1 *Running head*: Age structure affects productivity

2 Age structure affects population productivity in an exploited fish species

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12 ABSTRACT

13 Long-term changes in the age and size structure of animal populations are well-documented, yet their impacts on population productivity are poorly understood. Fishery exploitation can be a 14 15 major driver of changes in population age-size structure, because fisheries significantly increase 16 mortality and often selectively remove larger and older fish. Climate change is another potential 17 driver of shifts in the demographic structure of fish populations. Northeast Arctic (NEA) cod is 18 the largest population of Atlantic cod (Gadus morhua) and one of the world's most important 19 commercial fish stocks. This population has experienced considerable changes in population agesize structure over the past century, largely in response to fishing. In this study, we investigate 20 21 whether changes in spawner age structure have affected population productivity in NEA cod, 22 measured as recruits per spawning stock biomass, over the past 75 years. We find evidence that 23 shifts in age structure toward younger spawners negatively affect population productivity, 24 implying higher recruitment success when the spawning stock is composed of older individuals. The positive effect of an older spawning stock is likely linked to maternal effects and higher 25 26 reproductive output of larger females. Our results indicate a three-fold difference in productivity 27 between the youngest and oldest spawning stock that has been observed since the 1950s. Further, 28 our results suggest a positive effect of environmental temperature and a negative effect of 29 intraspecific cannibalism by older juveniles on population productivity, which partly masked the effect of spawner age structure unless accounted for in the model. Collectively, these findings 30 31 emphasize the importance of population age structure for the productivity of fish populations, 32 and suggest that harvest-induced demographic changes can have negative feedbacks for fisheries 33 that lead to a younger spawning stock. Incorporating demographic data into harvest strategies 34 could thus facilitate sustainable fishery management.

35 *Keywords:* age structure, demography, exploitation, population productivity, reproductive output

36 INTRODUCTION

37 Animal populations are inherently structured with respect to age, size, and life-history stage. The age structure of the adult population is determined by a species' life-history, in particular the 38 39 maturation schedule and longevity, as well as potential sources of mortality that alter the age 40 composition of the population. In fish populations, harvesting can be a major driver of changes in age and size structure, because fisheries increase mortality such that fewer individuals survive 41 42 to old age, and because fisheries often selectively remove larger and older fish (Law 2000; 43 Berkeley et al. 2004; Beamish et al. 2006; Barnett et al. 2017). These changes may persist after fishing pressure is reduced if fishing has resulted in evolutionary changes in traits related to 44 45 growth and maturation (Jørgensen et al. 2007; Swain et al. 2007; Wright and Trippel 2009; 46 Heino et al. 2015). Fisheries-induced demographic change of a population can have negative 47 repercussions for a fishery via increased variability in abundance (Anderson et al. 2008; Shelton 48 and Mangel 2011; Botsford et al. 2014). While the impact of large individuals on population 49 health and replenishment remains controversial (Brunel and Piet 2011; Andersen et al. 2019), the 50 importance of conserving diverse age-size structures of populations has been emphasized in the context of fisheries sustainability (Birkeland and Dayton 2005; Hsieh et al. 2010; Stige et al. 51 52 2017; Ahrens et al. 2020; Marshall et al. 2021).

In addition to exploitation, environmental changes contribute to shifting age structures through altered rates of growth and survival as well as the selection they impose on maturation schedules. One potential cause of contemporary changes in population age and size structure is climate warming (Daufresne et al. 2009; Gardner et al. 2011; Forster et al. 2012). Warming is expected to result in a faster life-history with higher growth rates and earlier maturation, as long as thermal conditions rarely exceed optimal temperatures for growth and survival (Ohlberger 2013;

