1	Quantifying the known unknowns: estimating
2	maximum intrinsic rate of population increase in the
3	face of uncertainty
4	Sebastián A. Pardo [*]
5	Department of Biology, Dalhousie University, Halifax, NS, B3H 4R2,
6	Canada
7	Earth to Ocean Research Group, Biological Sciences, Simon Fraser
8	University, Burnaby, BC, V5A 1S6, Canada
9	
10	Andrew B. Cooper
11	School of Resource & Environmental Management, Simon Fraser
12	University, Burnaby, BC, V5A 1S6, Canada
13	
14	John D. Reynolds
15	Earth to Ocean Research Group, Biological Sciences, Simon Fraser
16	University, Burnaby, BC, V5A 1S6, Canada
17	
18	Nicholas K. Dulvy
19	Earth to Ocean Research Group, Biological Sciences, Simon Fraser
20	University, Burnaby, BC, V5A 1S6, Canada
21	
22	August 8, 2019
23	Abstract
24	Scientists are often called upon to provide advice on the consequences of exploiting
25	data-poor and potentially threatened sharks and rays. For species lacking detailed
26	biological information, sensitivity to overfishing is often estimated using simple
27	models that depend upon life history parameters. Yet, there has been little explo-

1

ration of the degree to which uncertainty in life history parameters can influence 28 demographic parameter estimates and therefore fisheries management options. We 29 estimate the maximum intrinsic rate of population increase (r_{max}) for ten coastal 30 carcharhiniform shark populations using an unstructured life history model that 31 explicitly accounts for uncertainty in life history parameters. We also seek to un-32 derstand which parameters most influenced the estimate of r_{max} . The median r_{max} 33 estimate proved to be robust to the propagation of uncertainty of life history param-34 eters when that uncertainty is symmetric around the parameters' point estimates. 35 but accounting for uncertainty can lead to a wide range of plausible r_{max} estimates 36 for any given species. While natural mortality M can considerably impact r_{max} 37 estimates when its uncertainty is high it is very difficult to estimate this param-38 eter directly, hence we focused on the two directly estimated parameters: age at 39 maturity α_{mat} and annual reproductive output b. Uncertainty in age at maturity 40 values was low, yet it still resulted in moderate uncertainty in r_{max} estimates. The 41 model was particularly sensitive to uncertainty in annual reproductive output as 42 b approached values of less than 5 female offspring per year, which is not unusual 43 for large elasmobranchs and marine mammals. Furthermore, at very low b values 44 (<1), there is a threshold that results in implausible r_{max} estimates when both 45 M and α_{mat} are high. Managers and policy makers should be careful to restrict 46 mortality on species with very low annual reproductive output <2 females per year. 47 We recommend elasmobranch biologists to measure frequency distributions of litter 48 sizes (rather than just a range) and age at maturity, as well as improving estimates 49 of natural mortality of data-poor elasmobranchs. 50

Keywords: Bycatch, Carcharhinus, Chondrichthyes, Elasmobranchii, reference points, risk
 assessment, demography

53 1 Introduction

Many marine megafauna and predator populations are declining globally and are at in-54 creasing risk of local and regional extinction (Fowler et al., 2005; Christensen et al., 2014; 55 Dulvy et al., 2017). Sharks, rays, and chimaeras (class Chondrichthyes) play a complex 56 role as marine predators, hence there is concern for potential indirect impacts of predator 57 declines on marine ecosystems (Kitchell et al., 2002; Heithaus et al., 2008; Heupel et al., 58 2014). They are often large-bodied, long-lived, late-maturing and produce few offspring 59 (Compagno, 1990; Musick, 1999). Consequently, they tend to have low intrinsic rates 60 of population increase and weak compensatory density dependence in juvenile survival 61 (Compagno, 1990; Musick, 1999; Forrest and Walters, 2009); traits which make them less 62 able to withstand over-exploitation (Kindsvater *et al.*, 2016). 63

^{*}Corresponding author: email: spardo@dal.ca

There are relatively few stock-assessed elasmobranch species (Simpfendorfer and Dulvy, 64 2017) even though they can be directly targeted (Jaiteh et al., 2016, 2017) and are also 65 caught as bycatch in longline fisheries targeting large finfish, coastal gill-net, and trawl 66 fisheries (Kitchell et al., 2002; Ellis et al., 2005). Despite the large catch and high commer-67 cial value of elasmobranchs, our understanding of species-specific catches is poor because 68 many species are not directly targeted (Stevens, 2000) but are considered valuable by-69 catch. Hence, accurate information on population trends is lacking for most species. 70 These challenges to understanding sustainability of elasmobranch fisheries and using pre-71 cautionary approaches for their management are compounded further by multi-species 72 fisheries and poor species-specific monitoring (Barker and Schluessel, 2005; Lack and 73 Sant, 2009; Dulvy et al., 2017). 74

Many countries have recently adopted policy regulations that require them to assess 75 fisheries according to an Ecosystem-Based Management (EBM) approach (Jennings and 76 Rice, 2011; Rogers et al., 2007). The EBM approach requires, among other things, the 77 identification of safe ecological limits for bycatch species (Hobday et al., 2011; Salomon 78 and Holm-Müller, 2013). These species, which lack detailed stock assessments and are 79 not the focus of targeted commercial extraction, are usually understudied, resulting in a 80 dearth of information on their biology and demography. As such, the usual data-intensive 81 stock assessment methods are not applicable for a large diversity of bycatch, which has 82 led to a recent increase in the development of tools for the assessment of data-poor species 83 (Brooks et al., 2010). 84

Identifying which life history traits affect resilience to a range of fishing pressures is 85 crucial for averting over-exploitation or extinction of data-poor species (Reynolds, 2003; 86 Kindsvater et al., 2016). Life history traits are interrelated due to the evolutionary con-87 straints imposed by energy acquisition and processing (Law, 1979; Charnov, 1993). Some 88 of these relationships, widely known as Beverton-Holt dimensionless ratios, can be used 89 to predict other life history parameters and tied to population dynamics, albeit with 90 considerable uncertainty (Dulvy and Forrest, 2010). The link between life histories and 91 demography allows the use of life history traits to quantify a species' intrinsic sensitivity 92 (Frisk et al., 2001; Dulvy et al., 2004; Reynolds et al., 2005), which encompasses biological 93 traits that, in conjunction with exposure to threatening processes, determine their vul-94 nerability or extinction risk (Reynolds, 2003; Dulvy and Kindsvater, 2017). For example, 95 age- and stage-structured models have been used to estimate the intrinsic sensitivity of 96 numerous shark and ray species (e.g. Cortés, 2002; Mollet and Cailliet, 2002; Simpfendor-97 fer, 2005). Such models depend heavily on age- and stage-specific estimates of growth, 98 natural mortality and reproductive output, but such detailed information is often lackgq ing for most elasmobranchs, particularly natural mortality (Miller et al., 2003; Gedamke 100 et al., 2007). Alternatively, unstructured models do not require age- or stage-specific life 101 history estimates and instead use single trait estimates. Unstructured models have the 102

¹⁰³ advantage of relying on simple assumptions on how fertility or survival may vary with ¹⁰⁴ age or stage, and have been used to estimate relative intrinsic sensitivity for numerous ¹⁰⁵ data-poor elasmobranch species (Smith *et al.*, 1998; García *et al.*, 2008; Simpfendorfer ¹⁰⁶ and Kyne, 2009).

