed a decreasing proportion of females in the catch and an increasing proportion 223 of sexually mature females towards the end of the season... 224

Given these specific features, we developed a new generalized depletion model to fit 225 to the data from each fishing season separately. It includes immigration and emigration 226 like a previous model developed for the glass eel fishery of Taiwanese estuaries (Lin et al., 227 2017) but differs in an important aspect. In the case of the glass eel fishery, all surviving 228 immigrants from any pulse of recruitment leave the estuary at the time of emigration 229 (they are in transit), and therefore the magnitude of each emigration pulse is completely 230 predetermined by other parameters or data in the model. Conversely, in the present 231 case the magnitude of the emigration pulse is not predetermined because it involves an 232 unknown fraction of the stock, the mated female fraction. Thus, in the Asturian octopus 233 SSF the magnitude of the emigration pulse is a new free parameter in the model to be 234 estimated from the data. 235

Given those features, in any fishing season the total catch at week t can be modelled as

$$C_{t} = kE_{t}^{\alpha}N_{t}^{\beta} = kE_{t}^{\alpha}mf_{t}(M, N_{0}, C_{i < t}, R, S)$$

$$= kE_{t}^{\alpha}m\left(N_{0}e^{-Mt} - m\left[\sum_{i=1}^{i=t-1}C_{i,i}e^{-M(t-i-1)}\right] + \sum_{j=1}^{j=u}I_{j}R_{j}e^{-M(t-\tau_{j})} - \sum_{l=1}^{l=v}J_{l}S_{l}e^{-M(t-\nu_{l})}\right)^{\beta}$$
(1)

where m = exp(-M/2) is an adjustment that makes all catch happen instantaneously at mid-week. All variables and parameters in this model are described in Table 1. Essen-

tially, this model says that the expected catch on any week of the season is determined by 240 a proportionality constant (the scaling k) and two predictor variables, the fishing effort 241 E, which is observed exactly, and the stock abundance N, which is latent. Both predictors 242 are modulated by power parameters that measure non-linear effects, the effort response α 243 and the abundance response β . These are the continuum from effort saturation ($\alpha < 1$) 244 through proportionality ($\alpha \approx 1$) to synergy ($\alpha > 1$) and the continuum from abundance 245 hyperstability ($\beta < 1$) through proportionalyty ($\beta \approx 1$) to hyperdepletion ($\beta > 1$). The 246 latent predictor N is made manifest with Pope's recursive formula plus the effect of re-247 cruitment minus the effect of the female spawning emigration, which kick-in at different 248 weeks as determined by indicator variables I and J, which are zero before the event 249 (either recruitment or spawning emigration) and 1 afterwards. There might be a range 250 of time steps across which either recruitment or spawning female emigration might take 251 place. Episodes spread over several time steps are less precise because of fewer degrees 252 of freedom for optimization. The timing of recruitment and spawning emigration events 253 are also unknown parameters. In these models, the number and timing of recruitment 254 and spawning emigration events are non-differentiable free parameters. To identify these 255 parameters, the model is run with alternative values. The values that maximize the 256 likelihood (when the likelihood model is comparable across model fits) and/or are best 257 according to other criteria (see below), are chosen. In this work we fitted models with 258 one or two recruitment and spawning emigration events and four options for the timing of 259 these events. When fitting models with two recruitment or spawning events the timings 260 were put on adjacent weeks (t and t+1), thus assuming an extended event taking place 261 over two weeks. Good candidate values for the timings were determined by examination 262 of the non-parametric catch spike statistic, defined as (Roa-Ureta, 2015), 263

$$Spike_t = 10 \left(\frac{\chi_t}{max(\chi_t)} - \frac{E_t}{max(E_t)} \right)$$
(2)

where χ is the observed catch. It highlights time steps with excessively high or excessively low catch for the effort at that time step. Thus large positive spikes suggest recruitment and large negative spikes suggest emigration.

The model in Eq. 1 is the deterministic process for the expected catch under the 267 model. The statistical framework is completed by taking the observed catch as a random 268 variable whose mean time series is Eq. 1 with realized time series coming from any of a 269 number of distributions. These distributions define the likelihood function that is to be 270 maximised. Among these, the normal and lognormal distribution have simple formulas 271 for the adjusted profile likelihood, an approximation that eliminates the dispersion pa-272 rameter from the estimation problem. A total of six alternative likelihood functions or 273 approximations were employed in the estimation of parameters. These are all listed in 274 Roa-Ureta et al. (2019, Table 2). 275