59 Baudron et al. 2014; Huss et al. 2019). The effects of warming depend on currently experienced 60 temperatures relative to organism thermal constraints, and may vary by population within species, for instance along latitudinal gradients (Ohlberger 2013). While the impacts of climate 61 62 warming on fish body size also vary between species and may depend on local ecological 63 conditions and life-history traits (van Rijn et al. 2017; Audzijonyte et al. 2020; Denderen et al. 64 2020), changes in thermal regimes commonly result in altered population age-size structures. Shifts in demographic structure can affect population productivity through various mechanisms. 65 First, shifts toward younger and smaller female spawners are expected to cause a reduction in 66 average per capita reproductive output, because smaller females carry fewer and often smaller or 67 68 lower quality eggs (Kjesbu et al. 1996; Murawski 2001; Scott et al. 2006; Ohlberger et al. 2020). 69 In many marine fish species, female reproductive investment scales hyperallometrically with 70 body mass, such that the total energy invested into reproduction per unit biomass increases with 71 spawner body size (Hixon et al. 2014; Barneche et al. 2018). Second, a spawning stock that is 72 composed of older females may also result in higher population recruitment due to a variety of 73 maternal effects. In the Northeast Arctic (NEA) stock of Atlantic cod (Gadus morhua), for 74 instance, older females spawn in different locations and over longer periods of time (Kjesbu et 75 al. 1996; Wright and Trippel 2009; Opdal and Jørgensen 2015), are less likely to skip spawning 76 (Jørgensen et al. 2006), and produce eggs and larvae that have higher survival rates (Solemdal 77 1997). Third, an older spawning stock may exhibit a higher proportion of female spawners due to 78 sex-specific growth, maturation thresholds, and/or survival rates (Jørgensen 1990; Marshall et al. 79 2006). These studies suggest that spawner age structure may affect recruitment success and 80 population productivity.

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81 A diverse set of metrics has been used to describe changes in population age structure over time. 82 The most commonly used metrics include the biomass-weighted mean age or mean weight of spawners, spawner age diversity, the proportion of old individuals in the population, and the 83 84 proportion of repeat spawners (Marteinsdottir and Thorarinsson 1998; Ottersen et al. 2006; 85 Ottersen 2008; Brunel 2010; Barnett et al. 2017). While shifts in demographic structure cannot 86 be fully captured by any single age structure metric, such metrics are useful for illustrative and 87 predictive purposes. Furthermore, which metric best reflects observed changes in age structure over time may depend on the processes involved and the major drivers of demographic change. 88 89 For example, the proportion of old individuals in the population may best reflect shifting age 90 structures due to the removal of large fish in size-selective fisheries, whereas mean age of the 91 spawning stock may best reflect shifts in age structure in populations that have experienced long-92 term changes in age at first maturation, including evolutionary change. 93 While evidence exists that shifts towards a younger and less age diverse spawning stock can have negative effects on population recruitment and productivity, meta-analyses of marine fishes 94 95 have found that these effects vary by population, for instance in Atlantic cod (Brunel 2010; 96 Shelton et al. 2015). Populations differ in life-history characteristics such as growth, age at 97 maturation, maximum age, and intrinsic density regulation due to size-based intraspecific 98 competition and cannibalism (Anderson and Gregory 2000). Specifically, cannibalism mortality of pre-recruits may increase with the abundance of older juveniles that have recruited to the 99 100 fishery but have not matured and are therefore not part of the spawning stock, as is the case for 101 NEA cod (Bogstad et al. 1994; Yaragina et al. 2009). Accounting for other factors beyond 102 spawner biomass might thus be critical to fully understand how the age structure of a population 103 affects its productivity.

104 The NEA cod stock is currently the world's largest population of Atlantic cod and sustains a 105 large and profitable fishery. The stock mainly feeds in the Barents Sea and spawns along the 106 west and north coasts of Norway (Fig. 1). Changes in the population age structure of NEA cod 107 have occurred for almost a century, largely in response to intense exploitation (Ottersen 2008; 108 Eikeset et al. 2016). The typical age at maturation and the mean age of the spawning stock have both declined considerably during the 2nd half of the 20th century, although spawner age structure 109 110 has partly recovered over the past two decades (Fig. 2), coinciding with a reduction in fishing 111 mortality (Kjesbu et al. 2014). Here, we ask whether population productivity in NEA cod 112 (measured as the natural logarithm of recruits per spawning stock biomass) is affected by 113 changes in the age structure of the spawning stock. We test for effects of intraspecific predation of pre-recruits by older juveniles, and assess potential effects of other ecological conditions on 114 115 population productivity, including changes in temperature and species interactions.

