| 1 | Spatial, interannual, and generational sources of trait variability in a marine | | |
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| 24 | ABSTRACT | | |
| 25 | Life history traits of individuals in marine populations exhibit large sources of | | |
| 26 | variability. In marine fish, variation of individual size at a given age has three main | | |
| 27 | components: 1. spatial, correlated with the location in which individuals are caught, 2. | | |
| 28 | temporal, correlated with the time when individuals are caught, and 3. generational, | | |
| 29 | correlated with the year of birth of the examined individuals. These variations, if present, | | |
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30 have practical implications for individual fitness as well as for sampling, survey design, 31 and population assessment. Disentangling these variations and understanding their 32 sources is hard, given the potentially correlated nature of their effects on individual traits. 33 This study examines the size-at-age relationship of the Bering Sea Pacific cod -- an 34 economically and ecologically important groundfish. We used extensive records spanning 35 1994 to 2016 (inclusive) of 25,213 observations of both environmental variables and 36 catch lengths and ages. We found that the average size of individuals of the same age 37 could differ in size up to 7 cm. Notably, we found that the cohort composition of the 38 sampled population explained > 75% of the year effect, and that individuals caught in the 39 northwest and shallower portion of the sampling area were on average 5 cm smaller than 40 individuals caught in the southern and deeper portion. We further found that northwest 41 movement of young cod (age 1-5) as a result of warming places individuals in areas where we predict them to have smaller size-at-age. Smaller and less conditioned 42 43 individuals are less fecund and may not be able to perform long migrations to return to 44 their distant spawning grounds. Both the spatial distribution and water temperature 45 experienced by Pacific cod in the Bering Sea are changing, and this study provides a 46 mechanism for how these changes affect Pacific cod life-history-traits and individual 47 fitness.

48

49 KEY WORDS: traits, cohort, spatial ecology, phenotypic plasticity, growth, Bering Sea,

50 size-at-age

51 INTRODUCTION

52 Life history traits of individuals in marine populations exhibit large sources of 53 variability. Trait variability affects individual fitness (Webb et al. 2010) and the 54 assumptions necessary to sample the population (Puerta et al. 2019). Growth rate is one 55 of such traits that results in individuals having vastly different body sizes at a given age. 56 In turn, body size and growth rate have well-known fitness consequences, which for 57 marine fish are especially evident during early life stages (Sogard 1997, Houde 2008). 58 Observed variability of individual growth rates originates from multiple processes, 59 including heterogeneous environmental conditions experienced by different individuals 60 (Matta et al. 2010), long-lasting environmental effects experienced during early life

history stages (Hurst et al. 2012), complex genetic structures (Spies 2012), densitydependence (Stige et al. in press), or size-selective predation (Bailey and Houde 1989).
As a result of these multiple and interacting processes, individual size at a given age may
be grouped according to three main patterns of variability: *1. spatial*, correlated with the
location in which individuals are caught, *2. temporal*, correlated with the time (e.g., year
in multi-year sampling programs) when individuals are caught, and *3. generational*,
correlated with the year of birth of the examined individuals.

68 Decomposing trait variability among the three main patterns can lead to new insight 69 on the processes that generate such variability and on their potential consequences to 70 management of the population and fitness of individuals. However, identifying patterns 71 and processes driving growth variability in marine fish is challenging due to their 72 correlated nature. For example, temporal growth variability could be driven by spatial 73 variability, if the distribution of the individuals changes over time. Likewise, temporal 74 variability could be driven by a generational effect, if the proportion of individuals from 75 different cohorts changes over time. A typical approach to discern different sources of growth variability is that of using common garden experiments, where individuals from 76 77 different geographic origins are exposed to similar experimental conditions (e.g., 78 Hutchings et al. 2007); however, these approaches are hard to conduct in adult 79 individuals with long life span and slow growth rate (Germino et al. 2019). Retrospective 80 analyses of field data are a valid alternative (Thorson and Minte-Vera, 2016), but require 81 large sample sizes spanning over environmentally contrasting periods.

82 Pacific cod (Gadus macrocephalus) is a marine groundfish widely distributed across 83 the Bering Sea, Gulf of Alaska, and Aleutian Islands area (Thompson, 2016). It is one of 84 the most important species for commercial fishing off of Alaska. In addition, Pacific cod 85 is ecologically significant as both a predator and prey species. It serves as prey for 86 multiple marine mammals, including the endangered Steller sea lions (Calkins, 1998). 87 Gaichas and Francis (2008) found that Pacific cod is the most interconnected species in 88 the Gulf of Alaska food web, making it one of four critical groundfish species, together 89 with walleye Pollock (Gadus chalcogrammus), Pacific halibut (Hippoglossus stenolepis), 90 and arrowtooth flounder (Atherestes stomias). Having an accurate model of size-at-age is 91 necessary for managing sustainable fisheries, in which regulations for total allowable catch are made based on a stock assessment (Thompson, 2016). For Pacific cod, the stock
assessment estimates both the age structure of the population and the overall population
size (Methot and Wetzel, 2013). Therefore, it is important to have both accurate ageing
techniques and representative sampling criteria from which population demographic
variables are derived.