Recently, there has been increasing awareness of the importance of considering mul-107 tiple sources of uncertainty in demographic parameter estimation and risk assessment 108 (Simpfendorfer et al., 2011; Cortés et al., 2014; Jaiteh et al., 2016). In addition, demo-109 graphic modelling frameworks quantify the degree of caution that should be exercised for 110 their sustainable management and can have major implications for the conservation of 111 species (Caswell et al., 1998; Cortés, 2002; Cortés et al., 2014). The two main sources 112 of uncertainty that can be easily accounted for in a modelling framework are measure-113 ment error (or trait error), stemming from uncertainty in the empirical estimation of a 114 life history parameter (Harwood and Stokes, 2003; Quiroz et al., 2010), and coefficient 115 error, which is derived from the uncertainty in the values of the coefficients of a model 116 (Quiroz et al., 2010, e.g., uncertainty around the intercept of a linear model, see). While 117 multiple sources of uncertainty can be readily accounted for in stock assessments, this 118 has not happened to the same extent in data-poor situations, particularly in commonly 119 used unstructured models (for a recent example see Jaiteh et al., 2016). 120

In this study, we use an unstructured derivation of the Euler-Lotka demographic 121 model, which estimates the maximum intrinsic rate of population increase r_{max} (Myers 122 et al., 1997; Pardo et al., 2016; Cortés, 2016). We address how measurement error in 123 life history traits affects (1) uncertainty in productivity estimates, and (2) sensitivity 124 of these estimates to uncertainty in each trait. We examine model performance under 125 the estimated uncertainty of each required life history parameter for ten populations of 126 comparatively well-studied ground sharks (order Carcharhiniformes) found in the Gulf 127 of Mexico and northwest Atlantic Ocean. We selected these species as they are well 128 studied and there is relatively good life history information for them. Specifically, we 129 calculate uncertainty in r_{max} estimates through Monte Carlo resampling from probability 130 distributions of the three input parameters required in the model: annual reproductive 131 output, age at maturity, and instantaneous natural mortality. To assess sensitivity, we 132 also compare models that only include uncertainty from individual life history traits. 133

$_{134}$ 2 Methods

135

[Figure 1 about here.]

¹³⁶ We used a Monte Carlo simulation model (Fig. 1) based on published information ¹³⁷ on the biology of a species to iteratively estimate maximum intrinsic rate of population ¹³⁸ increase r_{max} using a derivation of the Euler-Lotka model (Cortés, 2016; Pardo *et al.*,

2016). The model starts with the data required (Values for age at maturity α_{mat} , maxi-139 mum age α_{max} , litter size l, and breeding interval i ("Data" section in Fig. 1), which are 140 then used to define probability distributions for each parameter (except breeding interval 141 whose value is fixed, see "Probability distributions" in Fig. 1). Values for age at maturity, 142 maximum age, and litter size are then drawn from these distributions (see "Parameters 143 drawn" in Fig. 1), and used to estimate natural mortality M and annual reproductive 144 output b (see "Model inputs" section), which in turn are required to obtain an estimate 145 of r_{max} (blue box in Fig. 1). The drawing of parameters from distributions is repeated 146 20,000 times to obtain 20,000 r_{max} estimates (see inner loop in Fig. 1). Finally, we re-147 peat the whole process after replacing the probability distributions of each parameter 148 with a fixed value to assess the sensitivity of the model to uncertainty in α_{mat} , b, and 149 M (see outer loop in Fig. 1). We apply this model to ten populations of ground sharks 150 (order Carcharhiniformes) to examine how the uncertainty in traits underlies uncertainty 151 in r_{max} . 152

¹⁵³ 2.1 Life history data

157

The population-specific life history information required for this simulation model consists of age at maturity (range of years), maximum age (in years), ranges of litter size (in number of female pups), and breeding interval (in years) (Table 1, Fig. 1 "Data" section).

The annual reproductive output of females (b) was calculated as b = 0.5 * l/i, where l 158 is litter size (in numbers of males and females) and i is breeding interval (in years). An-159 nual reproductive output estimates were derived from uniform distributions constrained 160 by the minimum and maximum litter sizes published in the literature. This was neces-161 sary because empirical distributions of litter sizes are lacking for most elasmobranchs. 162 We assumed a sex ratio of 1:1 to calculate numbers of females only per litter. Age at 163 maturity (α_{mat}) estimates were derived from uniform distributions constrained between 164 the minimum and maximum ages at maturity published in the literature (Table 1). 165

Instantaneous natural mortality M was estimated using the reciprocal of average lifes-166 pan $(M = 1/\omega)$, with average lifespan ω defined as the midpoint between age at maturity 167 and maximum age $(\omega = \frac{\alpha_{mat} + \alpha_{max}}{2})$, for rationale see Pardo *et al.* (2016). Given that 168 we obtained a distribution of age at maturity values for each population (see above), 169 we used this uncertainty in age at maturity as the basis to estimate uncertainty in M, 170 thus uncertainty of M was iteratively estimated using the same age at maturity dis-171 tribution described above. Uncertainty in instantaneous natural mortality M had very 172 little influence on r_{max} compared to the effect of uncertainty in age at maturity α_{mat} 173 and annual reproductive output b; however, this is an artifact of the constrained range 174

of M values produced by our estimation method. When accounting for uncertainty in 175 natural mortality using the reciprocal of lifespan equation, we only included uncertainty 176 in age at maturity as it is difficult to set a plausible range for maximum age. These 177 narrow estimates of M (see Fig. S2d in Supplementary Materials) resulted in uncertainty 178 in M having a very small effect on r_{max} estimates (see Results). We could increase the 179 degree of uncertainty in M estimates, yet this increase would be arbitrary. We explored 180 an alternative scenario where we arbitrarily increase uncertainty in our M estimate and 181 as expected, its importance on r_{max} estimates increased considerably (see "Alternative 182 scenario with a more uncertain M" in Supplementary Materials). The effect of uncer-183 tainty in M on r_{max} estimates will depend on the M estimator used and the degree of 184 uncertainty associated with it (Then et al., 2015). Because of the difficulties of specifying 185 an adequate level of uncertainty in M as well as how resource intensive it would be to 186 obtain better estimates of M, we focus our analysis on the effects of including uncertainty 187 in the other parameters required to estimate r_{max} : α_{mat} and b. 188

189 2.2 Estimating r_{max}

We estimated the maximum intrinsic rate of population increase r_{max} , which in theory, 190 occurs at low population sizes (i.e., in the absence of density dependence) whereupon it is 191 equivalent to the fishing mortality required to drive a population to extinction F_{ext} (Dulvy 192 et al., 2004; Gedamke et al., 2007; Cortés et al., 2014). These two metrics are equivalent 193 because, in order for a species to become extinct from fishing, fishing mortality needs 194 to be to equal or exceed the maximum population growth rate $(F_{ext} \geq r_{max})$. Unlike 195 previous estimates of r_{max} for chondrichthyans (García *et al.*, 2008; Dulvy *et al.*, 2014b), 196 this equation accounts for juvenile mortality which has been previously overlooked (Pardo 197 et al., 2016; Cortés, 2016) 198

$$l_{\alpha_{mat}}b = e^{r_{max}\alpha_{mat}} - e^{-M}(e^{r_{max}})^{\alpha_{mat}-1} \tag{1}$$

where $l_{\alpha_{mat}}$ is survival to maturity in the absence of fishing and is calculated as $l_{\alpha_{mat}} = (e^{-M})^{\alpha_{mat}}$. Because $l_{\alpha_{mat}}$ is derived from M and α_{mat} we did not examine the effect of uncertainty in $l_{\alpha_{mat}}$ independently. Equation 1 is equivalent to equation 8 in (Myers and Mertz, 1998) which assumes age at selectivity (i.e., age at which they begin to be captured) is 1. We used Monte Carlo simulation to propagate uncertainty of input parameters. We drew parameters from their respective distributions iteratively 20,000 times, and solved for r_{max} (inner loop in Fig. 1)

We calculated two metrics that quantify uncertainty in the estimation of r_{max} . We first calculated the range between the 2.5% and 97.5% quantiles, which encompasses 95% of the r_{max} values in each distribution and we refer to as the 95% quantile interval. In order to compare variation for parameters of different magnitudes, we also calculated a coefficient of variation (CV, %) by dividing the mean by the standard deviation of each distribution.

212 2.3 Model sensitivity

To assess how uncertainty in each parameter affected estimated of r_{max} , we repeated the Monte Carlo simulation for each of the seven possible model combinations with uncertainty in: (i) only b, (ii) only α_{mat} , (iii) only M, (iv) $b + \alpha_{mat}$, (v) b + M, (vi) $\alpha_{mat} + M$, and (vii) a full model of $b + \alpha_{mat} + M$ (Fig. 1g).