The new generalized depletion model was programmed in a new version of the R 276 package CatDyn (Roa-Ureta, 2019). In CatDyn all parameters are free parameters to 277 be estimated and none of them can be fixed at arbitrary values. The latest version also 278 estimates fishing mortality per time step by using a numerical resolution (R function 279 *uniroot*) of Baranov's catch equation from estimates of abundance, natural mortality and 280 catch per time step. CatDyn depends on package optimx (Nash and Varadhan, 2011), 281 which makes it simple to call several numerical optimization routines as alternatives to 282 minimise the negative log-likelihood. In this work we tried the spg, CG, Nelder-Mead and 283 BFGS routines because these have yielded reliable results in previous applications. The 284 combination of options for number of recruitment and spawning emigration events, tim-285 ing of those events, likelihood function, and numerical optimization routine led to fitting 286 dozens of alternative model settings for each season of data. Some of these model fits did 287 not pass built-in numerical quality control checks. From the remaining fits, we selected 288 the best model by employing numerical, biological and statistical criteria. Firstly, all fits 289 returning a numerical gradient higher than 1 for any parameter were eliminated. This is 290 commonly employed in stock assessment (Lee et al., 2011; Anderson et al., 2014; Hurtado-291 Ferro et al., 2015; Thorson et al., 2015). Secondly, all fits that produced a biologically 292 unrealistic estimate of weekly natural mortality ($M > 0.1 \ week^{-1}$ or $M < 0.01 \ week^{-1}$) 293 were also eliminated. In these models, unrealistic natural mortality estimates are con-294 nected with solutions that also return unrealistic abundance estimates. Thirdly, from the 295 short list of model fits, the best fit was selected as the one with the lowest standard errors 296 and with histogram of correlation coefficients between parameter estimates more concen-297 trated around zero. The histogram of correlation coefficients presents the distribution of 298 pairwise correlations between parameter estimates. It is desirable that these correlations 299 are as far away from 1 or -1 as possible because that means that each parameter was a 300 necessary component of the model. Information theory model selection methods such as 301 the Akaike Information Criterion (AIC) are not useful at this stage because the models 302 to select from have been fitted with different likelihood functions or approximations to 303 the likelihood. 304

305 2.4 Inference on stock-recruitment

In the dynamics of populations with non-overlapping generations, all individuals alive in the next time step are recruits. If the octopus population had completely non-overlapping generations, then recruitment from generalized depletion models would be quantified as the sum of the N_0 estimate and the back-calculated (to the first week of the fishing season) in-season pulse of recruitment R. Under this scenario, the in-season recruitment pulse Rwould be interpreted as a second wave of recruitment from the same cohort. However, it is highly likely that some octopuses from last year cohort are alive at the time of the start

of the new fishing season, when N_0 is estimated. Lifespan of O. vulgaris from several 313 regions in the Atlantic frequently exceed one year and may reach a maximum of nearly 314 two years (Jereb et al., 2015; Katsanevakis and Verriopoulos, 2006). Therefore, the safest 315 assumption is that the N_0 estimate is composed of both new recruits as well as surviving 316 octopuses from the previous cohort. It is for this reason that in order to have a clean 317 recruitment magnitude of year y+1 to match with female spawning abundance in year 318 y, we used recruitment estimates from the in-season positive pulses exclusively, which 319 almost surely were fully composed of new recruits. This means that our recruitment 320 estimates probably are under-estimates and consequently, the MSY from the SR model 321 would also be an under-estimate. From a management point of view, under-estimating 322 MSY entails a conservative stance. Nevertheless, we fitted SR models using N_0 plus the 323 back-calculated recruitment pulse and results are reported in the Supplementary Data 324 (see section 3.2 below). 325

Graphical examination of the relation between \hat{S}_y and \hat{R}_{y+1} indicated that there was strong overcompensation. Therefore, we fitted three stock-recruitment models with overcompensation: 2-parameters Ricker's (Ricker, 1954),

$$R_{y+1} = S_y e^{a\left(1 - \frac{S_y}{S_R}\right)}, \quad a > 0, S_R > 0$$
(3)

³²⁹ 3-parameters Shepherd's (Shepherd, 1982),

$$R_{y+1} = \frac{bS_y}{\left(1 + \left(\frac{S_y}{Q}\right)^{\gamma}\right)}, \quad b > 0, Q > 0, \gamma > 0$$

$$\tag{4}$$

and 3-parameters Saila-Lorda's (Saila et al., 1988),

$$R_{y+1} = S_y^{\gamma} e^{a\left(1 - \frac{S_y}{S_R}\right)}, \quad a > 0, S_R > 0, \gamma > 0$$
(5)

A comparative analysis of these three models as applied to flatfish can be found in Iles (1994).

From a statistical point of view, these stock-recruitment models are nonlinear response-333 predictor models with the complication that both the predictor and the response are 334 random variables. This problem has been recognized in the context of stock-recruitment 335 modelling by Quinn and Deriso (1999, Chapter 3, p. 108), calling it the measurement 336 error approach although no specific solution was offered. In the statistical literature this 337 topic is called errors-in-variable (EIV) regression and our case here corresponds to a non-338 linear, non-classical errors EIV with continuous random predictor. We develop here a 339 new solution within the non-Bayesian hierarchical modelling framework based on hybrid 340 likelihood functions (Roa-Ureta, 2010). First, note that the observations, the estimates 341 \hat{S}_y and \hat{R}_{y+1} , form a 36-dimensional vector $\hat{\mu} = [\hat{S}_{01}, \hat{R}_{02}, \hat{S}_{02}, \hat{R}_{03}, \hat{S}_{03}, ..., \hat{R}_{19}]$ where the 342 sub-index shows the last two digits of the main year of all 19 fishing seasons, all coming 343

from the fits of the 19 best intra-annual generalized depletion models (Eq. 1). Second, note that \hat{R}_y and \hat{S}_y are obtained from the same model fit, and therefore from the hierarchical inference point of view they are bivariate random variables. Thus, the covariance matrix for the complete observations is block-diagonal as follows,