97 In this study, we use abundance, length, and age data collected during a long-term 98 fishery monitoring program, to identify patterns of variability (i.e., temporal, spatial and 99 generational) and processes correlated with these patterns in the Pacific cod size-at-age of the Bering Sea. The analysis is applied to 23 years of standardized collections spanning a 100 101 period of highly contrasting environmental conditions. The data that we analyze and the 102 ensuing results are instrumental in characterizing patterns and isolating drivers of 103 individual trait variability in wild populations, providing a level of understanding that is 104 necessary to sample and sustainably manage these commercially important populations 105 (Puerta et al. 2019), and to predict individual fitness in a changing climate.

106 Data and Methods

107 Sampling area and field collections

108 We used individual size and age data collected during National Oceanic and Atmospheric 109 Administration (NOAA), Alaska Fisheries Science Center (AFSC) groundfish surveys. 110 The survey obtained catch samples from a standardized set of stations in the Eastern 111 Bering Sea every year from 1982 to 2016 (Fig. 1). Due to a potential bias in age 112 determinations from the first part of the time series, the size-at-age data for this analysis 113 only includes samples from 1994 onwards (Roberson et al, 2005, Matta and Kimura, 114 2012). At each station, there is a record of the position (latitude and longitude 115 measurements), date and time of haul, weight of fish caught, number of fish caught, 116 duration and distance of haul. Additionally, the surface and bottom temperatures and 117 depth have been recorded at each station (Conner and Lauth, 2018). For a subsample of 118 the hauls, there are measurements of size and age of a subsample of the fish caught, with 119 age determined by otolith analysis. Over time, there has been an increase in both the 120 number of stations containing Pacific cod in the sample (min: 21, mean: 94, max: 257) 121 and fish sub-sampled for ageing (min: 571, mean: 1126, max: 1819). The years 2015 and 122 2016 had the most stations containing Pacific cod in the sample (231 and 257, respectively) and numbers of fish sub-sampled for ageing (1819 and 1624, respectively), because two parallel sub-sampling strategies were implemented (Puerta et al. 2018). All samples from 2015-16 were included in the current analyses because of the limited differences in size-at-age functional relationships estimated from the parallel strategies (Puerta et al. 2018). The total sample size in the full data set was 25,213.

128 Analyses on full data set

129 We applied different formulations of Generalized Additive Models (GAMs) to the 130 available size-at-age data. GAMs are a nonlinear regression technique that does not require *a priori* specification of the form of the relationship between a set of covariates 131 132 and a response (Wood, 2017). The models represented different levels of complexity, as 133 shown in Table 1, and they all regressed fish length (in mm) as a function of the 134 intervening factors and covariates. Hereon we use *covariate* when referring to numerical 135 variables that are included in the regression analyses as continuous and smooth effects 136 (i.e., age, water temperature, latitude and longitude of sampling). We instead use *factor* 137 when referring to numerical and categorical variables that are included in the regression 138 analyses as either a random or fixed effects, altering the model intercept (i.e., year of 139 sampling, year of birth, individual sex).

140 The reference model only included age of the fish as a covariate, and was used to 141 test the null hypothesis that there are no spatial, temporal, and generational patterns of 142 variability in cod-size-at-age. The successive five models fitted to the full data set 143 included covariate and factors to differentiate sources of variability among the spatial 144 (latitude and longitude), *interannual* (year of capture), and *generational* (year of birth) 145 components, and to account for the effect of environmental conditions (i.e., bottom 146 temperature at the sampled location) and sex (males vs females) on individual size-at-147 age. However, these five models differ in the way covariates and factors are assumed (or 148 not) to interact with each other. Specifically, in model 2, all covariates and factors 149 examined, except year of birth, are assumed to have a fixed and additive effect on fish 150 size. In model 3, we added an interaction between age and bottom temperature, assuming 151 different effects of temperature on age. In model 4 we added an interaction between 152 temperature with age and sex, assuming different effects of temperature on different age 153 groups and sex levels. Because of collinearity, year of birth and year of sampling could

not be included as fixed terms in the same models. Thus, these factors were either
included in separate models (model 5 is similar to model 4 but with year of birth instead
of year sampled), or one as fixed (year sampled) and the other as a random (year of birth)
term (model 6).