In order to visualise the parameter space of r_{max} values created by ranges of α_{mat} , b, and M, we created two-dimensional contour plots, showing r_{max} estimates along gradients of α_{mat} and b, plotted separately for three levels of M: low M = 0.05 year⁻¹, medium M= 0.1 year⁻¹, and high M = 0.2 year⁻¹. We chose these three values of M as they span the natural mortality values we estimated for the ten shark populations examined.

All models were built in R version 3.2.4 (R Core Team, 2016). The r_{max} equation was solved using the nlminb optimisation function by minimising the sum of squared differences.

225 **3** Results

226 3.1 Estimation of r_{max} and comparison of uncertainty in input 227 parameters

The median r_{max} estimates were robust to uncertainty in all populations examined likely due to the symmetric uncertainty in the underlying parameters. As expected, uncertainty in r_{max} estimates varied considerably among species as a result of uncertainty in the underlying traits (Fig. 2).

Estimates of r_{max} are most sensitive to uncertainty in annual reproductive output b(Fig. 2). This is particularly pronounced in the least fecund species (Fig. 3b), that is, those with ranges of annual reproductive output b less than 5 such as the Finetooth Shark C. isodon (b = 2.7; Fig. 2b) and Blacknose Shark C. acronotus (b = 1.8; Fig. 2c) as these species had larger differences in coefficients of variation between b and α_{mat} (Table 2).

By focusing on the Atlantic Sharpnose Shark *R. terraenovae* we see that the uncertainty r_{max} values for a model only incorporating uncertainty in *b* is approximately twice as great as those in the model only incorporating uncertainty in α_{mat} (Fig. 2i).

For this species the coefficient of variation (CV) in r_{max} estimates is 32% when only 242 accounting for uncertainty in b compared to 10% when only accounting for uncertainty 243 in α_{mat} (Table 2). While the ranges of plausible age at maturity values were low for all 244 ten populations examined when compared with variation in the other traits (see Fig. 2b 245 in Supplementary Materials), they still resulted in considerable uncertainty in r_{max} esti-246 mates (Fig. 2). Furthermore, CVs of r_{max} estimates were moderately higher in species 247 with lower estimates of α_{mat} , which are often thought to be relatively resilient to fishing, 248 than those with higher α_{mat} estimates (Fig. 3a). The CV of r_{max} estimates increased as 249 average b values of decreased (Fig. 3b). The species in the lower left corner of Fig. 3b 250 that have low b values but do not have high variability in r_{max} CV are C. leucas and 251 C. brevipinna; these species have the highest minimum litter sizes among those with low 252 b values (see Table 1). Thus, CV is reduced as parameter draws of litter size are very 253 constrained and never below six, which result in b estimates that are also constrained 254 (hence low CV in r_{max} estimates) but that never approximate zero. 255

For all ten populations, the full model incorporating all uncertainties $(b + \alpha_{mat} + M)$ had a slightly smaller CV than the $\alpha_{mat} + b$ model due to the close correlation between α_{mat} and M (Table 2). This same pattern exists when comparing models with just α_{mat} versus $\alpha_{mat} + M$.

Accounting for uncertainty in life history parameters is important: theoretical biological reference points based on the 2.5% quantile of r_{max} (equivalent to F_{ext}) were on average 60% lower when all sources of uncertainty were accounted for than when the deterministic model was used (Fig. 4).

[Figure 4 about here.]

[Table 2 about here.]

²⁶⁶ 3.2 Model sensitivity

The interactive effects of annual reproductive output and age at maturity on r_{max} are 267 nonlinear and vary based on the values of natural mortality (M = 0.05, 0.1, 0.2 year⁻¹; 268 Fig. 5). Overall, r_{max} drops steeply at low b values regardless of α_{mat} or M (bottom left 269 corner of all plots in Fig. 5). At medium to high values of annual reproductive output, 270 the estimate of r_{max} becomes increasingly sensitive to variation in age at maturity. With 271 increasing M values, there are increasing combinations of α_{mat} and b values that result 272 in implausible r_{max} values ($r_{max} \leq 0$; red areas in Fig. 5b & c). This "implausibility" 273 threshold is particularly apparent when natural mortality M is less than 0.2 year⁻¹, b is 274 very low (b < 1), and α_{mat} is over 5 years (Fig. 5b & c). Nonetheless, it is highly unlikely 275 that any species have this combination of life histories. 276

[Figure 5 about here.]

264

265

278 4 Discussion

The availability of simple methods for estimating key population parameters has opened 279 the door to comparative risk assessment of a wider range of bycatch species (Stobutzki 280 et al., 2002; Hobday et al., 2011; Dulvy et al., 2014a). One such simple method is the 281 Euler-Lotka approach to estimating the maximum intrinsic rate of population increase 282 using point estimates of three life history traits (García et al., 2008; Hutchings et al., 283 2012; Dulvy et al., 2014a). However, all life history parameters are estimated with some 284 associated uncertainty. Here, we show that the degree of uncertainty in life history 285 parameters has a considerable effect on the distribution of the resulting range of maximum 286 intrinsic rate of population increase, but little effect on median values. Fully propagating 287 the uncertainty in natural mortality M, age at maturity α_{mat} , and annual reproductive 288 output b, increased the coefficient of variation of r_{max} values by between 11 and 46% 289 (Table 2). These findings have important implications for the use of r_{max} estimates to set 290 fishing limits for sharks and other data-poor species (Fig. 5). Acknowledging the level of 291 uncertainty associated with estimates is crucial when using the precautionary approach, 292 as the degree of risk associated with specific management practices can be estimated 293 (Harwood and Stokes, 2003; Artelle et al., 2013). 294

As we have shown, r_{max} is particularly sensitive to differences in annual reproductive 295 output, particularly for species with very low annual reproductive output (b < 5 females 296 per year; Fig. 3b). That demography is influenced by fecundity of the least fecund species 297 is apparent from some demographic models, but it depends on how reproductive output is 298 parameterised. Our finding is consistent with that of more data-intensive age-structured 299 models. For example, an age-structured model of dogsharks (order Squaliformes) re-300 vealed that biological reference points can be strongly influenced by their low fecundity 301 (Forrest and Walters, 2009). In contrast, we caution that another commonly used un-302 structured model—the rebound potential model (Au and Smith, 1997)—is agnostic to 303 annual reproductive output as the values of b on both sides of the equation cancel out 304 and hence are not considered mathematically in this model (Au et al., 2015). This differ-305 ence in the implementation of annual reproductive output (b) between two superficially 306 similar unstructured models may help explain differences in species' sensitivity between 307 these methods. For example, Ward-Paige et al. (2013) used the rebound potential model 308 to compare the sensitivity of manta rays (Mobula spp.) to that of other elasmobranchs. 309 They found that manta rays were intermediate in sensitivity (r), are more similar to Spin-310 ner Shark (Carcharhinus brevipinna) or Silky Shark (C. falciformis). However, when the 311 very low annual reproductive output of manta rays is accounted for using r_{max} , they were 312 found to have one of the lowest population growth rates r_{max} observed in chondrichthyans 313 (Dulvy et al., 2014a). The annual reproductive output of manta rays is highly uncertain, 314 but with the potential of skipped mating, reproductive output may be as low as one fe-315

male pup every second or third year (Couturier *et al.*, 2012; Marshall and Bennett, 2010), resulting in r_{max} varying from 0.089 to 0.139 year⁻¹ (Dulvy *et al.*, 2014a). Being aware of major differences in the implementation of annual reproductive output in different models is important when choosing the model best suited to the research question.