$$\hat{\boldsymbol{\Sigma}}_{SR} = \begin{bmatrix} \boldsymbol{\Sigma}_{\hat{S}_{01}} & 0 & 0 & 0 & 0 & \cdot & 0\\ 0 & \boldsymbol{\Sigma}_{\hat{R}_{02}} & \boldsymbol{\Sigma}_{\hat{S}_{02},\hat{R}_{02}} & 0 & 0 & \cdot & 0\\ 0 & \boldsymbol{\Sigma}_{\hat{S}_{02},\hat{R}_{02}} & \boldsymbol{\Sigma}_{\hat{S}_{02}} & 0 & 0 & \cdot & 0\\ 0 & 0 & 0 & \boldsymbol{\Sigma}_{\hat{R}_{03}} & \boldsymbol{\Sigma}_{\hat{S}_{03},\hat{R}_{03}} & \cdot & 0\\ 0 & 0 & 0 & \boldsymbol{\Sigma}_{\hat{S}_{03},\hat{R}_{03}} & \boldsymbol{\Sigma}_{\hat{S}_{03}} & \cdot & 0\\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot\\ 0 & 0 & 0 & 0 & 0 & 0 & \boldsymbol{\Sigma}_{\hat{R}_{19}} \end{bmatrix}$$
(6)

Conceptually, our solution treats the sequence $S_y \to R_{y+1} \to S_{y+1} \to R_{y+2} \to S_{y+3} \to \dots$ 348 as a Markov chain with infinitely many state spaces, where the steps from S_y to R_{y+1} are 349 controlled by Eq. 3, Eq. 4 or Eq. 5, which are of interest, and the steps from R_y to S_y 350 are controlled by another model which is of no interest. In fact, graphical examination of 351 the relation between \hat{R}_y and \hat{S}_y suggest that an adequate dummy model for $S_y = f(R_Y)$ 352 is a constant, the average \hat{S}_y . Third, considering asymptotic properties of maximum like-353 lihood estimates \hat{R}_y and \hat{S}_y , it is reasonable to assume that the vector $\hat{\mu}$ is multivariate 354 normal. From these considerations, the hybrid (marginal-estimated) likelihood function 355 for the observations $\hat{\boldsymbol{\mu}}$ is 356

$$L_{HL}(\boldsymbol{\theta}_{SR}|\boldsymbol{\hat{\mu}}) \propto |\boldsymbol{\hat{\Sigma}}_{SR}|^{-1/2} exp\left[-\frac{1}{2}(\boldsymbol{\hat{\mu}} - \boldsymbol{\mu}(\boldsymbol{\theta}_{SR}))^T \boldsymbol{\hat{\Sigma}}_{SR}^{-1}(\boldsymbol{\hat{\mu}} - \boldsymbol{\mu}(\boldsymbol{\theta}_{SR}))\right],$$

$$\boldsymbol{\theta}_{SR} = [a, S_R, \bar{S}_y] \quad \lor \quad [b, Q, \gamma, \bar{S}_y]$$
(7)

where $\hat{\Sigma}_{SR}$ replaces the unknown covariance matrix of $\hat{\mu}$.

The statistical models described from Eq. 3-7 were programmed in ADMB-IDE (Magnusson, 2009; Fournier *et al.*, 2012). Some parameters were estimated under unbounded optimization while others were fit within bounds. Acceptable solutions had estimates from bounded optimization falling within the interval, not at any of its bounds. Templates for Shepherd model and data file, including the covariance matrix, are shown in Supplementary Fig. SM3 and SM4.

To quantify the stability properties of the best SR model fitted to spawning and recruitment abundance we conducted two further calculations. Firstly, we estimated the largest Lyapunov exponent of the SR dynamics. This parameter is a measure of the rate of divergence of trajectories of dynamical systems under small separations of initial position. When the parameter is >0, the map is chaotic to a certain degree. This was done with R package DChaos (Sandubete and Escot, 2019). We re-programmed the *logistic.ts* function in the package to replace the simple logistic map by the SR map

selected in this study, including the specific parameter estimates obtained here but with 371 abundance trajectories confined to the unit interval. Secondly, the dynamics following 372 small perturbations from equilibrium points were mapped using Verlhust diagrams (also 373 known as cobweb plots) to illustrate the kind of behaviour that could be expected from 374 fishing removals. Using the selected SR model we predicted next year's recruitment 375 with this year's spawning abundance. In the time between recruitment and spawning of 376 the same year, we set a 2/3 survival rate, which was the mean rate observed in the 19 377 seasons. The stock was started 5% under the spawning abundance at replacement and 378 5% under the spawning abundance at the MSY and was followed over 19 generations. 379 These starting abundances were selected because they represented small perturbations 380 away from interesting and potentially stable points, namely the spawning abundance that 381 produces the MSY and the equilibrium spawning abundance, so if the population did not 382 return to these potentially stable points under those perturbations then it would not 383 return under most perturbations. On the other hand, if the system were stable, starting 384 at 5% under the spawning abundance at replacement, it would return to the equilibrium 385 point, which is the point of crossing of the replacement diagonal and SR curve, forming 386 a cobweb structure with the center at the crossing. 387