The selection of the best model among those implemented was based on the lowest Akaike Information Criterion (AIC), Generalized Cross-Validation (GCV), and highest percentage of variance explained (\mathbb{R}^2). Once the best model was determined, we inspected the residuals for potential violation of the model assumptions, particularly with regard to normality, constant variance, and independence (Zuur et al, 2009).

163 Effect of water temperature on cod distribution

164 We found significant variability of Pacific cod size-at-age correlated with the 165 location of capture (spatial effect). Previous work (Ciannelli and Bailey 2005) and 166 preliminary analyses (Fig. 1) indicate that bottom water temperature is a strong driver of 167 Pacific cod spatial distribution. Therefore, we conducted an additional analysis on the full 168 data set (1992 to 2016) to determine the age-specific effect of bottom temperature on 169 Pacific cod distribution using variable coefficient models (Ciannelli et al. 2012). Namely, 170 the predicted catch per unit effort (*cpue*, number of individuals ha⁻¹) of Pacific cod for a 171 given location (*lat, lon*), year, and age group is modeled as follows:

172 $\ln (cpue_{age, \, lat, lon, year} + 1) = \delta_{age, year} + s_{1, age}(lat, lon) + \beta_{age, \, lat, lon}(Temp_{lat, lon})$

173 where $\delta_{age,year}$ is the model intercept capturing the age-specific interannual variability of 174 Pacific cod cpue, $s_{age,1}(lat,lon)$ is a smooth function capturing the age specific spatial 175 variability of Pacific cod cpue, $\beta_{lat,lon}$ is a spatially variable linear coefficient 176 determining the variation of Pacific cod cpue due to a unit variation of bottom 177 temperature at the corresponding location. Model error was assumed to be log-normally 178 distributed, and stations with zero catches were removed from the analyses.

179

180 *Cohort analyses*

The analyses conducted on the full data set indicated that there is a significant amount of variability in cod size-at-age that is correlated with the year of birth (cohort effect) of the examined individuals. Therefore, we conducted additional analyses, which we refer to as *cohort analyses*, to examine the mechanisms driving this variability. Cohort analyses were conducted on a restricted data set that only included individuals of age-1 to age-5, and cohorts that were fully represented in this age range (i.e., from age-1 to age-5). This operation resulted in a trimmed data set of 16,236 observations, including the 1993 to 2011 cohorts. We restricted the analyses on individuals from age-1 to age-5 because these are the stages when individuals experience fast growth, and when even subtle differences in growth rate at an early age may cause large variations in size-at-age at later ages.

191 All models implemented in the cohort analyses include location of capture 192 (latitude and longitude), bottom temperature at the capture location, and sex (males vs females), as these covariates and factors were found to be statistically significant when 193 194 tested in the full data set. Additional factors included in the models are year of birth and 195 year sampled, which were necessary to partition between interannual and generational 196 sources of size-at-age variability and to establish the correlation between them. We also 197 included environmental covariate and factors aimed at discerning between an effect of 198 early environmental exposure and/or genetic origin on the generational variability of cod 199 size-at-age. Specifics of all the models and associated hypotheses tested follow (Table 2).

200 As a first step to the cohort analyses, we determined whether the year effect was 201 correlated with the cohort composition of the population, and if so, to what extent. 202 Accordingly, models 1 and 2 are used to quantify interannual and generational sources of 203 variability and to establish the correlation between the two (Appendix S1: Section S1 204 Correlation between year and cohort effects). We then proceeded to test for both the 205 early environmental exposure and the genetic hypotheses, by (1) using temperature 206 experienced by each cohort during the age-1 stage as an index of early-life environmental 207 exposure (Model 3), and (2) location (center of distribution) of the cohort during the age-208 1 stage as an index of the relative spawning origin of the cohort (Model 4). See Appendix 209 S1: Section S2 Determining temperature and location of the age-1 groups for additional 210 details on these analyses. Models 5 and 6 include both temperature and location of the 211 age-1 cohorts and therefore simultaneously test for both hypotheses. However, because 212 both of these variables vary in relation to the cohort, their estimated effects would 213 compete if they are included as covariate in the same model. Thus in model 5 temperature 214 during the age-1 stage is included as continuous and smooth effect, while cohort location 215 is included as a factor with two levels separating eastward- versus westward-located

216 cohorts (Appendix S1: Section S2 Determining temperature and location of age-1 217 groups). In model 6, cohort location is a smooth effect and temperature during age-1 is a 218 factor separating warm versus cold cohorts. The breakpoint between the two levels (east-219 west or cold-warm) was determined by minimizing the model AIC across a range of 220 values that leave at least 20% (4 cohorts) in either level. Similarly to the analyses 221 implemented on the full data set, the selection of the best model was based on AIC, GCV, 222 and \mathbb{R}^2 .