116 METHODS

117 Study species and region

118 NEA cod are mainly distributed throughout the Barents Sea off the northern coasts of Norway 119 and Russia. Adults perform annual migrations to the spawning grounds along the west coast of 120 Norway, where they spawn primarily in March-April (Fig. 1; Ottersen et al. 2014). Spawned 121 eggs drift northeastward in the Norwegian Coastal Current and develop into pelagic larvae and 122 juveniles that reach the main feeding grounds in the Barents Sea after about five months of drift. 123 The fish remain in the Barents Sea until they reach maturity, typically at the age of 6-8 years 124 (Olsen et al. 2010). Compared to other populations of Atlantic cod, NEA cod are relatively slow 125 growing and late maturing (Köster et al. 2013). NEA cod can grow to over 1 m in length and live

over 20 years (Holt and Jørgensen 2014). The stock has been harvested for centuries along the

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127 Norwegian cost, and more recently (since the 1930s) in the Barents Sea. 128 **Data sources** We used annual estimates of numbers at age, weight at age, and proportion mature at age as 129 130 reported in the NEA cod stock assessment (ICES 2020). NEA cod are assumed to recruit to the 131 fishery at age-3, and recruitment is measured as the abundance of 3-year-old fish (ICES 2020). 132 Numbers at age include cod ages 1-13 and a plus group combining all fish ages 14 and older. 133 Temperature data were obtained from the Kola transect (Tereschenko 1996), an indicator of the 134 thermal conditions in the Barents Sea (Ottersen and Stenseth 2001). We used a mean temperature 135 value averaged over six months (July-December), across Kola stations 3-7 (Fig. 1), and vertically 136 from 0-200m depth (available online at: www.pinro.ru). Temperature records were available for 137 the years 1946-2017, except during August-December 2016. These data were added using 138 bivariate interpolation of temperature data (using function *interp* in R) across years and months. 139 Data on biomass and abundances of interacting species were obtained from various sources. 140 These include estimates of total abundance of capelin (Mallotus villosus) in the Barents Sea for the years 1972-2015 (ICES 2020), estimates of Norwegian spring spawning herring (Clupea 141 142 harengus) biomass (ages 1-2) for the years 1950-2015 (ICES 2020), an index of krill abundance 143 for the years 1950-2005 based on Russian bottom surveys in winter (Zhukova et al. 2009), and a 144 zooplankton abundance index (copepod nauplii) based on Russian surveys in April-May and 145 June-July for the years 1959-1990 (Stige et al. 2010). We also included a more recent index of zooplankton biomass in the southwestern and central Barents Sea in summer (August-146 147 September) for the years 1981-2015 (Stige et al. 2018). Previous studies suggested that 148 recruitment success in NEA cod depends on the abundance of mesozooplankton, a critical food

149source for early life-stages of cod, the abundance of capelin, another important prey species, via150increased growth and reduced inter-cohort cannibalism, as well as the biomass of herring, which151feed on capelin larvae and thus affect capelin recruitment (Hamre 1994; Hjermann et al. 2007;152Langangen et al. 2017).153*Calculating stock metrics*154Spawner biomass of cod at age a in year y (S_{a,y}) was calculated from annual numbers at age (155
$$N_{a,y}$$
), weight at age ($W_{a,y}$), and proportion mature at age ($M_{a,y}$):156 $S_{a,y} = N_{a,y}W_{a,y}M_{a,y}$, (1)157Total spawning stock biomass in a given year was then calculated as the sum across ages:158 $S_y = \sum_a S_{a,y}$.159The biomass of 3-6 year-old cod was used as a proxy for potential cannibalism on pre-recruits:160 $C_y = \sum_{a=3}^{a=6} N_{a,y}W_{a,y}$.

161 This index of cannibal biomass is only weakly correlated with spawning stock biomass because

162 NEA cod typically do not mature before age-6 (Olsen et al. 2010).

163 We used biomass-weighted mean age of spawners (\overline{A}_y) as a metric of spawner age structure, as

done previously for this and other stocks (Ottersen et al. 2006; Ottersen 2008):

165
$$\overline{A}_{y} = \frac{\sum_{a} S_{a,y} a}{\sum_{a} S_{a,y}}.$$
 (4)

166 We also used the biomass-weighted mean weight (\overline{W}_y) of spawners (Langangen et al. 2019):

167
$$\overline{W}_{y} = \frac{\sum_{a} S_{a,y} W_{a,y}}{\sum_{a} S_{a,y}}.$$
 (5)

Previous work that explored various metrics of spawner age and size structure as predictors of changes in the abundance and distribution of NEA cod eggs found that biomass-weighted mean age and weight were better predictors than other metrics (Stige et al. 2017), and spawner mean age appears to reflect the major shift in spawner age structure in this population (Appendix S1: Fig. S1). However, we considered other commonly used metrics of spawner age structure in our model selection, specifically the proportion of individuals in the oldest age class (+group), the Shannon index of age diversity, and the proportion of repeat spawners, (Marteinsdottir and

- 174 Shannon muck of age diversity, and the proportion of repeat spawners, (Wartenisdotti
- 175 Thorarinsson 1998; Brunel 2010; Barnett et al. 2017).