388 3 Results

³⁸⁹ 3.1 Intra-annual generalized depletion models

We run 90 generalized depletion model versions in 15 out of 19 fishing seasons; in the rest, 390 the number of version runs ranged from 36 in 2003-2004 to 408 in 2001-2002 (Supplemen-391 tary Table SM2). Amongst these, none of the versions with more than one recruitment 392 week and one spawning emigration week passed the basic numerical requirements in Cat-393 Dyn so these were not considered further. After the selection criteria of biological realism, 394 statistical quality and numerical diagnostics, a short list of between 2 to 14 fits for each 395 season were finally considered. This short list contained models that, within each season, 396 did not differ much in parameter estimates (Supplementary Table SM3). Tables of these 397 estimates for the 19 selected models, as well as plots demonstrating the close fit of the 398 model to the data, are shown in Supplementary Figs. SM5 to SM23 and Table SM4. 399 These estimates had moderately low correlations in 9 out of 19 seasons (Supplementary 400 Fig. SM24). 401

Further insights into how identifiable these depletion models are can be gleaned by examining the fit of the models to data from Season 2001-2002. This was the most difficult season to model, with 408 model versions fitted (Supplementary Table SM2). As shown in Fig. 3, top-right panel, six weeks were tried as the timing of the spawning emigration pulse, but the model with the pulse set at season 65 (counting from the first week of the

season in December 2001) was selected. Of particular interest is a contrast between fits 407 with the emigration pulse set at week 64 and 65, since they are contiguous and the spike 408 catch statistic shows a downward trend (consistent with emigration out of the vulnerable 409 stock) that includes these two weeks, so they seem indistinguishable at first sight. We 410 fitted the depletion model to data from Season 2001-2002 setting the emigration pulse at 411 week 64 or 65 (as noted above, setting both weeks as spawning emigration weeks did not 412 yield convergence) while all other settings (initial parameter values, timing of recruitment 413 pulse, likelihood model and numerical optimization method) were equal in both fits. The 414 ratio of parameter estimates of the model with the spawning emigration week set at 415 week 64 over the same estimates from the model with the emigration set at week 65 416 were very close to 1 except for natural mortality, which was close to 1.5. Second order 417 properties however differed much more. The model with the emigration pulse at week 418 64 failed to produce standard errors for N_0 and the recruitment pulse while the selected 419 model produced standard errors for all parameter estimates. Likewise, the model with 420 the emigration pulse at week 64 produced standard errors for the effort response and the 421 abundance response parameters that were 2 and 3 times higher, respectively, than those 422 from the model with the emigration pulse set at week 65, whereas the standard errors for 423 the remaining estimates were very similar between the two settings. These results show 424 that the objectively best depletion model can be identified even when alternative timings 425 for immigration or emigration pulses are very close. 426

In all models, the recruitment pulse of octopuses that reached 1 kg occurred earlier than the spawning emigration pulse by a minimum of 2 weeks (2007-2008) and a maximum of 18 weeks (2003-2004), which is to be expected since a single cohort has individuals growing first and maturing later. In some of the tried models we set the pulse of emigration before the pulse of recruitment to challenge the previous reasoning (Fig. but in all instances they failed to perform better. Recruitment generally happened in January while the spawning emigration tended to occur in February-March.

Parameter estimates show high natural mortality (M), scaling (k) generally in the 434 order of 10^{-6} thousand octopuses per unit effort and unit abundance, slightly synergistic 435 effort response (α) and proportional abundance response (β) (Fig. 4). Statistical pre-436 cision is generally acceptable or good, except in season 2008-2009 for natural mortality, 437 scaling and abundance response. The selected model for each of the 19 seasons pre-438 dicted minimum and maximum escapement abundances, weekly fishing mortality, and 439 weekly exploitation rate of 162 thousands (2016-2017) to 1265 thousands (2003-2004), 440 $8.5x10^{-4}$ week⁻¹ (2011-2012) to $5.5x10^{-3}$ week⁻¹ (2015-2016), and 0.083% to 0.555%, 441 respectively. 442

In seasons with higher natural mortality (4-times as high in seasons 2008-2009 and 2013-2014 than in seasons 2001-2002, 2004-2005, 2005-2006, 2006-2007, 2009-2010, and 2015-2016) spawners abundance was much lower, while fishing mortality had no apparent effect on spawners abundance (Supplementary Fig. SM25). Natural mortality was much higher than fishing mortality in all seasons and in most weeks in each season, and the annual exploitation rate (total catch over initial biomass) was less than 10% in all seasons except 2001-2002, 2004-2005 and 2015-2106, when it was between 10% and 20% (Supplementary Fig. SM26).

451 **3.2** Stock-recruitment models

Among the three stock recruitment models fitted to the spawning and recruitment abundance observations, the Saila-Lorda model had the lowest AIC but it yielded unrealistic predictions at the extremes. Namely, it predicted virtually 0 recruitment below 80 thousand spawners and over 300 thousand spawners. On those grounds this model was not considered further. The Shepherd model, more versatile than the Ricker model due to a third parameter controlling the degree of overcompensation, had a much lower AIC (5420 versus 5998, respectively).