223

All models were fit using the mgcv package 1.8-23 in R version 3.4.3. All data and 224 R code are available via GitHub: https://github.com/lciannel/Cod-size-at-age

225 Sensitivity analyses

226 In 2011 the Alaska Fisheries Science Center underwent a study to estimate potential bias 227 in Pacific cod otolith readings (Kastelle et al. 2017). Across all ages, the study found that 228 the probability of correctly determining otolith age was 61%. The probability of 229 overestimating age by 1 year was 25%, and that of underestimating by 1 year was 13%. A 230 two-year error (over- and under-estimating) was very unlikely (<1%). We used these 231 probabilities to assess the sensitivity of the year effect (interannual variability) to the 232 ageing bias (Appendix S1: Section S3 Sensitivity analyses).

Results 233

234 During the time considered in this analysis, the average temperature of the Bering 235 Sea middle shelf (> 50 m and < 100 m depth) has varied between -0.13 °C in 2012 and 236 3.72 °C in 2016. Prior to 1999, cold and warm years alternated on a yearly basis. After 237 1999, warm and cold years came as stanzas, with warm periods from 2002-2005, cold 238 from 2006-2013, and warm again after 2013 (Fig. 1). Overall, Pacific cod is widely 239 distributed across the Bering Sea shelf. However, the distribution is influenced by water 240 temperature. Cod tend to avoid extremely cold (e.g., $< 0^{\circ}$ C) and extremely warm (e.g., >241 6 °C) water. This is evidenced by the sharp differences in distribution between one of the 242 coldest (1999) and one of the warmest (2003) years on record (Fig. 1). There are also 243 differences in the distributions of the various age groups. In general, younger individuals 244 are more abundant in the inner (<50 m depth) and middle shelf, while older and larger 245 individuals are more abundant in the middle and outer shelf (Appendix S1: Fig. S1). The 246 interannual consistency of habitat use (quantified by the percentage of variance explained by a GAM that only includes spatial coordinates to estimate cod abundance) is greatest in younger individuals (age-1 and age-2) and progressively declines in older and larger individuals (Appendix S1: Fig. S1). Spatial distributions of males and females were visually very similar across the years, although unsexed individuals were more clustered near the coast due to their younger age.

252 Analyses on full data set

253 Table 1 summarizes the AIC (d-AIC), Generalized Cross Validation (GCV), and R^2 values for six different GAMs of length as a function of age and other environmental 254 variables fitted to the full data set. The reference GAM, obtained by simply correlating 255 256 individual size with individual otolith age, explains more than 90% of the variability in 257 individual size-at-age. This result confirms that otolith age is indeed the primary 258 predictor of fish size; but, as evidenced by the scatterplot of fish age vs fish size (Fig. 2), 259 there is also biologically and statistically significant left-over variability. We extracted 260 the raw residuals from the reference model and plotted their average value by each 261 location to determine if there are spatial variations of cod size at age. We found that residuals in the inner and northwest portions of the sampled area are consistently smaller 262 263 than those from the outer shelf (Fig. 2), and thus confirmed that in the reference GAM 264 there are unexplained sources of spatial variability in cod size-at-age.

265 Longitude, latitude, and bottom temperature were all found to be significant 266 covariates, and the year of catch, birth year, and sex were all significant factors. The 267 inclusion of environmental covariates, in addition to fish age, resulted in models with 268 lower AIC and GCV compared to the reference model. Different combinations of 269 environmental covariates also resulted in slight improvement of model performances, but 270 to a lower extent. The best model that did not include birth year as a factor was the 4th 271 formulation in Table 1, and included an interaction between fish age, water temperature, 272 and individual sex (males vs females). Visual inspection of the residual variogram by 273 year did not indicate the presence of spatially structured patterns, implying that the fixed 274 part of the intervening model is sufficient to capture the spatial patterns of cod size. Figure 3 shows the spatial effect estimated from this model (i.e., 4th formulation in Table 275 276 1), as predictions of fish length at a reference age (age-3 in this example). In agreement 277 with the residual pattern of the reference model (Fig. 2), we found that the predicted fish