We show that the highest demographic uncertainty occurred in species with very low 320 annual reproductive outputs—less than five female pups per year. Many elasmobranchs 321 have this reproductive rate (Cortés, 2000). Nonetheless, we reached this conclusion based 322 on assuming a uniform distribution of litter sizes, but they are unlikely to be uniform 323 in the real world. For us to explore the validity of this assumption requires a better 324 understanding of the empirical distribution of litter sizes. By having more accurate 325 distributions of litter size, the uncertainty in annual reproductive output b is likely to 326 decrease, and thus result in more accurate estimates of r_{max} . Hence, we urge biologists to 327 report frequency distributions of individual litter sizes: choosing adequate distributions 328 based on empirical data will result in reduced uncertainty in annual reproductive output. 329 As we have shown in our study, this has considerable downstream effects in the uncertainty 330 of r_{max} estimates. 331

The updated model for estimating r_{max} includes juvenile survival which is derived 332 from adult natural mortality M (Pardo *et al.*, 2016). Yet, because of the known trade-off 333 between offspring size and litter size (Smith and Fretwell, 1974; Hussey et al., 2010), the 334 least fecund species often have the largest offspring. As is typical for marine fishes, such 335 larger offspring will likely have a greater survival probability than the smaller offspring of 336 species with r_{max} among species. An example of this can be illustrated by comparing the 337 Spinner Shark (C. brevipinna) with the Scalloped Hammerhead (S. lewini). The Spinner 338 Shark litter size ranges between 3–15 individuals born between 60 and 80 cm in length, 339 while the Scalloped Hammerhead has a larger litter size ranging between 13–41 indi-340 viduals but which are born smaller, between 45 and 50 cm in length (Last and Stevens, 341 2009). Spinner Sharks likely have lower young-of-year survival rates than Scalloped Ham-342 merheads, resulting in a higher survival to maturity and thus higher r_{max} estimates than 343 those from our study. Additionally, local-scale differences in habitat have also been shown 344 to relate with M (Heupel and Simpfendorfer, 2011). Nuances in relation to differential 345 juvenile mortality among species are not accounted for in our model but should be the 346 focus of further study. 347

Natural mortality is one of the most important parameters in fisheries modelling but one of the hardest to estimate (Pope, 1975; Vetter, 1988; Kenchington, 2014). Our estimates of r_{max} are relatively insensitive to uncertainty in M for shark-like life histories (Figs. 2) because of the method we used for accounting for uncertainty in M. For example, the CV of r_{max} estimates for R. terraenovae is 1% when accounting for uncertainty in only M yet it increases to 31.5% if only uncertainty in annual reproductive output is taken into account (Table 2). Our finding is similar to Au *et al.* (2015), who showed that ³⁵⁵ M had only a minor role in the estimation of rebound potential when compared with ³⁵⁶ α_{mat} . However, as natural mortality is a difficult parameter to estimate it is unrealistic ³⁵⁷ for its uncertainty to be narrowly constrained as it was with our method. This begs the ³⁵⁸ question of how to assess how much uncertainty in M is "enough" or "too much".

Furthermore, there is considerable debate as to which empirical model should be used 359 to estimate natural mortality M (Hewitt and Hoenig, 2005; Quiroz et al., 2010; Then 360 et al., 2015). Here, we used the reciprocal of average lifespan; however, other methods, 361 such as Chen and Watanabe (1989) and Peterson and Wroblewski (1984), have been used 362 as they provide varying values of M through ontogeny as required for age-structured 363 demographic modelling (Pardo *et al.*, 2012). We note the differences in r_{max} estimates in 364 our study compared to Cortés (2016) arise because Cortés uses the minimum estimate of 365 a range of mortality estimators, whereas we use one simple method for consistency and 366 transparency. 367

Improving natural mortality estimates, and identifying the best indirect estimator, 368 would require the use of data-intensive methods such as extensive catch data to analyse 369 catch curves, mark recapture experiments, virtual population analyses (VPA), or even 370 fully integrated stock assessments (Kenchington, 2014; Sippel et al., 2017). Therefore, 371 research efforts on data-poor species might be better spent improving on life history 372 estimates of the other parameters age at maturity and annual reproductive output. Fur-373 ther increasing uncertainty in natural mortality (by an arbitrary amount) does increase 374 uncertainty in r_{max} (see Supplementary Materials). While in our study M is relatively 375 unimportant, more complex age- and stage-structured models consistently show that ju-376 venile mortality has important contributions to population growth rate (Cortés, 2002; 377 Frisk et al., 2005) and realized recovery potential (Hutchings and Kuparinen, 2017). This 378 difference in importance of M needs to be borne in mind when comparing across demo-379 graphic model types. 380

While age-dependent mortality estimates are needed for matrix models, only average 381 natural mortality values (and the uncertainty around them) are needed for unstructured 382 models. Natural mortality estimates in which correlation of parameters can be accounted 383 for (e.g., Pauly, 1980) reduced uncertainty of estimates and their error when applied to 384 elasmobranchs (Quiroz et al., 2010). A recent study by Then et al. (2015) suggests that 385 the Pauly (1980) mortality model should not be used, and instead a new variant that 386 eliminates temperature from the equation is preferred. Regardless, our results showing 387 the effect of uncertainty in age at maturity and annual reproductive output on r_{max} 388 estimates are likely to be robust to the choice of natural mortality estimator used. 389

We show that accounting for uncertainty in trait estimates is important as it can lead to much more conservative estimates of fishing limits than if uncertainty is ignored. Incorporating uncertainty also considerably increased the potential range of maximum population growth rate r_{max} estimates in these relatively well-studied sharks. Furthermore, we

urge managers and policy makers to focus on restricting mortality in species with annual 394 reproductive outputs <2 females per year, particularly if this mortality occurs among 395 younger age classes. For data-limited species, we recommend incorporating all sources 396 of uncertainty in life history parameters, especially when lacking directly-estimated life 397 history parameters. This uncertainty in r_{max} can be reduced by understanding the corre-398 lation in life history parameters, and we encourage researchers studying chondrichthyan 399 reproductive biology to report distributions of litter sizes and offspring sizes as to reduce 400 uncertainty in these parameter distributions and thus better quantify known uncertainty 401 in demographic productivity models. 402

403 Acknowledgements

We would like to thank two anonymous reviewers as well as Adrian Hordyk, John Carlson, Enric Cortés, Aleksandra Maljković, Holly Kindsvater, and Joel Harding for their thorough reviews of the manuscript, members of the Earth to Ocean Research Group for their helpful feedback, JC Quiroz for his helpful insight into uncertainty in demographic models, and Nicolás Huerta for his help with coding the models. ABC, JDR, and NKD were supported by the Natural Science and Engineering Research Council and NKD was supported by a Canada Research Chair.

411 References

Artelle, K. A., Anderson, S. C., Cooper, A. B., Paquet, P. C., Reynolds, J. D., and
Darimont, C. T. 2013. Confronting Uncertainty in Wildlife Management: Performance
of Grizzly Bear Management. PLoS ONE, 8: e78041. URL http://dx.doi.org/10.
1371%2Fjournal.pone.0078041.

Au, D. W. and Smith, S. E. 1997. A demographic method with population density
compensation for estimating productivity and yield per recruit of the leopard shark
(*Triakis semifasciata*). Canadian Journal of Fisheries and Aquatic Sciences, 54: 415–420.

Au, D. W., Smith, S. E., and Show, C. 2015. New abbreviated calculation for measuring
intrinsic rebound potential in exploited fish populations-example for sharks. Canadian
Journal of Fisheries and Aquatic Sciences, 72: 767-773. URL http://dx.doi.org/
10.1139/cjfas-2014-0360.

Barker, M. J. and Schluessel, V. 2005. Managing global shark fisheries: suggestions for
prioritizing management strategies. Aquatic Conservation: Marine and Freshwater
Ecosystems, 15: 325-347. URL http://doi.wiley.com/10.1002/aqc.660.

Barreto, R. R., Lessa, R. P., Hazin, F. H., and Santana, F. M. 2011. Age and growth of the
blacknose shark, *Carcharhinus acronotus* (Poey, 1860) off the northeastern Brazilian
Coast. Fisheries Research, 110: 170–176. URL http://linkinghub.elsevier.com/
retrieve/pii/S0165783611001354.

⁴³¹ Bigelow, H. B. and Schroeder, W. C. 1948. Sharks. *In* Fishes of the Western North
⁴³² Atlantic. Part I. Memoir Sears Foundation for Marine Research, edited by J. Tee-Van,
⁴³³ C. Breder, S. Hildebrand, A. Parr, and W. Schroeder, pp. 59–546. Sears Foundation
for Marine Research, Vola University, New Hayen

- 434 for Marine Research, Yale University, New Haven.
- Branstetter, S. 1987a. Age and Growth Estimates for Blacktip, *Carcharhinus limbatus*,
 and Spinner, *C. brevipinna*, Sharks from the Northwestern Gulf of Mexico. Copeia,
 1987: 964-974. URL http://www.jstor.org.proxy.lib.sfu.ca/stable/1445560.