Fig. 5a presents a scatter-plot of observations of spawners in year y and recruitment 459 in year y+1 as well as the fitted Shepherd model and the replacement line. This surface 460 is complex because (i) it has variance heterogeneity at each point on both axes and (ii) 461 the covariance structure connecting spawners and recruitment in the same year has a 462 large impact on inference but it is not visually represented in the SR surface. In this SR 463 surface, covariances are non-zero for horizontal bands and vertical bands in contiguous 464 years. However, some visual clues can be obtained by noting that (1) at less than 100 465 thousand spawners all most precise recruitment observations (those with a very short 466 vertical line: 2017, 2018, and 2010) are clustered close to the ascending arm of the fitted 467 SR curve, (2) between 100 and 250 thousand spawners, maximum recruitment occurs, 468 with four very precise recruitment observations (2002, 2005, 2011, 2019) clustered around 469 the top of the SR curve, and (3) with more than 250 thousand spawners all recruitment 470 observations (2003, 2006, 2013) are close to the descending arm of the SR curve and all 471 are very precise. The combination of location and precision of estimates (plus the hidden 472 covariance structure) determine the shape of the SR curve. Thus, on the grounds of lowest 473 AIC, the Shepherd model was selected to describe the stock recruitment relationship of 474 O. vulgaris from Asturias. When using N_0 plus the back-calculated recruitment pulse as 475 the recruitment matching the spawning abundance we obtained a similar result, with the 476 Shepherd model selected as the best fit over Ricker's and Saila-Lorda's. This is shown in 477 Supplementary Table SM5 and Fig. SM27. 478

We computed derived parameters from the Shepherd model according to formulas in Table 2 of Iles (1994). These were the slope at the origin, spawning abundance yielding maximum recruitment, maximum recruitment, and replacement spawning abundance (which also is the inflection point and the equilibrium spawning abundance), shown in

Fig. 5a as the point where the diagonal line crosses the predicted (Shepherd) model. 483 Direct estimates and derived parameters are shown in Table 2. The MSY (in numbers) 484 is estimated at 5 times higher than the mean yield over the last decade. The largest 485 Lyapunov exponent is over 0, hence the stock tends to cycles of abundance or chaotic 486 fluctuations after small perturbations. This is illustrated in Fig. 5b, where recruitment 487 predicted by the Shepherd model -given observations of spawners abundance- follows an 488 irregular cycle of peaks and troughs. It is also illustrated in Fig. 5c, where a small per-489 turbation (comparable to fishing removals) from the equilibrium point at the crossing of 490 the diagonal and the SR curve gets the stock locked into an irregular cycle, not returning 491 to the equilibrium point. In Fig. 5d, where the stock suffers a small perturbation from 492 the point of maximum recruitment, the cycle is regular, with the stock fluctuating among 493 3 points, never approaching the equilibrium point. In both cases the stock gets locked 494 into fluctuations that are not random and do not dissipate variability as time progresses. 495

496 4 Discussion

The stock assessment of octopus stocks (and cephalolopods more generally) is a special 497 case due to distinct life history features such as short life cycles, semelparous repro-498 duction, high natural mortality rates, rapid growth, and complex population structures 499 (Arkhipkin et al., 2020). At the same time, their importance in fisheries worldwide is 500 increasing due to growing landings (Arkhipkin et al., 2015; Sauer et al., 2019). Yet glob-501 ally, octopus fisheries are typically running blind because little is known about their 502 productivity (Sauer et al., 2019). Therefore stock assessment models adapted to octopus 503 life history and their fisheries are greatly needed. The conventional approach of using a 504 relative index of abundance from catch per unit of effort (cpue) did not seem adequate 505 in a holobenthic octopus fishery in southeast Australia because the cpue remained stable 506 in spite of expected impact of fishing mortality on recruitment (Leporati et al., 2009). 507 Conventional "closed population" depletion models applied at monthly time steps jointly 508 for 21 years of data provided estimates of annual recruitment and monthly abundance 509 in the Moroccan octopus fishery; the model however, had to include several strong as-510 sumptions such a constant and known value of natural mortality during the 21-yr period, 511 known and fixed seasonal cycle of recruitment, and further statistical restrictions (Robert 512 et al., 2010). It would be better to estimate all important parameters within the stock 513 assessment model. In western Australia, Hart et al. (2019) used the standardized cpue 514 index of relative abundance, confirmed to be proportional to absolute abundance with 515 local depletion experiments, to derive a harvest strategy taking advantage of records that 516 go back to the very start of the fishery. Our stock assessment methodology followed the 517 advice in Arkhipkin et al. (2020) to develop innovative depletion models. Our "open 518 population" depletion models harvest the rich information present in the rapid time step 519

dynamics of the weekly fishing operations to estimate total vulnerable biomass, as well 520 as natural mortality, recruitment and spawning stock for each year of data separately. 521 These results are further combined in a non-Bayesian hierarchical inference approach to 522 model the spawners and recruitment relation in the annual dynamics. This approach 523 of combining a depletion model for the rapid fishing dynamics and a population model 524 for the annual dynamics has been used successfully in data-poor SSF, although in previ-525 ous cases the annual dynamics was the Pella-Tomlinson logistic map instead of the SR 526 relation (Roa-Ureta et al., 2015, 2019, 2020). 527