278 size-at-age is consistently smaller in the inner than outer shelf (Fig. 3). Bottom 279 temperature at the sampled location had a slight positive effect on fish size from 0°C to 280 about 2°C, to then revert to a slightly negative effect at higher temperature values 281 (Appendix S1: Fig. S2). However, because the 4th model contains an interaction between age and temperature, by sex, the relative predictions indicate that older females (>age 7+) 282 283 achieve statistically significantly larger sizes than similarly aged males from the same 284 temperature environment (Appendix S1: Fig. S2). The inclusion of birth year as a random 285 effect in addition to year of capture as a fixed effect resulted in lower AIC and GCV of 286 all examined models (Table 1, Model 6). This particular formulation estimates that the 287 cohort-to-cohort standard deviation is about one third of the residual error standard 288 deviation, and therefore is an important source of variability of cod size-at-age. The fixed 289 effects of Model 6 were similar to those shown for Model 4.

290 *Effect of water temperature on cod distribution*

291 In situ values of bottom temperature are important drivers of fish distribution 292 across all age groups, but particularly so for age groups from 1-5 (see Fig. 4). Consistent 293 with previous studies (e.g., Ciannelli and Bailey 2005, Stevenson and Lauth 2018), we 294 found that cod abundance increases in the northwest region of the sampled area when 295 temperature also increases. The effect is such that, when local bottom temperature 296 increases by 1°C, cod catches can double in the said region. Particularly for the age 297 groups 1-5, an increase in temperature can result in more biomass in the areas where we 298 estimated lower individual size (compare Figs. 3 and 4).

299 Cohort analyses

300 A simple image of the distribution of each cohort during the age-1 stage, overlaid on the 301 bottom temperature, revealed that cohorts differ in term of the temperature and east-west 302 location experienced during the age-1 stage (Appendix S1: Fig. S3). For example, the 303 average temperatures experienced by the 1998 and 2005 cohorts during the age-1 stage were -0.18 °C and 1.02°C respectively, while those of the 2001 and 2002 cohorts were 304 4.07° C and 4.23° C respectively. Further, the center of distribution of the 2005 cohort 305 306 during age-1 stage was about 294 km to the west of the 2011 cohort. Temperature and 307 location during the age-1 stage are not linearly correlated with each other (Pearson 308 correlation = -0.10).

The first two GAMs applied on the restricted data set were intended to quantify the variability associated to the sampled year and birth year terms (Fig. 5). The model that contains sampled year (Table 2, Model 1) slightly outperforms the model that contains birth year (Table 2, Model 2). We found that the population cohort composition, weighted by the respective cohort effects, explains about 75% of the year-to-year variability in average cod size at age (Appendix S1: Fig. S4). Therefore, we conclude that the cohort composition is the primary driver of the estimated year effect.

316 The next four models (Models 3-6 of Table 2) are meant to investigate the possible drivers of the cohort effect, and therefore include environmental variable in lieu 317 318 of the sample year or year of birth. Both the temperature and location experienced by 319 each cohort during its first year of life significantly correlate with the size-at-age that 320 individuals from the respective cohorts experience up to age-5. The best cohort model is 321 achieved when age-1 temperature is a smooth continuous effect, and location is a factor, 322 separating eastward vs. westward cohorts (Model 5 in Table 2). The estimated shapes and 323 magnitudes of these effects are shown in Fig. 6. Notably, cohorts that during the age-1 324 stage are exposed to intermediate values of bottom temperature ($\sim 2^{\circ}$ C) are about 3 cm 325 larger than cohorts exposed to either the lowest (~ 0° C) or highest (~4° C) range of 326 bottom temperature. Also, westward cohorts tend to be 1.5 cm smaller than eastward 327 cohorts, up to age-5. The boundary between westward and eastward cohorts is estimated 328 at about 231 km from the northwest origin of the least square lines through the age-1 329 center of distribution (Appendix S1: Fig. S5). The combined additive effect of location 330 and age-1 temperature are on the order of 5 cm, in agreement with the estimated 331 magnitude of the cohort effects from Model 2 (Table 2).

332 Sensitivity analyses

The inclusion of an age determination error in the raw data set resulted in Pacific cod size-at-age to be underestimated by an average of 11.02 mm for an individual of age-3 during the period 1994-2011. While this is a statistically significant bias, the ensuing estimate of cod size-at-age interannual variability does not visibly change from the one

337 estimated with the uncorrected data (Appendix S1: Fig. S6).