We calculated an index of the proportion of the oldest fish in the population as the log ratio of the proportion of individuals in the plus group in any given year relative to the proportion of individuals in the plus group at the beginning of the time series (PG_y) (Barnett et al. 2017):

179
$$PG_y = \log\left(\frac{pPG_y}{pPG_{y=1946}}\right)$$
, with $pPG_y = \frac{N_{a \ge 15,y}}{\sum_{a=1}^{a=14} N_{a,y}}$, (6)

180 where pPG_y is the proportion of the plus group individuals (ages 15+) in the population.

181 The Shannon diversity index (DIV_y) was calculated based on the frequency of mature biomass at 182 age $(f_{a,y})$:

183
$$DIV_y = -\sum_a (f_{a,y} \ln(f_{a,y})), \text{ for } f_{a,y} > 0.$$
 (7)

184 The proportion repeat spawners (PRS_y) was calculated based on the proportions mature in each 185 age and year:

186
$$PRS_y = \frac{\sum_{a} (M_{a-1,y-1}/M_{a,y}) S_{a,y}}{\sum_{a} S_{a,y}}.$$
 (8)

187 Statistical analyses

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188 Our analysis is based on a Ricker stock-recruitment model (Ricker 1954) to describe the

189 relationship between spawning stock biomass in year $y(S_y)$ and subsequent recruitment (R_{y+3})

190 three years later. The linearized version is:

191
$$\ln\left(\frac{R_{y+3}}{S_y}\right) = \alpha + \beta S_y + \epsilon_y,$$
 (9)

192 where α is the intercept, β is the rate at which productivity declines with spawner biomass (

193 $\beta \le 0$), and ϵ_y is an error term that was modeled to account for autocorrelation in the residuals:

194
$$\epsilon_y = \epsilon_{y-1}\varphi + \omega_y,$$
 (10)

195 where φ is the autocorrelation coefficient and $\omega_{\rm v} \sim N(0,\sigma^2)$ are normal random errors.

196 The natural logarithm of recruits per spawner biomass was thus used as a metric of population 197 productivity. To explain variation in population productivity over time beyond the effect of 198 spawner biomass, we extended this model to incorporate other predictor variables:

199
$$\ln\left(\frac{R_{y+3}}{S_y}\right) = \alpha + \beta_0 S_y + \beta_1 X_1 + ... + \beta_n X_n + \epsilon_y,$$
 (11)

where $\beta_1, ..., \beta_n$ are the regression coefficients and $X_1, ..., X_n$ are the covariate time series lagged relative to spawn year when the covariate is hypothesized to affect population productivity via effects on spawners, eggs, larvae, or pre-recruit juveniles. By using a linearized Ricker model, we implicitly assume that potential covariate effects are additive on log scale (multiplicative on arithmetic scale), and we test whether covariates affect population productivity, not whether they modulate the density dependence between recruitment and spawner biomass.

We considered the following continuous predictor variables in addition to total spawner biomass, which was set as a fixed term in the regression analysis: biomass of age 3-6 cannibals in the year after spawning (as a proxy of intraspecific predation by preceding cohorts during the pre-recruit