We estimated the timing of the recruitment pulse and spawning emigration pulse in 528 the fit of generalized depletion models (see Fig. 3) and these estimates can be compared 529 with results of biological studies carried out on O. vulgaris stocks across European wa-530 ters. In our models, recruitment to the fishery (reaching 1 kg of body weight) generally 531 happened in mid winter while the spawning emigration tended to occur in late winter-532 early spring. In coastal Greek waters settlement of larvae to the benthos happened in 533 summer (Katsanevakis and Verriopoulos, 2006) and the main spawning occurred in late 534 winter-early spring. In the Gulf of Cadiz, recruitment to the fishery (reaching 1 kg of 535 body weight) was observed in winter while spawning was inferred to occur between July 536 and October (Sobrino et al., 2011). Comparing the spawning seasons in north-west Por-537 tugal (in the Canary-Iberian upwelling system) and southern Portugal Lourenco et al. 538 (2012) observed marked differences, with the northern stock spawning from late winter 539 to early summer while the southern stock spawned in summer. Both Otero *et al.* (2007)540 and Guerra et al. (2015) reported that the spawning season in Galician waters occurred 541 in spring. Thus, the timings of recruitment and spawning determined from our models 542 agree well with the findings of the biological studies conducted in the northern part of 543 the Iberian Peninsula. It should be noted though that the measurements of recruitment 544 and spawning differ, particularly the latter. Our estimates of spawning time describe 545 emigration pulses, episodic events happening in a single week each fishing season, while 546 biological studies generally measure gonad maturity progression at monthly time steps. 547 The progression of gonad maturation will be necessarily gradual while the spawning emi-548 gration of females could happen more rapidly, as the culmination of maturity progression. 549 A further comparison of our modelling results with empirical findings in previous 550 studies can be made with regards to octopus density in the field. Considering the area 551 of the fishing grounds off Asturias (228 to 397 km^2) and the abundance estimates from 552 our depletion models, we find that octopuses live at densities ranging from 1250 to nearly 553 5000 per km^2 . Hart *et al.* (2019) used local depletion experiments in unfished areas to 554 estimate O. tetricus density between 500 and 800 octopus per km^2 , Arechavala-Lopez et 555 al. (2018) reported a maximum density of 800 adult octopuses per km² in waters that are 556

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highly impacted by anthropic activities around the island of Mallorca, southern Spain, Katsanevakis and Verriopoulos (2006) obtained on average around 400 octopus per $\rm km^2$ in 558

Greece, Garofalo *et al.* (2010) reported a maximum of 200 recruits and 100 spawners per per km² in the Strait of Sicily. Thus, our density estimates are much higher, which could be interpreted as the continental shelf off Asturias being a rich habitat for *O. vulgaris* and/or that fishing pressure has depleted the stock to a lesser degree than in other areas as a positive result of sound co-management policies during the past two decades.

Wide interannual fluctuations in recorded catch of O. vulgaris have been observed 564 and analyzed in connection with environmental drivers in West Africa (Faure *et al.*, 2000; 565 Cabellero-Alfonso et al., 2010) and southern Spain (Sobrino et al., 2020; Vargas-Yáñez 566 et al., 2009). In Galicia, a region influenced by the Canary-Iberian upwelling system 567 immediately west of our study area, Otero et al. (2008) used additive approximations to 568 analyze the impact of meteorological indices on cpue and concluded that a large frac-569 tion of the annual variability in catch could be explained by variability in upwelling, 570 with the link occurring through the impact of upwelling on the survival of planktonic life 571 stages. Remarkably, they also show evidence for density-dependence by obtaining a con-572 cave shape of the additive coefficients as a function of a density-dependent proxy, which 573 implies overcompensation in the SR relation. Our study area is close to the Canary-574 Iberian upwelling system and microsatellite DNA variation have demonstrated genetic 575 homogeneity amongst O. vulgaris stocks in this region (Cabranes et al., 2008). Our re-576 sults confirm Otero et al. (2008) implications with regards to density-dependence and 577 overcompensation in O. vulgaris, further clarifying the nature of the processes underlying 578 these dynamics. Recently, Sobrino et al. (2020) also found a strong effect of environmen-579 tal processes on abundance in the O. vulgaris stock of the Gulf of Cadiz, namely previous 580 year's rainfall having a negative effect on next year's abundance. When combined with 581 a recruit index from surveys, their additive approximation explained nearly 90% of total 582 variability in catches. Our results show that in addition to the strong impact of en-583 vironmental conditions on the variability of octopus recruitment and catches, intrinsic 584 population dynamic processes determining strong density-dependent and overcompensa-585 tion cause fluctuations in O. vulgaris stocks abundance that need to be considered when 586 designing effective policies for sustainable exploitation. 587

Given the strong degree of overcompensation observed in the stock-recruitment rela-588 tionship the question arises as to what might be causing it. Overcompensation is usually 589 understood to be caused by cannibalism or other forms of aggression of individuals in 590 the pre-existing cohorts against individuals from the new cohort of recruits. Escola and 591 Geritz (2007) derived explicit mechanisms involving aggression between individuals from 592 a cohort of adults and a cohort of juveniles and the timing of reproduction, leading 593 in some cases to overcompensation as in the Ricker model. In the present case, given 594 the likelihood of some degree of overlapping generations of O. vulgaris considering its 595 longevity, aggression of surviving octopuses from the previous cohort against recruits 596 and among recruits could certainly contribute to overcompensation. However, unlike in 597