Branstetter, S. 1987b. Age and growth validation of newborn sharks held in laboratory
aquaria, with comments on the life history of the Atlantic sharpnose shark, *Rhizopri- onodon terraenovae*. Copeia, 1987: 291–300. URL http://www.jstor.org/stable/
1445764.

Branstetter, S. 1987c. Age, growth and reproductive biology of the silky shark, *Carcharhinus falciformis*, and the scalloped hammerhead, *Sphyrna lewini*, from the northwestern Gulf of Mexico. Environmental Biology of Fishes, 19: 161–173. URL http://dx.doi.org/10.1007/BF00005346.

Branstetter, S. 1990. Early life-history implications of selected carcharhinoid and lamnoid
sharks of the northwest Atlantic. *In* Elasmobranchs as living resources: advances in
the biology ecology systematics and the status of the fisheries, edited by H. L. J. Pratt,
S. H. Gruber, and T. Taniuchi, vol. 90, pp. 17–28. NOAA Technical Report NMFS 90.

⁴⁵⁰ Branstetter, S. and Stiles, R. 1987. Age and growth estimates of the bull shark, *Car-*⁴⁵¹ *charhinus leucas*, from the northern Gulf of Mexico. Environmental Biology of Fishes,
⁴⁵² 20: 169–181. URL http://dx.doi.org/10.1007/BF00004952.

⁴⁵³ Brooks, E. N., Powers, J. E., and Cortés, E. 2010. Analytical reference points for age⁴⁵⁴ structured models: application to data-poor fisheries. ICES Journal of Marine Science,
⁴⁵⁵ 67: 165–175.

⁴⁵⁶ Carlson, J. K., Cortés, E., and Bethea, D. M. 2003. Life history and population dynam⁴⁵⁷ ics of the finetooth shark (*Carcharhinus isodon*) in the northeastern Gulf of Mexico.
⁴⁵⁸ Fishery Bulletin, 101: 281–292.

Carlson, J. K., Sulikowski, J. R., and Baremore, I. E. 2006. Do differences in life history
exist for blacktip sharks, *Carcharhinus limbatus*, from the United States South Atlantic

Bight and Eastern Gulf of Mexico? Environmental Biology of Fishes, 77: 279-292.
 URL http://www.springerlink.com/index/10.1007/s10641-006-9129-x.

Castro, J. I. 1993. The biology of the finetooth shark, *Carcharhinus isodon*. Environmental Biology of Fishes, 36: 219–232. URL http://dx.doi.org/10.1007/BF00001717.

Castro, J. I. 1996. Biology of the blacktip shark, *Carcharhinus limbatus*,
off the Southeastern United States. Bulletin of Marine Science, 59: 508522. URL http://www.ingentaconnect.com/content/umrsmas/bullmar/1996/
00000059/00000003/art00005.

Caswell, H., Brault, S., Read, A. J., and Smith, T. D. 1998. Harbor Porpoise and fisheries:
an uncertainty analysis of incidental mortality. Ecological Applications, 8: 1226–1238.

⁴⁷¹ Charnov, E. L. 1993. Life history invariants: some explorations of symmetry in evolutionary ecology. Oxford Series in Ecology and Evolution. Oxford University Press, New
⁴⁷³ York, 167 pp. URL http://books.google.ca/books?id=_u7aJr9uevkC.

⁴⁷⁴ Chen, S. and Watanabe, S. 1989. Age dependence of natural mortality coefficient in fish
⁴⁷⁵ population-dynamics. Nippon Suisan Gakkaishi, 55: 205–208.

⁴⁷⁶ Christensen, V., Coll, M., Piroddi, C., Steenbeek, J., Buszowski, J., and Pauly, D. 2014.
⁴⁷⁷ A century of fish biomass decline in the ocean. Marine Ecology Progress Series, 512:
⁴⁷⁸ 155–166. URL http://www.int-res.com/abstracts/meps/v512/p155-166/.

Cliff, G. and Dudley, S. F. J. 1991. Sharks caught in the protective gill nets off
Natal, South Africa. 4. The bull shark *Carcharhinus leucas* Valenciennes. South
African Journal of Marine Science, 10: 253-270. URL http://dx.doi.org/10.2989/
02577619109504636.

- ⁴⁸³ Compagno, L. J. V. 1984. Sharks of the world: an annotated and illustrated guide of
 ⁴⁸⁴ shark species known to date. Part 2, Carcharhiniformes. FAO Fisheries Synopsis, 125:
 ⁴⁸⁵ 251–655.
- Compagno, L. J. V. 1990. Alternative life-history styles of cartilaginous fishes in time and
 space. Environmental Biology of Fishes, 28: 33-75. URL http://www.springerlink.
 com/index/10.1007/BF00751027.

⁴⁸⁹ Cortés, E. 2000. Life history patterns and correlations in sharks. Reviews in Fish⁴⁹⁰ eries Science, 8: 299-344. URL http://www.tandfonline.com/doi/abs/10.1080/
⁴⁹¹ 10408340308951115.

⁴⁹² Cortés, E. 2002. Incorporating uncertainty into demographic modeling: application to
⁴⁹³ shark populations and their conservation. Conservation Biology, 16: 1048–1062.

- ⁴⁹⁴ Cortés, E. 2016. Perspectives on the intrinsic rate of population growth. Methods
 ⁴⁹⁵ in Ecology and Evolution, 7: 1136–1145. URL http://dx.doi.org/10.1111/2041⁴⁹⁶ 210X.12592.
- ⁴⁹⁷ Cortés, E., Brooks, E. N., and Shertzer, K. W. 2014. Risk assessment of cartilaginous
 ⁴⁹⁸ fish populations. ICES Journal of Marine Science, 72: 1057–1068. URL http://dx.
 ⁴⁹⁹ doi.org/10.1093/icesjms/fsu157.
- Couturier, L. I. E., Marshall, A. D., Jaine, F. R. A., Kashiwagi, T., Pierce, S. J.,
 Townsend, K. A., Weeks, S. J., *et al.* 2012. Biology, ecology and conservation of
 the Mobulidae. Journal of Fish Biology, 80: 1075–1119. URL http://dx.doi.org/
 10.1111/j.1095-8649.2012.03264.x.
- Drew, M., White, W. T., Dharmadi, Harry, A. V., and Huveneers, C. 2015. Age, growth
 and maturity of the pelagic thresher *Alopias pelagicus* and the scalloped hammerhead
 Sphyrna lewini. Journal of Fish Biology, 86: 333–54. URL http://www.ncbi.nlm.
 nih.gov/pubmed/25557431.
- ⁵⁰⁸ Driggers, W. B., Carlson, J. K., Cullum, B., Dean, J. M., Oakley, D., and Ulrick, G.
 ⁵⁰⁹ 2004a. Age and growth of the blacknose shark, *Carcharhinus acronotus*, in the western
 ⁵¹⁰ North Atlantic Ocean with comments on regional variation in growth rates. Environ⁵¹¹ mental Biology of Fishes, 71: 171–178.
- ⁵¹² Driggers, W. B. and Hoffmayer, E. R. 2009. Variability in the reproductive cycle of
 ⁵¹³ finetooth sharks, *Carcharhinus isodon*, in the northern Gulf of Mexico. Copeia, 2009:
 ⁵¹⁴ 390-393. URL http://www.bioone.org/doi/abs/10.1643/CE-08-167.
- Driggers, W. B., Oakley, D. A., Ulrich, G., Carlson, J. K., Cullum, B. J., and Dean, J. M.
 2004b. Reproductive biology of *Carcharhinus acronotus* in the coastal waters of South
 Carolina. Journal of Fish Biology, 64: 1540–1551. URL http://doi.wiley.com/10.
 1111/j.0022-1112.2004.00408.x.
- ⁵¹⁹ Dulvy, N. K., Ellis, J. R., Goodwin, N. B., Grant, A., Reynolds, J. D., and Jennings,
 ⁵²⁰ S. 2004. Methods of assessing extinction risk in marine fishes. Fish and Fisheries, 5:
 ⁵²¹ 255–276.
- ⁵²² Dulvy, N. K. and Forrest, R. E. 2010. Life histories, population dynamics, and extinction
 ⁵²³ risks in chondrichthyans. *In* Sharks and Their Relatives II: Physiological Adaptations,
 ⁵²⁴ Behavior, Ecology, Conservation, and Management, edited by J. C. Carrier, J. A.
 ⁵²⁵ Musick, and M. R. Heithaus, Marine Biology, pp. 639–679. CRC Press. URL http:
- ⁵²⁶ //dx.doi.org/10.1201/9781420080483-c17.