209 life-stages), average temperature of the Kola section in the Barents Sea from July through 210 December, i.e. during the larval and 0-group stages, and one of the age structure metrics: 211 biomass-weighted mean age or mean weight of spawners, the Shannon index of age diversity, the 212 proportion of individuals in the plus group, and the proportion of repeat spawners. We did not 213 include more than one age structure metric in the same model due to high pairwise correlations 214 among these metrics. We considered other seasonal temperature averages during our preliminary 215 analysis that were less strongly associated with our response variable. All of the above covariate 216 time series were available for all years with data on spawner biomass and recruitment (1946-217 2017), with the exception that the proportion repeat spawners could not be computed for the first 218 year. A lag of one year post spawning was used for the cannibal biomass covariate because 219 cannibalism mortality is highest among 1-year old cod (Yaragina et al. 2009). We also tested for 220 effects of food web interactions, using indices of capelin abundance, biomass of young herring 221 (ages 1-2), krill abundance, and mesozooplankton abundance, which were not available for all 222 years. The model selection was run using years with observations for each predictor, and was 223 extended to include more years as predictors with shorter time series were dropped from the 224 model. Information on covariates included in the model selection, available data, lags 225 considered, and potential mechanisms are presented in the Supplementary Material (Appendix 226 S1: Table S1). We considered non-linear temperature effects by including a quadratic term in 227 addition to the linear effect, and tested for an interaction effect between temperature and age 228 structure (Ottersen et al. 2006), by constructing a dummy variable representing 'high' and 'low' 229 values. The optimal threshold for splitting the age structure metric into two categories was 230 determined by testing a range of quantiles (0.2-0.8).

231 Model selection was performed using the *dredge* function of the package *MuMIn* (v. 1.43.15, 232 Burnham and Anderson 2002) in R (R Core Team 2020) and was based on Akaike's Information 233 Criterion corrected for small sample size (AICc). All variables were centered and standardized to 234 a mean of zero and a standard deviation of one for the analysis to ensure that main effects are 235 biologically interpretable in the presence of interactions and that slopes are comparable within 236 and between models (Schielzeth 2010). We tested for the inclusion of model weights for 237 explaining the variance structure of the residuals using fixed and exponential functions of the 238 selected covariates (Zuur et al. 2010). Because we tested a variable threshold effect for the 239 interaction between temperature and mean age, we penalized the interaction model when 240 calculating the AICc value by counting the threshold as one additional parameter (Ottersen et al. 2013). We assessed multicollinearity between selected explanatory variables using variance 241 242 inflation factors (VIF) (Zuur et al. 2010).

To assess the ability of the models of varying complexity to make out-of-sample predictions, we performed a model cross validation. The data were randomly split into a training dataset (75% of data) and a test dataset (25% of data), and all sub-models contained in the selected model with the lowest AICc value were run on the training data to estimate the model parameters and subsequently predict the remaining test data. We then calculated the root mean squared prediction error (RMSE) as our performance metric:

249 RMSE =
$$\sqrt{\frac{\sum_{1}^{n} (\hat{y} - y)^{2}}{n}}$$
, (12)

where \hat{y} and y are model-predicted and observed ln(recruits/SSB) in each year, respectively, and *n* is the number of years. This procedure was repeated 1000 times by randomly drawing the training and test datasets from the observations. The median root mean squared prediction errors across runs were compared among all sub-models to assess which of the models would produce

the best out-of-sample predictions, i.e. smallest median prediction errors. Code for the statistical

analyses is provided as supporting information (Data S1) and is available online in Zenodo at:

256 https://doi.org/10.5281/zenodo.5851638.

257 **RESULTS**

- 258 Over the past 75 years, spawning stock biomass of NEA cod has varied between 0.1 and 2.64
- 259 million tons with an average of 0.62 million tons, and recruitment at age-3 has varied between

260 0.11 and 2.59 billion recruits with an average of 0.75 billion recruits (Fig. 2). Population

261 productivity measured as ln(recruits/SSB) has varied considerably over time and was particularly

low during the 2010s when spawning stock biomass was high.

Population age structure was an important predictor of population productivity in NEA cod.
Several of the age structure metrics performed similarly well in terms of AICc and model
predictive ability (Appendix S1: Table S4; Fig. S2), and our model selection showed support for
including the same covariates in models with alternative age structure metrics. In addition to
spawning stock biomass, the final models included the biomass of age 3-6 cannibals, mean
temperature, and one of the age structure metrics:

269
$$\ln\left(\frac{R_{y+3}}{S_y}\right) = \alpha + \beta_0 S_y + \beta_1 A_y + \beta_2 C_{y+1} + \beta_3 T_y + \epsilon_y,$$

where A_y is the age structure metric in year y, C_{y+1} is biomass of potential cannibals in the following year, and T_y is mean environmental temperature in year y from July to December. Time series of selected covariates are presented in Fig. 2. Productivity of NEA cod was not associated with any of the abundance or biomass indices of the interacting species that we Page 15 of 34

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considered in the model. We did not find evidence for the inclusion of model weights to explainthe variance structure in the data.