338 Discussion

339 By performing a retrospective analysis of cod size-at-age we can see definite 340 variation across the Bering Sea region and over time. The best-performing model – where 341 length is described as a function of longitude and latitude, year of sampling, and age 342 interacting with temperature by sex -- predicts an overall pattern of larger fish farther 343 offshore. In separate models, we found additional sources of variability correlated with 344 the year of birth, and confirmed that the cohort composition of the sampled population 345 drives the estimated interannual variability. The geographic origin and the average water 346 temperature experienced by the cohort have long lasting effects on the individual traits, 347 and significantly contribute to cod size-at-age variability in the eastern Bering Sea. 348 Identifying and quantifying these sources of trait variability have important implications 349 for ecology and management of marine species, especially in light of the abrupt changes 350 in abundance and spatial distribution that several species of the Bering Sea have recently 351 undergone (Stevenson and Lauth 2019).

352 Interannual variation of Pacific cod size-at-age can result in individuals differing 353 by as much as 6-7 cm in size at a given age. Other authors have found interannual 354 variations of growth parameters in marine fish (Thorson and Minte-Vera 2016), however, 355 there is no clear understanding as to what drives such variation. At a first examination 356 (compare Fig. 5 upper panel with Fig. 1 lower panel), the variability associated with 357 sample year that we have identified seems to align with the warm-cold stanzas of the 358 eastern Bering Sea: size-at-age anomalies are lowest and negative during the warm period 359 2000-2006, and highest and positive during the cold period 2007-2013. However, after 360 2013, size-at-age anomalies continued to increase, even though the eastern Bering Sea 361 entered a (very) warm regime (Stabeno et al. 2017). Thus we find unlikely that the annual 362 average size-at-age is driven by a direct and plastic effect of the Bering Sea temperature 363 on cod growth. Instead, based on the fact that about 75% of the observed interannual 364 variability of cod size-at-age is correlated with the relative cohort composition of the 365 surveyed population, we find more likely that cohort effects drive the temporal variability 366 of cod size at age. Cohort-related effects could be driven by both long lasting plasticity of 367 the fish reaction norm in relation to conditions experienced early in life (early 368 environmental exposure hypothesis), and/or a genetic effect (genetic hypothesis). The 369 evidence gathered in this study lends support to both hypotheses.

370 With regard to environmental exposure we found that the size-at-age of Pacific 371 cod is highest through age-5, when the age-1 cohorts experience average temperature of 372 1.5 to 2.5°C (Fig. 6). Hurst et al. (2018) found that age-0 cod in the eastern Bering Sea 373 experience higher potential for growth during cold than during warm years. They 374 proposed that different prey compositions and temperature, that in certain coastal 375 locations may exceed the maximum for growth (11.6° C), reduce growth. Hurst et al. 376 (2012) suggested that variation of water temperature experienced during the year of birth 377 alter the phenotype of the individuals at later ages. Collectively, these studies indicate 378 that cod experiencing low temperatures during the age-1 stage may have a growth 379 advantage, provided that temperature continue to stay low in later years. The range of 380 average ambient temperature for maximum cohort growth that we have identified in our 381 analyses $(1.5 \text{ to } 2.5^{\circ}\text{C})$ includes the most frequently occurring ambient temperature 382 experienced by age-1 groups (median = 2.31° C), and is likely to explain the growth 383 advantage conferred even at later ages. With regard to genetic origins, we found that 384 eastward cohorts experience slightly (1-2 cm) but statistically significantly larger size-at-385 age than westward cohorts. Spies (2012) has shown that, based on neutral markers, there 386 is genetic isolation between the spawning aggregations of Unimak and Pribilof Islands. 387 While differentiation of neutral markers does not necessarily imply adaptive selection, 388 the presence of such isolation underscores a genetic difference among spawning sub-389 populations that could result in the observed patterns of size-at-age.

390 The location of capture had a large contribution to cod size-at-age variability, 391 with individuals of all ages being on average about 5 cm smaller near the coast than at the 392 edge of the Bering Sea shelf. This strong spatial variation may be attributed to 393 environmentally driven phenotypic plasticity, which is either trophically and/or thermally 394 driven. The Bering Sea habitat is heterogeneous in temperature and prey/predator 395 distribution, all of which could affect cod growth and distribution. For instance, sea ice 396 melt interacts with local topography (Stabeno et al, 2012) to cause water stratification 397 that results in a cold pool across the middle of the region during summer months. This 398 thermal barrier restricts the movement of fish populations in the region and can determine 399 ecosystem interaction (Ciannelli and Bailey 2005, Mueter and Litzow 2008). Visually, 400 the region of lower-than-average size-at-age identified in this study overlaps with the area 401 of the cold pool, which is located in the northwest region of the sampled area (Fig. 1). 402 Assuming that cod inhabit the near-bottom portion of the water column (Nichol et al. 403 2007), individuals in the low size-at-age area would then be exposed to temperatures $< 2^{\circ}$ 404 C. Hurst et al. (2010) conducted experimental studies to characterize Pacific cod growth 405 in relation to water temperature and found that post-settlement juveniles grew 2.9 406 (growth in mass) and 3.7 (growth in length) times faster at 9° C than they did at 2° C. We 407 are unaware of similar experiments conducted on older Pacific cod stages, but it is highly 408 likely that growth is impaired at low temperatures even in post age-0 stages. Therefore, there is support to the hypothesis that the observed spatial patterns of cod size-at-age are 409 410 caused by thermally-driven phenotypic plasticity.