⁵²⁷ Dulvy, N. K., Fowler, S. L., Musick, J. A., Cavanagh, R. D., Kyne, P. M., Harrison,
⁵²⁸ L. R., Carlson, J. K., *et al.* 2014a. Extinction risk and conservation of the world's
⁵²⁹ sharks and rays. eLife, 3: e00590. URL http://elifesciences.org/content/3/
⁵³⁰ e00590.abstract http://www.pubmedcentral.nih.gov/articlerender.fcgi?
⁵³¹ artid=3897121&tool=pmcentrez&rendertype=abstract.

⁵³² Dulvy, N. K. and Kindsvater, H. K. 2017. The Future Species of Anthropocene Seas.
⁵³³ In Conservation for the Anthropocene Ocean, edited by P. S. Levin and M. R.
⁵³⁴ Poe, pp. 39-64. Elsevier. URL http://linkinghub.elsevier.com/retrieve/pii/
⁵³⁵ B9780128053751000039.

⁵³⁶ Dulvy, N. K., Pardo, S. A., Simpfendorfer, C. A., and Carlson, J. K. 2014b. Diagnosing
 the dangerous demography of manta rays using life history theory. PeerJ, 2: e400.
 URL https://peerj.com/articles/400.

Dulvy, N. K., Simpfendorfer, C. A., Davidson, L. N. K., Fordham, S. V., Bräutigam,
A., Sant, G., and Welch, D. J. 2017. Challenges and Priorities in Shark and Ray
Conservation. Current Biology, 27: R565–R572. URL http://dx.doi.org/10.1016/
j.cub.2017.04.038.

Ellis, J. R., Dulvy, N. K., Jennings, S., Parker-Humphreys, M., and Rogers, S. I. 2005.
Assessing the status of demersal elasmobranchs in UK waters: a review. Journal of the
Marine Biological Association of the United Kingdom, 85: 1025–1047.

Forrest, R. E. and Walters, C. J. 2009. Estimating thresholds to optimal harvest rate for
long-lived, low-fecundity sharks accounting for selectivity and density dependence in
recruitment. Canadian Journal of Fisheries and Aquatic Sciences, 66: 2062–2080.

Fowler, S. L., Cavanagh, R. D., Camhi, M., Burgess, G. H., Cailliet, G. M., Fordham,
S. V., Simpfendorfer, C. A., *et al.*, eds. 2005. Sharks, rays and chimaeras: the status of
the Chondrichthyan fishes. Status survey. IUCN/SSC Shark Specialist Group, Gland,
Switzerland and Cambridge, UK, x + 491 pp.

Frisk, M. G., Miller, T. J., and Dulvy, N. K. 2005. Life histories and vulnerability to
exploitation of elasmobranchs: inferences from elasticity, perturbation and phylogenetic
analyses. Journal of Northwest Atlantic Fishery Science, 37: 27–45. URL http:
//journal.nafo.int/35/frisk/4-frisk.pdf.

Frisk, M. G., Miller, T. J., and Fogarty, M. J. 2001. Estimation and analysis of biological
parameters in elasmobranch fishes: a comparative life history study. Canadian Journal
of Fisheries and Aquatic Sciences, 58: 969–981. URL http://www.nrc.ca/cgi-bin/
cisti/journals/rp/rp2_abst_e?cjfas_f01-051_58_ns_nf_cjfas58-01.

García, V. B., Lucifora, L. O., and Myers, R. A. 2008. The importance of habitat and life
 history to extinction risk in sharks, skates, rays and chimaeras. Proceedings of the Royal
 Society B, 275: 83-89. URL http://www.pubmedcentral.nih.gov/articlerender.
 fcgi?artid=2562409&tool=pmcentrez&rendertype=abstract.

Gedamke, T., Hoenig, J. M., Musick, J. A., DuPaul, W. D., and Gruber,
S. H. 2007. Using Demographic Models to Determine Intrinsic Rate of Increase and Sustainable Fishing for Elasmobranchs: Pitfalls, Advances, and Applications. North American Journal of Fisheries Management, 27: 605-618.
URL http://www.informaworld.com/openurl?genre=article&doi=10.1577/M05157.1&magic=crossref%7C%7CD404A21C5BB053405B1A640AFFD44AE3.

Harry, A. V., Macbeth, W. G., Gutteridge, A. N., and Simpfendorfer, C. A. 2011. The
life histories of endangered hammerhead sharks (Carcharhiniformes, Sphyrnidae) from
the east coast of Australia. Journal of Fish Biology, 78: 2026–2051. URL http:
//www.ncbi.nlm.nih.gov/pubmed/21651548.

Harwood, J. and Stokes, K. 2003. Coping with uncertainty in ecological advice: lessons
from fisheries. Trends in Ecology & Evolution, 18: 617–622. URL http://linkinghub.
elsevier.com/retrieve/pii/S0169534703002489.

Heithaus, M. R., Frid, A., Wirsing, A. J., and Worm, B. 2008. Predicting ecological consequences of marine top predator declines. Trends in Ecology & Evolution,
23: 202-210. URL http://www.cell.com/trends/ecology-evolution/abstract/
S0169-5347(08)00057-8.

Heupel, M. R., Knip, D., Simpfendorfer, C. A., and Dulvy, N. K. 2014. Sizing up the
ecological role of sharks as predators. Marine Ecology Progress Series, 495: 291–298.
URL http://www.int-res.com/abstracts/meps/v495/p291-298/.

Heupel, M. R. and Simpfendorfer, C. A. 2011. Estuarine nursery areas provide a lowmortality environment for young bull sharks jem¿Carcharhinus leucasj/em¿. Marine Ecology Progress Series, 433: 237–244. URL http://www.jstor.org/stable/
24875428.

Hewitt, D. A. and Hoenig, J. M. 2005. Comparison of two approaches for estimating
natural mortality based on longevity. Fishery Bulletin, 103: 433–437.

⁵⁹¹ Hobday, A. J., Smith, A. D. M., Stobutzki, I. C., Bulman, C., Daley, R., Dambacher,
⁵⁹² J. M., Deng, R. A., *et al.* 2011. Ecological risk assessment for the effects of fishing.
⁵⁹³ Fisheries Research, 108: 372–384.

Hussey, N. E., Wintner, S. P., Dudley, S. F. J., Cliff, G., Cocks, D. T., and Aaron MacNeil,
 M. 2010. Maternal investment and size-specific reproductive output in carcharhinid
 sharks. Journal of Animal Ecology, 79: 184–193. URL http://dx.doi.org/10.1111/
 j.1365-2656.2009.01623.x.

Hutchings, J. A. and Kuparinen, A. 2017. Empirical links between natural mortality
 and recovery in marine fishes. Proceedings of the Royal Society B: Biological Sci ences, 284. URL http://rspb.royalsocietypublishing.org/content/284/1856/
 20170693.abstract.

Hutchings, J. A., Myers, R. A., García, V. B., Lucifora, L. O., and Kuparinen, A. 2012.
Life-history correlates of extinction risk and recovery potential. Ecological Applications,
22: 1061–1067. URL http://dx.doi.org/10.1890/11-1313.1.

Jaiteh, V. F., Hordyk, A. R., Braccini, M., Warren, C., and Loneragan, N. R. 2016. Shark
 finning in eastern Indonesia: assessing the sustainability of a data-poor fishery. ICES
 Journal of Marine Science: Journal du Conseil, p. fsw170. URL https://academic.
 oup.com/icesjms/article-lookup/doi/10.1093/icesjms/fsw170.