276 We found that population productivity was negatively associated with spawning stock biomass 277 (mature fish age 6 or older) and the biomass of potential cannibals (mostly immature fish ages 3-278 6), and positively associated with mean temperature and the age structure metrics (Fig. 3). While 279 spawner mean age performed best in terms of model predictive ability, other age structure 280 metrics resulted in similar prediction errors and AICc values (Appendix S1: Table S4; Fig. S2). 281 Specifically, the log ratio of the proportion of old individuals (ages 15+) in the population and 282 spawner age diversity were similarly good predictors of population productivity (Fig. 3). 283 The AICc-based model selection of covariates resulted in competing models with similar AICc 284 support (Appendix S1: Table S2). The more complex model included an interaction effect 285 between temperature and the age structure metric as categorical variable (e.g. spawner mean age 286 with a threshold at the 0.7 quantile, Appendix S1: Fig. S3). However, the simpler model received 287 support based on the model cross-validation due to lower root mean squared prediction errors 288 and was selected as the most parsimonious model (Appendix S1: Fig. S4). Residuals suggested 289 no violation of assumptions of normality and homoscedasticity and model predictions captured 290 much of the trends and interannual variability in population productivity (Appendix S1: Fig. S5). 291 The estimated model coefficients (per unit standard deviation) are provided in Appendix S1: 292 Table S3. The standard deviation of the normal random error was 0.54, and the autocorrelation 293 coefficient was 0.47 (mean age model). While spawning stock biomass, metrics of spawner age 294 structure, and cannibal biomass are intrinsic population metrics, pairwise correlations between 295 covariates of the fitted models were low (Pearson correlation coefficients <0.4), and a variance 296 inflation factor analysis of the selected covariates raised no concern of multicollinearity (all

297 values <1.2). Inclusion of alternative age structure metrics did not appreciably alter the estimated 298 coefficients for spawning stock biomass, biomass of cannibals, and mean temperature (Fig. 3). 299 The selected models were used to predict ln(recruits/SBB) as a function of spawning stock 300 biomass for different values of the age structure metrics while setting other covariates (cannibal biomass and temperature) to median values. We used the 2.5th and 97.5th percentiles of spawner 301 302 mean age, log ratio of the proportion plus group, and the spawner age diversity index that have 303 been observed over the past 75 years. The predictions illustrated the large effect that spawner age 304 structure has on expected recruits per spawning stock biomass (Fig. 3). For example, the ratio of 305 model-predicted recruits/SBB at the highest compared to the lowest mean age was 3.04. A 306 spawning stock with a mean age of about 11 years is expected to produce three times as many 307 recruits per unit spawner biomass compared to a spawning stock with a mean age of about 7 308 years. We further found that the effects of spawner age structure were slightly weaker when the 309 biomass of age 3-6 cod was not included in the model. Dropping cannibal biomass from the 310 model resulted in smaller effect sizes of spawner age structure, and reduced model predictive 311 ability (Appendix S1: Fig. S4, Fig. S6).

312 **DISCUSSION**

We find evidence that the mean age of spawners, or alternatively age diversity or the proportion of old individuals in the population, has a positive effect on population productivity, measured as recruits per spawning stock biomass. Our results suggests a three-fold difference in population productivity between the lowest and highest mean ages of spawners that have been observed over the past 75 years. In addition, we find evidence that the biomass of potential cannibals negatively affects population productivity, and that increasing temperatures have a positive effect on the productivity of this high-latitude cod population.