iteroparous species, mass mortality of reproducing octopuses would diminish the impact 598 of inter-cohort interactions so the strong degree of overcompensation observed here could 599 also be connected to additional factors of the special population dynamics of octopuses. 600 We hypothesize that availability of good quality dens for egg clutches and the compe-601 tition to mate further drives the stock into overcompensation. To see this, first let the 602 number of good quality dens for broods be fixed and limiting, such that females that do 603 not secure a good quality den will suffer a higher chance of failing to turn broods into 604 recruits. Second, let the number of females determine the strength of the competition 605 between males to mate such that when there are too many females the strength of the 606 competition to mate is low and virtually all males, even weaker ones, are able to mate. 607 Third, let the quality of male gametes vary such that a substantial number of males, 608 the weakest of them, are poor progenitors. Under these three conditions, a high number 609 of females will cause overcompensation by letting too many of the good quality dens be 610 taken by females impregnated by low quality males, which in turn will lead to many 611 unsuccessful broods thereby undermining next year recruitment. Conversely when the 612 number of females is relatively low and the strength of competition to mate is relatively 613 high then only the strongest males will mate leading to dens being taken by females 614 impregnated by the strongest males, and more successful broods. This hypothesis is sup-615 ported by some findings of cephalopod reproductive biology. In removal experiments, 616 Hartwick et al. (1978) observed that smaller octopus tended to occupy newly dug dens 617 whereas larger octopus occupied natural dens. This suggests that dens are a limiting 618 resource in octopus reproduction. Female cephalopods and female O. vulgaris in par-619 ticular can be impregnated by multiple males leading to clutches of eggs with multiple 620 paternity (Quinteiro et al., 2011), a phenomenon called polyandry. Squires et al. (2012) 621 have demonstrated experimentally that polyandry in a squid is advantageous despite the 622 cost of multiple mating because polyandrous females had eggs that developed faster and 623 turned into larger hatchlings relative to egg masses of monandrous females. The authors 624 hypothesized that the increased reproductive rate of polyandrous females could be con-625 nected to the chance to receive better quality spermatophores. It is straightforward to 626 see that an over-abundance of opportunities to mate would cause fewer females having 627 the chance to mate multiple times thus decreasing next year recruitment if good quality 628 dens are in limited supply. Thus we suggest that a combination of inter-cohort aggression 629 early during recruitment and less competition to mate under limiting supply of dens later 630 during mating could be driving the fall in recruitment at high spawners abundance. 631

One of the major issues that Sidney Holt defended during his career in fisheries management was that the MSY is an excessive yield policy. Holt recently elaborated his objections mostly around the arguments that the MSY is economically wasteful for fishers and that it increases by-catch and other harms to the ecosystem (Holt, 2020; Holt and Raicevich, 2018). He also expressed doubts that a stock could be kept producing the

same surplus even when having the same total abundance and density because population 637 growth rates vary for other reasons, especially the biological composition and demography 638 of the stock (Holt, 2011). In this work we provide further reasons for a less-than-MSY 639 policy in fisheries management with potentially broad relevance. In our study case the 640 MSY is excessive because the population has intrinsic properties that result in unstable 641 equilibrium points and thus cannot be kept stable at the size that maximizes the popula-642 tion growth rate. The intrinsic factor is the mode of relationship between spawning stock 643 and recruitment. The Shepherd mechanism describing strong overcompensation sets the 644 equilibrium spawners abundance at the inflection point, which is unstable. Any small 645 perturbation, such as modest fishing removals, will set the population trajectory away 646 from stationary for a long time, with the stock oscillating irregularly or cyclically, not 647 declining or increasing. Thus, the concept of removing the maximum sustainable surplus 648 from a stable population is simply not adequate. The MSY can still be calculated with 649 the usual formulas but if removals close to MSY (under a constant harvest policy) or 650 MSY-derived reference points (such as the fishing mortality at MSY) are applied when 651 the stock is at the low points in the trajectory, the risk of fishery decline or collapse is 652 high. 653

Our results regarding the inadequacy of MSY for fluctuating abundance dynamics 654 could be seen as just having relevance for stocks with the special life history of octopuses 655 and other short-lived species. However, the MSY also resulted excessive in a multi-cohort 656 stock of long-lived sea urchins that fluctuates because of a high intrinsic population growth 657 rate (r > 3) in the Pella-Tomlinson logistic map (Roa-Ureta *et al.*, 2015). Thus, one 658 important implication of our results is that the MSY may not be valid for many stocks 659 exploited by small-scale fisheries (SSF) as well as stocks with special characteristics such 660 as cephalopods. This is because these stocks may posses intrinsic properties that make 661 them prone to population dynamics consisting of irregular or cyclic fluctuations. A new 662 sustainable rate of exploitation, less than the rate entailed by the MSY, would need to 663 be defined. In Roa-Ureta et al. (2015) we proposed the latent productivity averaged 664 over the peaks and troughs of stock fluctuations as the less-than-MSY sustainable yield. 665 Application of our recommended policy by managers has been accompanied by a long 666 period of stability in the largest sea urchin fishery in the world (FAO, 2021). We applied 667 the same approach of using annual biomass predictions by the depletion models to fit 668 the Pella-Tomlinson logistic map to the Asturias octopus stock (ICES, 2020, section 2.3). 669 Having estimated the Pella-Tomlinson model, we estimated the mean latent productivity 670 as the sustainable harvest rate. This estimate turned out to be close to the maximum 671 landings along the time series and only 44% higher than the historical mean landings since 672 1990, while the MSY, computed from the estimated Pella-Tomlinson model, was six times 673 higher than mean historical catch and three times higher that the highest recorded catch. 674 Asturias management set the annual global catch as equal to the mean latent productivity 675

minus two times the standard error of the estimate as a precautionary, sustainable and economically viable annual harvest rate. In this connection, it should be noted that the latent productivity is the general surplus production of which the MSY is a special case, the case when the stock has one stable equilibrium. For all other cases, those of stocks that tend to get locked into stable cycles because of intrinsic properties, the MSY is not adequate while the latent productivity, which varies with fluctuations in abundance, is the sustainable surplus production.