Jaiteh, V. F., Loneragan, N. R., and Warren, C. 2017. The end of shark finning? Impacts of declining catches and fin demand on coastal community livelihoods. Marine Policy, 82: 224–233. URL http://linkinghub.elsevier.com/retrieve/pii/ S0308597X17301720.

Jennings, S. and Rice, J. 2011. Towards an ecosystem approach to fisheries in Europe: a perspective on existing progress and future directions. Fish and Fisheries, 12: 125–137. URL http://dx.doi.org/10.1111/j.1467-2979.2011.00409.x.

Kenchington, T. J. 2014. Natural mortality estimators for information-limited fisheries.
Fish and Fisheries, 15: 533-562. URL http://dx.doi.org/10.1111/faf.12027.

Kindsvater, H. K., Mangel, M., Reynolds, J. D., and Dulvy, N. K. 2016. Ten principles
from evolutionary ecology essential for effective marine conservation. Ecology and
Evolution, 6: 2125–2138. URL http://dx.doi.org/10.1002/ece3.2012.

⁶²¹ Kitchell, J. F., Essington, T. E., Boggs, C. H., Schindler, D. E., and Walters, C. J. 2002.

⁶²² The role of sharks and longline fisheries in a pelagic ecosystem of the Central Pacific.

Ecosystems, 5: 202-216. URL http://www.springerlink.com/openurl.asp?genre=

624 article&id=doi:10.1007/s10021-001-0065-5.

Lack, M. and Sant, G. 2009. Trends in global shark catch and recent developments in management. Tech. rep., TRAFFIC International.

- Last, P. R. and Stevens, J. D. 2009. Sharks and Rays of Australia. CSIRO Publishing,
 Melbourne, 2nd edn., 656 pp.
- Law, R. 1979. Optimal life histories under age-specific predation. The American Naturalist, 114: 399–417. URL http://www.jstor.org/stable/2460187.
- Lombardi-Carlson, L. A., Cortés, E., Parsons, G. R., and Manire, C. A. 2003. Latitudinal variation in life-history traits of bonnethead sharks, *Sphyrna tiburo*, (Carcharhiniformes: Sphyrnidae) from the eastern Gulf of Mexico. Marine and Freshwater Research,
 54: 875–883.
- Marshall, A. D. and Bennett, M. B. 2010. Reproductive ecology of the reef manta ray
 Manta alfredi in southern Mozambique. Journal of Fish Biology, 77: 169–190. URL
 http://dx.doi.org/10.1111/j.1095-8649.2010.02669.x.
- Miller, T. J., Frisk, M. G., and Fogarty, M. J. 2003. Comment on Mollet and Cailliet
 (2002): confronting models with data. Canadian Journal of Fisheries and Aquatic
 Sciences, 54: 737–738.
- Mollet, H. F. and Cailliet, G. M. 2002. Comparative population demography of elasmobranchs using life history tables, Leslie matrices and stage-based matrix models.
 Marine and Freshwater Research, 53: 503–516.
- Musick, J. A. 1999. Criteria to Define Extinction Risk in Marine Fishes: The American
 Fisheries Society Initiative. Fisheries, 24: 6–14. URL http://dx.doi.org/10.1577/
 1548-8446(1999)024%3C0006:CTDERI%3E2.0.C0 2.
- Myers, R. A. and Mertz, G. 1998. The limits of exploitation: A precautionary approach.
 Ecological Applications, 8: 165–169.
- Myers, R. A., Mertz, G., and Fowlow, P. S. 1997. Maximum population growth rates and
 recovery times for Atlantic cod, *Gadus morhua*. Fishery Bulletin, 95: 762–772.
- Pardo, S. A., Cooper, A. B., and Dulvy, N. K. 2012. Critical review and analysis
 of existing risk-based techniques for determining sustainable mortality levels of bycatch species. Tech. rep., Canadian Science Advisory Secretariat Research Document
 2012/014.
- Pardo, S. A., Kindsvater, H. K., Reynolds, J. D., and Dulvy, N. K. 2016. Maximum
 intrinsic rate of population increase in sharks, rays, and chimaeras: the importance of
 survival to maturity. Canadian Journal of Fisheries and Aquatic Sciences, 73: 1159–
 1163. URL http://dx.doi.org/10.1139/cjfas-2016-0069.

- Parsons, G. R. 1983. The reproductive biology of the Atlantic sharpnose shark, *Rhizo- prionodon terraenovae* (Richardson). FIshery Bulletin, 81: 61–73.
- Parsons, G. R. 1985. Growth and Age Estimation of the Atlantic Sharpnose Shark,
 Rhizoprionodon terraenovae: A Comparison of Techniques. Copeia, 1985: 80-85. URL
 http://www.jstor.org/stable/1444793.
- Pauly, D. 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. Journal du Conseil
 International pour l'Exploration de la Mer, 39: 175-192. URL http://icesjms.
 oxfordjournals.org/content/39/2/175.abstract.
- Peterson, I. and Wroblewski, J. S. 1984. Mortality rate of fishes in the pelagic ecosystem.
 Canadian Journal of Fisheries and Aquatic Sciences, 41: 1117–1120.
- Pope, J. G. 1975. Estimation of unknown natural mortality. In International Commission
 for the Northwest Atlantic Fisheries Dumm. Doc. 75/2. International Commission for
 the Northwest Atlantic Fisheries Dumm. Doc.
- Quiroz, J., Wiff, R., and Caneco, B. 2010. Incorporating uncertainty into estimation of natural mortality for two species of Rajidae fished in Chile. Fisheries
 Research, 102: 297-304. URL http://linkinghub.elsevier.com/retrieve/pii/
 S0165783610000044.
- ⁶⁷⁷ R Core Team 2016. R: A Language and Environment for Statistical Computing. URL
 ⁶⁷⁸ https://www.r-project.org/.
- Reynolds, J. D. 2003. Life histories and extinction risk. In Macroecology, edited by T. M.
 Blackburn and K. J. Gaston, pp. 195–217. Blackwell Publishing, Oxford.
- Reynolds, J. D., Dulvy, N. K., Goodwin, N. B., and Hutchings, J. A. 2005. Biology of extinction risk in marine fishes. Proceedings of the Royal Society B, 272: 2337-44. URL http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid= 1559959&tool=pmcentrez&rendertype=abstract.
- Rogers, S. I., Tasker, M. L., Earll, R., and Gubbay, S. 2007. Ecosystem objectives to sup-
- port the UK vision for the marine environment. Marine Pollution Bulletin, 54: 128–44.
- URL http://www.sciencedirect.com/science/article/pii/S0025326X06005091.
- Salomon, M. and Holm-Müller, K. 2013. Towards a sustainable fisheries policy in Europe.
 Fish and Fisheries, 14: 625–638. URL http://dx.doi.org/10.1111/faf.12009.
- ⁶⁹⁰ Simpfendorfer, C. A. 2005. Demographic models: life tables, matrix models and rebound
- potential. In Management Techniques for Elasmobranch Fisheries. FAO Fisheries Tech-
- nical Paper. No. 474, edited by J. A. Musick and R. Bonfil, p. 251. FAO, Rome.