320 Previous work has evaluated the effect of spawner age structure on cod population recruitment. 321 Ottersen (2008) analyzed data on NEA cod and found no clear link between the mean age of 322 spawners and subsequent recruitment. Brunel (2010) studied multiple stocks of Atlantic cod and 323 found that the effects of spawner mean age and age diversity on recruitment were positive but 324 non-significant for most cod stocks, including NEA cod. Shelton et al. (2015) used stock-recruit 325 relationships that included maternal age structure to model the recruitment of several stocks of 326 Atlantic cod and found that in many stocks a model with a maternal age effect was preferred, 327 though they reported a relatively weak effect for NEA cod. However, these studies did not 328 account for potential cannibalism of pre-recruits by older juveniles that have recruited to the 329 fishery but are not part of the spawning stock. Because NEA cod rarely mature before age 6, and 330 predation by 3-6 year-olds accounts for most of the cannibalism mortality among pre-recruits 331 (Bogstad et al. 1994; Yaragina et al. 2009), the majority of potential cannibals are not part of the 332 spawning stock. We therefore included cannibal biomass as an additional variable in our model. Ignoring this component of intrinsic population regulation likely affects inferences about other 333 334 factors affecting productivity, especially because cannibalism in NEA cod appears to be more 335 pronounced than in other stocks (Holt et al. 2019). This is in line with our finding that the effect 336 of spawner age structure was weaker when the biomass of age 3-6 cod was not included in the 337 model. It should be noted that our analysis relies on data from a stock-assessment model that are 338 assumed to represent true values. The NEA stock assessment model considers cannibalism 339 mortality, in addition to a fixed natural mortality, and the underlying estimation of consumption 340 of cod by cod based on stomach content data is uncertain and affected by temperature (ICES 341 2020). This might introduce bias into our model estimates, in particular the cannibalism effect.

342 The higher recruitment success per unit spawner biomass of an older and more age diverse 343 spawning stock is in part caused by an increase in mass-specific reproductive investment with 344 female body size. Hyperallometric scaling of reproductive output is commonly observed in 345 marine fishes, including Atlantic cod (Barneche et al. 2018), and interannual variation in relative 346 fecundity is associated with variation in the size composition of the spawning stock in NEA cod 347 (Marshall et al. 2006). While the approach applied here does not allow us to quantify the 348 contributions of different mechanisms, our findings suggest that other factors linked to maternal 349 effects contribute to increased population productivity of an older spawning stock, because 350 productivity was more strongly linked to the mean age of spawners than the mean weight of 351 spawners. Maternal effects may arise from various mechanisms, including differences between 352 young and old spawners in the duration of spawning, frequency of skipped spawning, and factors 353 such as larger eggs that can result in higher offspring survival (Solemdal et al. 1995; Kjesbu et 354 al. 1996; Nissling et al. 1998; Vallin and Nissling 2000; Jørgensen et al. 2006). Other 355 mechanisms appear to be less important, for instance, a broader spatial distribution of eggs has 356 little effect on recruitment in NEA cod (Stige et al. 2017; Langangen and Stige 2021). 357 We found a positive but relatively weak link between NEA cod productivity and temperature, as 358 reported previously (Ottersen and Loeng 2000; Stige et al. 2010; Ohlberger et al. 2014). Higher 359 temperatures likely increase growth and survival during early life-stages. Impacts of warming 360 may also differ between life-stages (Peck et al. 2009), and manifest though various mechanisms, 361 including changes in the abundance and distribution of predators and prey (Ohlberger 2013; 362 Ottersen et al. 2014). In NEA cod, higher temperatures also appear to be linked to spawning at 363 higher latitudes (Sundby and Nakken 2008; Langangen et al. 2019; but see Opdal and Jørgensen 364 2015). Importantly, climate warming can affect populations of the same species differently. The

365 relationship between environmental temperature and recruitment of Atlantic cod varies by 366 population, with positive effects at higher latitudes and negative effects at lower latitudes (Drinkwater 2005). Interestingly, we found similar support for a model that included an 367 368 interaction between temperature and age structure (as a categorical variable), which suggested a 369 positive temperature effect at low mean age, age diversity or proportion plus group, but no effect 370 at high values. While that model was not selected as the most parsimonious due to its lower 371 predictive performance, such an interaction would be consistent with previous work that 372 suggested a strengthening of the climate-recruitment link during the second half of the 20th 373 century (Ottersen et al. 2006). 374 The reduction in population productivity associated with shifting spawner age structure is of 375 particular importance because fisheries increase mortality and often selectively remove large 376 individuals from the spawning populations. Fishing commonly leads to population age structures 377 shifting towards younger and smaller fish (Anderson et al. 2008; Sharpe and Hendry 2009) and 378 may result in evolutionary changes toward earlier maturation (Kuparinen and Merilä 2007; 379 Heino et al. 2015). While evidence exists that changes in the age structure of NEA cod largely 380 occurred in response to exploitation (Ottersen 2008; Eikeset et al. 2016), it is conceivable that 381 increasing temperatures contribute to reduced mean age of spawners via effects on growth and 382 maturation (Forster et al. 2012; Baudron et al. 2014; Huss et al. 2019). Our results thus suggest 383 that intense capture fisheries can affect the productivity of the populations they depend on, not 384 only via changes of total spawner abundance, but also by altering the age structure of the 385 spawning stock. Changes related to species life-histories, such as shifting spawner age structures, 386 are increasingly recognized to impact population recruitment (Shelton et al. 2015). Our study 387 shows that age structure can have significant impacts on fish stock productivity, which in turn