411 The spatial effects identified in this study include individuals from multiple 412 cohorts and age groups. While horizontal and vertical mobility may be limited during the 413 first year of life, adult and subadult cod are known to move extensively across the Bering 414 Sea shelf (Shimada and Kimura 1994). Therefore, smaller individuals caught in the 415 northwest sampled area may be from cohorts that were not originated in the same area. If 416 this assertion were correct, then one would expect that the residual patterns observed in Fig. 1 becomes progressively stronger as individuals from younger cohorts are excluded 417 418 from the analyses. We thus separately plotted the residuals of the reference model (Table 419 1, Model 1) by age groups, and found that the spatial pattern of residuals is visually 420 prominent for the older (i.e., age-3+), but not in younger age groups (i.e., age 1-3, 421 Appendix S1: Fig. S7), confirming that the spatial effect is mostly associated with 422 phenotypic expression of older individuals.

423 Variation in size-at-age can affect individual fitness through two main processes: 424 reproductive success and size-selective predation. With regard to reproductive success, 425 variation in size-at-age and body condition are linked to maturity and fecundity (i.e., 426 number of eggs, Jung et al. 2009) and to swimming abilities and migratory performances 427 during the spawning season (e.g., Slotte and Fiksen, 2000). In the Bering Sea, the size at 428 which a cohort is 50% mature is around 58 cm, which corresponds to individuals of about 429 age-5. However, there is large variability, and individuals can mature as early as age-3 430 (Stark 2007). Potential fecundity (PF, number of eggs in ovary) varies allometrically with size, with length (cm) exponent equal to 4.48 ($PF = 0.0133 \times Length^{4.48}$ 431

 $PF = 0.0133 \times Length^{4.48}$, Jung et al. 2009). With these relationships, small body size 432 433 variations, on the order of those observed in our study (i.e., 5 cm), can result in a 434 decrease/increase of about 25-30% of the number of eggs produced at a given age.

435 Pacific cod in the Bering Sea is also known to conduct extended seasonal migrations from summer feeding grounds, primarily in the shelf area, to spawning 436 437 grounds, primarily in the slope area (Shimada and Kimura 1994, Rand et al. 2014). 438 Although there are no direct estimates for Pacific cod migratory performances in relation 439 to individual traits, several studies have shown that migration performance and 440 swimming abilities in other temperate and sub-arctic fish species are linked to fish size 441 and condition (Slotte and Fiksen 2000, Sundby and Nakken 2008, Opdal 2010). 442 Therefore, it is likely that the reproductive success of Pacific cod in the Bering Sea is 443 affected by their size-at-age also via altering migration performances, especially on 444 younger and newly matured individuals. Of note is a series of apparently unprecedented 445 northward migration of Pacific cod in recent warm years (Stevenson and Lauth 2018), 446 which correspond to areas where we estimate lower than average size-at-age. In such a 447 scenario, we predict that younger and smaller-than-average reproductively mature 448 individuals may no longer be able to complete their spawning migration, and therefore fail to reproduce. 449

450 Fitness consequences of reduced size-at-age can also be mediated through size-451 selective predation (e.g., Ottersen and Loeng 2000, Stige et al., in press). Size-selective 452 predation is particularly impactful on fish from high latitudes, given the strong 453 seasonality of sub-polar environments, during the first winter of life (Sogard 1997), and 454 during the transition from pelagic to benthic environments (Stige et al. in press). All of 455 these conditions apply to age-0 Pacific cod in the Bering Sea. However, in our study, the 456 first age group monitored is the age-1, and survivors may have already gone through the 457 dominant processes that regulate year class strength via predation pressure. Thus, we do 458 not expect additional predation on age-1 and older individuals to be a driver of Pacific 459 cod year class strength in the Bering Sea.