Stocks exploited by SSF compose the bulk of the large majority of stocks that remain 683 un-assessed and yet SSF provide most of worldwide landings (Costello et al., 2012) and 684 employment (The World Bank, 2012). Extending stock assessment practices to SSF-685 stocks will enrich our knowledge of marine population dynamics and will broaden the 686 practice of sustainable fisheries management. Our study shows that a small Octopus vul-687 garis stock presents rich dynamics that result from intrinsic properties of the stock as well 688 as from small perturbations from moderate fishing removals and possibly environmental 689 forces. The greatest difficulty in assessing SSF stocks lies in the paucity of elementary 690 data such as reliable time series of catch and effort (Bañon et al., 2018). Our study shows 691 that when the fishery is co-managed, the data provided by the fishers on their daily oper-692 ations, complemented with simple biological data that can be obtained at fairly low cost, 693 could be sufficient to understand the fishery and population dynamics, and thus achieve 694 sustainable exploitation at rates that guarantee sufficient supply of seafood and economic 695 returns to fishers. 696

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Data availability. The data underlying this article will be shared on reasonable
 request to Fernández-Rueda or García-Flórez.

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Phase	Concept	Notatior
	Fishing effort	E
	Catch in weight	W
Data	Mean weight	w
	Time step (week)	t, i, j, l
	Number of seasons	19
	Number, timing of immigration pulses	u, τ
	Number, timing of emigration pulses	v, ν
	Expected catch in numbers	C
	Observed catch in numbers $(W \div w)$	χ
	Abundance	N
	Scaling	k
Phase 1	Effort response	α
Intra-annual	Abundance response	β
generalized	Initial abundance	N_0
depletion	Natural mortality	M
models	Recruitment magnitude	R
	Female spawners magnitude	S
	Event indicator, 0 before, 1 otherwise	I,J
	Variance of spawning abundance	Σ_S
	Variance of recruitment	Σ_R
	Covariance of spawning, recruitment	$\Sigma_{S,R}$
	Spawning abundance	S
Phase 2	Recruitment	R
Spawners	Slope at start	$e^a, 1/b$
recruitment	Replacement spawning abundance	S_R
model	Threshold spawning abundance	Q
	Degree of compensation	γ

Table 1: Notation used in this work. Phase 1 is the estimation of parameters connected to the data; Phases 2 is the estimation of hyper-parameters as a function of estimated parameters.

Parameter	Estimate	Standard error
b	2.5251	0.0033
Q (thousands)	311.3700	5.6508
γ	8.0132	0.6090
Slope at the origin	0.3960	0.0051
Spawning abundance at maximum recruitment (thousands)	244.1800	4.4739
Maximum recruitment (thousands)	539.6362	12.670
Maximum spawning abundance at replacement (thousands)	321.2733	6.3023
MSY (thousands)	295.4544	9.8369
Largest Lyapunov exponent	0.3564	0.0217

Table 2: Parameter estimates of the Shepherd spawning stock and recruitment model fitted to the spawning and recruitment abundance observations in the fishery for *Octopus vulgaris* in Asturias, north-west Spain.



Figure 1: Fishing grounds for Octopus vulgaris in Asturias, north-west Spain.



Figure 2: Raw catch, fishing effort and mean weight data from 19 seasons of the fishery for *Octopus vulgaris* in Asturias, north-west Spain.



Figure 3: Catch spike statistic and the location of recruitment week (ascending black arrows) and spawning emigration week (descending black arrows) in the fishery for *Octopus vulgaris* in Asturias, north-west Spain. Alternative weeks of recruitment (ascending gray arrows) and spawning emigration (descending gray arrows) from model configurations that were discarded are also shown. The weeks are counted since the calendar week at the start of the season.



Figure 4: Generalized depletion model estimates ± 1 standard error across 19 seasons in the fishery for *Octopus vulgaris* in Asturias, north-west Spain.



Figure 5: Female spawning stock and recruitment dynamics in *Octopus vulgaris* from Asturias, Northern Spain. a): Spawning stock and recruitment observations from generalized depletion models (dots) ± 0.25 times standard errors bars for the predictor and the response (crosses over dots), fitted spawning stock and recruitment model (line), replacement spawning abundance (diagonal), and MSY (vertical line). Years below dots are recruitment years. b): Predicted recruitment from spawning abundance observations ± 3 standard errors. c) Population trajectory under small perturbations from maximum spawners abundance at replacement. d) Population trajectory under small perturbations from spawners abundance at maximum recruitment. In panels c) and d) the star indicates initial state and the filled circle marks the final state.