388 might affect the long-term sustainable yield of commercial fisheries and the livelihoods that 389 depend on these fisheries. A model including spawner mean age had a slightly better predictive 390 ability compared to models including alternative age structure metrics in our study. While mean 391 age has been criticized as a poor descriptor of the age composition of a population and is difficult 392 to link to individual-level traits (Shelton et al. 2015), spawner mean age appears to capture the 393 shift in age composition of the NEA cod spawning stock (Appendix S1: Fig. S1), likely because 394 these shifts are associated with changes in age at first maturation. Alternative metrics such as the 395 proportion of old individuals in the population may be better suited to reflect age structure 396 changes in other exploited populations, for example those that have not experienced long-term 397 changes in maturation schedules.

398 Our findings highlight the potential of preserving spawner age structure as a tool to sustaining 399 population productivity. Shifting age structures of fish populations can also cause increased 400 variability in abundance and reduced population resilience (Anderson et al. 2008; Hsieh et al. 401 2010; Shelton and Mangel 2011). Incorporating demographic information into the fishery 402 management process could help preserve an older and more diverse age structure and thereby 403 facilitate fisheries sustainability. Whether the best approach to preserving spawner age structure 404 is via size or weight limits, spatial fishery closures, or reduced fishing mortality, likely depends 405 on the ecology of the exploited population as well as fishing methods and current management 406 practices (Berkeley et al. 2004; Kjesbu et al. 2014; Ahrens et al. 2020). For instance, the NEA 407 cod fishery is currently managed via a harvest control rule that is used to set the total allowable 408 catch each year based on reference points for spawning stock biomass and fishing mortality. This 409 rule was designed to ensure that the stock is harvested sustainably (ICES 2009; Eikeset et al. 410 2013), and its implementation in the mid-2000s appears to have contributed to increased spawner

411	biomass and mean age (Kjesbu et al. 2014; Fig. 1). In addition to biomass or fishing mortality
412	limits, harvest control rules could adopt reference points based on the demographic status of a
413	population to further ensure that population reproductive capacity is maintained.
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621 FIGURE CAPTIONS

622 Fig. 1: Map showing the spawning locations and general distribution of NEA cod. Juvenile

and adult NEA cod are mostly distributed in the Barents Sea (shaded area). The fish perform

624 annual migrations to the spawning grounds (dark gray) along the Norwegian coast. Also

625 indicated is the Kola section (station 3-7) in the Barents Sea (thick black line).

626 Fig. 2: Time series data. Shown are (a) spawning stock biomass (SSB, million tons) and

627 recruitment (billions), (b) biomass of age 3-6 cod that are considered cannibals on pre-recruits,

628 (c) temperature of the Kola section in the Barents Sea (red and blue indicate temperatures above

and below the long-term average of 4.8°C, respectively), and (d) three age structure metrics:

biomass-weighted mean age of the spawning stock (blue), the log ratio of the proportion of old

631 individuals (age 15+) in the population (green), and the Shannon index of spawner age diversity632 (orange).

633 Fig. 3: Estimated covariate effects and spawner-recruit predictions for models including

634 alternative age structure metrics. Shown are standardized effect size estimates of all covariates in the three alternative models, including total spawner biomass, biomass of age 3-6 cannibals, 635 636 mean temperature, and the age structure metric, where lines are 95% confidence intervals (a-c), 637 partial effects on ln(recruits/SSB) of the age structure metrics, where shaded polygons are 95% 638 confidence intervals (d-f), and predicted relationships between spawning stock biomass (million 639 tons) and recruitment (billions) for the alternative age structure metrics (g-i). Predictions were 640 made for two different values of the respective age structure metric, taken as the 2.5th and 97.5th 641 percentiles, and assuming median values for the other predictors in the model (biomass of age 3-642 6 cod and mean temperature). Thin dashed lines represent two times the standard error of the predictions. 643