- Simpfendorfer, C. A. and Dulvy, N. K. 2017. Bright spots of sustainable shark fish ing. Current Biology, 27: 97-98. URL http://www.sciencedirect.com/science/
 article/pii/S0960982216314646.
- Simpfendorfer, C. A., Heupel, M. R., White, W. T., and Dulvy, N. K. 2011. The importance of research and public opinion to conservation management of sharks and rays:
 a synthesis. URL http://dx.doi.org/10.1071/MF11086.
- Simpfendorfer, C. A. and Kyne, P. M. 2009. Limited potential to recover from over fishing raises concerns for deep-sea sharks, rays and chimaeras. Environmental
 Conservation, 36: 97-103. URL http://www.journals.cambridge.org/abstract_
 S0376892909990191.
- Sippel, T., Lee, H. H., Piner, K., and Teo, S. L. H. 2017. Searching for M: Is there more
 information about natural mortality in stock assessments than we realize? Fisheries
 Research, 192: 135-140. URL http://www.sciencedirect.com/science/article/
 pii/S0165783616304192.
- Smith, C. C. and Fretwell, S. D. 1974. The optimal balance between size and number
 of offspring. The American Naturalist, 108: 499–506. URL http://www.jstor.org/
 stable/2459681.
- Smith, S. E., Au, D. W., and Show, C. 1998. Intrinsic rebound potentials of 26 species
 of Pacific sharks. Marine and Freshwater Research, 49: 663–678.
- Stevens, J. 2000. The effects of fishing on sharks, rays, and chimaeras (chondrichthyans),
 and the implications for marine ecosystems. ICES Journal of Marine Science,
 57: 476-494. URL http://icesjms.oxfordjournals.org/cgi/doi/10.1006/jmsc.
 2000.0724.
- Stevens, J. D. and Lyle, J. M. 1989. Biology of Three Hammerhead Sharks (*Eusphyra blochii*, *Sphyrna mokarran* and *S. lewini*) from Northern Australia. Australian Journal of Marine and Freshwater Research, 40: 129–146.
- Stobutzki, I., Miller, M., and Brewer, D. 2002. Sustainability of fishery bycatch: a
 process for assessing highly diverse and numerous bycatch. Environmental Conservation, 28: 167–181. URL http://www.journals.cambridge.org/abstract_
 S0376892901000170.
- Then, A. Y., Hoenig, J. M., Hall, N. G., and Hewitt, D. A. 2015. Evaluating
 the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. ICES Journal of Marine Science, 72:
 82–92. URL http://icesjms.oxfordjournals.org/content/early/2014/08/

- 19/icesjms.fsu136.abstract https://academic.oup.com/icesjms/article lookup/doi/10.1093/icesjms/fsu136.
- Vetter, E. F. 1988. Estimation of natural mortality in fish stocks: A review. Fishery
 Bulletin, 86: 25-43.
- ⁷³¹ Ward-Paige, C. A., Davis, B., and Worm, B. 2013. Global population trends and human
- use patterns of *Manta* and *Mobula* rays. PLoS ONE, 8: e74835. URL http://dx.
- ⁷³³ doi.org/10.1371/journal.pone.0074835.

Species	Litte	er size	Breeding	Mean	Age a	it mat.	Max.	Source
opecies	mm	шал	mervar	0	111111	шал	age	
Carcharhinus $acronotus$	1	6	2.0	1.8	4.0	5.0	19.2	Driggers <i>et al.</i> (2004a,b); Barreto <i>et al.</i> (2011); Branstetter (1990)
Carcharhinus brevipinna	6	10	2.0	4.0	7.0	8.0	16.0	Cortés (2002); Branstetter (1987a)
Carcharhinus isodon	2	6	1.5	2.7	3.3	5.3	8.0	Castro (1993); Carlson <i>et al.</i> (2003); Drig- gers and Hoffmayer (2009)
Carcharhinus leucas	6	12	2.0	4.5	17.0	19.0	31.0	Branstetter (1990); Cliff and Dudley (1991); Cortés (2002); Branstetter and Stiles (1987)
$Rhizo prionodon \ terraenovae$	1	12	1.0	6.5	2.8	3.9	9.0	Parsons (1983); Bigelow and Schroeder (1948); Branstetter (1987b); Parsons (1985)
Sphyrna lewini	12	38	1.0	25.0	13.0	15.0	36.0	Branstetter (1987c); Drew <i>et al.</i> (2015); Stevens and Lyle (1989); Cortés (2002)
Sphyrna mokarran	13	42	2.0	13.8	7.4	9.5	31.7	Harry <i>et al.</i> (2011); Compagno (1984); Stevens and Lyle (1989); Last and Stevens (2009)
Sphyrna tiburo	3	15	1.0	9.0	2.9	4.0	7.5	Lombardi-Carlson <i>et al.</i> (2003); Cortés (2002)
Carcharhinus limbatus ATL	2	10	2.0	3.0	5.7	7.7	21.6	Carlson <i>et al.</i> (2006); Branstetter (1990); Castro (1996)
Carcharhinus limbatus GULF	2	10	2.0	3.0	4.7	6.7	14.4	Carlson <i>et al.</i> (2006); Branstetter (1990); Castro (1996)

Table 1: Values and sources of life history parameters used to estimate r_{max} for the ten populations studied. Note that annual reproductive output b is not obtained directly from the literature but is estimated from litter size and breeding interval.

ng levels of uncertainty in age at maturity, natural	Means, medians and standard deviations are also		
Table 2: Coefficients of variation (CV) in r_{max} estimates of seven models with varyi	mortality and annual reproductive output for the ten shark populations examined.	presented for the full model which accounts for uncertainty in all three parameters.	

Species l Cambanhinus isodon -	Model	l Coeff	icient	of Variatic	on (CV, '	(%		$b + \alpha_m$	$_{at} + M$ (F	ull) Model
Carcharhinne jeodon	p	α_{mat}	M	$b+\alpha_{mat}$	b+M	$\alpha_{mat} + M$	$b + \alpha_{mat} + M$	Mean	Median	St.Dev
7 aronoei emiliilimio mo	25.0	16.4	4.1	30.0	25.4	12.3	27.9	0.197	0.188	0.061
Carcharhinus limbatus GULF 2	25.2	10.2	1.4	27.3	25.2	8.8	26.8	0.195	0.195	0.015
Rhizoprionodon terraenovae 🤅	31.5	9.6	1.0	33.1	31.6	8.7	32.8	0.185	0.185	0.052
Carcharhinus limbatus ATL 2	21.8	7.9	0.7	23.2	21.8	7.2	23.0	0.112	0.112	0.009
Carcharhinus acronotus	31.9	5.5	0.5	32.5	31.9	4.9	32.4	0.428	0.405	0.133
Carcharhinus brevipinna	7.1	3.9	0.5	8.1	7.1	3.4	7.8	0.240	0.239	0.021
Carcharhinus leucas	7.4	3.3	0.4	8.1	7.4	2.8	7.9	0.316	0.315	0.037
Sphyrna tiburo	21.0	9.8	1.1	23.2	21.0	8.7	22.8	0.462	0.453	0.103
Sphyrna mokarran	9.7	6.6	0.2	11.7	9.7	6.4	11.6	0.202	0.197	0.045
Sphyrna lewini	7.9	4.0	0.2	8.8	7.9	3.8	8.7	0.204	0.199	0.053



Figure 1: Flow chart illustrating the structure of the Monte Carlo simulation model used in this study. The model starts with the data required (Values for age at maturity α_{mat} , maximum age α_{max} , litter size l, and breeding interval i), which are then used to define probability distributions for each parameter (except breeding interval whose value is fixed). Values for age at maturity, maximum age, and litter size are then drawn from these distributions, and used to estimate natural mortality M and annual reproductive output b, which in turn are required to obtain an estimate of maximum intrinsic rate of population increase r_{max} . The drawing of parameters from distributions is repeated 20,000 times to obtain 20,000 r_{max} estimates. Finally, we replace the probability distributions of each parameter with a fixed value to assess the sensitivity of the model to uncertainty.



Figure 2: Predicted values of maximum intrinsic rate of increase r_{max} for ten different shark populations when including uncertainty in annual reproductive output b (blue box plots), age at maturity α_{mat} (yellow box plots), and natural mortality M (red box plots). Boxes indicate median, 25% and 75% quantiles, while the lines encompass 95% of the values (2.5% and 97.5% quantiles).



Figure 3: Coefficient of variation (CV, %) in r_{max} estimates for ten different shark populations when accounting for uncertainty in (a) age at maturity α_{mat} , (b) annual reproductive output b, and (c) natural mortality M, plotted against the median values of the respective life history parameter. Lines are loss-smoothed curves.



Figure 4: Comparison of potential fishing limits based on r_{max} when estimated with no uncertainty accounted for (grey diamonds) and when accounting for uncertainty from all sources in the model (using 2.5% quantile, red diamonds). Points were slightly jittered horizontally to avoid overlap. Note that r_{max} is equivalent to F_{ext} , i.e. the point at which fishing mortality is equal to the maximum rate of population increase.



Figure 5: Contour plots of r_{max} values for varying ranges of age at maturity α_{mat} and annual reproductive output b, with values of instantaneous natural mortality M set as (a) low (0.05 year⁻¹), (b) medium (0.1 year⁻¹, and (c) high (0.2 year⁻¹).