460 From a management perspective, by not accounting for additional covariates (i.e., 461 spatial, temperature, year of birth) in estimates of fish size-at-age, there is the risk of 462 assigning fish to wrong age groups. This has consequences on estimates of numbers at

463 age obtained from an age-structured stock assessment. In a recently published study 464 Puerta et al. (2019) conducted a sampling strategy evaluation to quantify the effect of 465 different sampling strategies (i.e., random vs length-stratified) and assumptions about 466 age-length relationships (e.g., with and without spatial terms) on the estimates of the cod 467 population age structure (i.e., numbers of individuals at any given age) in the eastern 468 Bering Sea. From these analyses, we found that not accounting for spatial effects in the 469 age-length relationships results in misidentifying age by at least one year in 7.85% of the 470 individuals in the population. Including spatial effects results in age misidentification in 5.00% of the individuals. The spatial term is not the only factor affecting fish age (sex, 471 472 water temperature, year of sampling and year of birth also affect fish size-at-age), so our 473 calculations are conservative. In the model without spatial terms, most of the individuals 474 assigned to the wrong age group were age 1-3. Considering that these are the most 475 abundant groups in a population, the error can have significant contribution in 476 recruitment estimates.

477 In this study, we have analyzed an extensive data set of individual size-at-age that 478 spans over a period of 23 years. The analyses have uncovered previously unknown 479 spatial, temporal, and generational patterns of size-at-age variation that are correlated 480 with both the geographic origin and the early environmental exposure of the fish. Recent 481 studies predict progressive warming of the eastern Bering Sea shelf (Hermann et al. 482 2016). Our study demonstrates that northwest movement of young cod (age 1-5), as a 483 result of warming, places individuals in areas where we predict them to have smaller 484 size-at-age. Smaller and less conditioned individuals are less fecund and may not be able 485 to perform long migrations to return to their spawning grounds, which are primarily 486 located at the southern edge of the sampling area (Neidetcher et al. 2014). Both of these 487 effects are likely to negatively influence recruitment.

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- 496 paper of those of the author(s) and do not necessarily represent the views of the National
- 497 *Marine Fisheries Service.*
- 498Reference to trade names does not imply endorsement by the National Marine Fisheries
- 499 Service, NOAA.
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| 637 | DATA AVAILABILITY |
| 638 | Data and code for the analyses are available on Zenodo: |
| 639 | http://doi.org/10.5281/zenodo.3463664 |
| 640 | |
| 641 | TABLES |
| 642 | |
| 643 | Table 1. Statistical comparison among the Generalized Additive Models (GAM) |
| 644 | implemented to estimate the expected Pacific cod size (l) of individual i as a function of |
| 645 | the following variables: otolith age (age), individual sex (sex, male or female), |
| 646 | geographic coordinates of the site of capture (lat,lon, latitude and longitude), bottom |
| | |

647 temperature at the site of capture (*Temp*), year of capture (*year*), and year of birth 648 (*cohort*). The coefficients β are intercept parameters that vary according to the year of 649 capture (year), or the individual year of birth (cohort). The coefficient δ is an intercept 650 parameter that varies according to the individual sex. The symbol I is an indicator 651 variable for the individual sex. The parameter η_{cohort} represents normally distributed 652 variability associated to the individual year of birth. The symbols s represents 653 unidimensional or two-dimensional smooth functions of the respective variables. For 654 each model, AIC is the Akaike Information Criteria, d-AIC is the difference between the 655 target model and the one with the lowest AIC tested, GCV is the generalized cross 656 validation, and R² is the proportion of variance explained. The sample size for all of the 657 models listed was 25,213. The models represented differ by i. the number of covariate included (1st vs all others), ii. whether the environmental variables are included additively 658 $(1^{st} \text{ and } 2^{nd})$ or non-additively (all the others), and iii. whether the year of birth is included 659 660 as a fixed (5th) or random (6th) effect.

661 662

| Model | Equation | AIC | GCV | R ² |
|-------|---|---------|------|----------------|
| | | (d-AIC) | | |
| 1 | $l_{i,cohort,lat,lon,year} = \beta + s_1(age_i)$ | 276557 | 3397 | 0.909 |
| | | (6696) | | |
| 2 | $l_{i,cohort,lat,lon,year} = \beta_{year} + \delta_{sex} + s_1(age_i) + s_2$ | 270531 | 2675 | 0.929 |
| | $(lat, lon) + s_3(Temp_{lat, lon})$ | (670) | | |
| 3 | $l_{i,cohort,lat,lon,year}) = \beta_{year} + \delta_{sex} + s_1(age_i,Temp_{lat})$ | 270346 | 2655 | 0.929 |
| | _ | (485) | | |
| 4 | $l_{i,cohort,lat,lon,year} = \beta_{year} + I_{sex} * s_1(age_i,Temp_{lat,lon})$ | 270133 | 2633 | 0.930 |
| | r | (272) | | |
| 5 | $l_{i,cohort,lat,lon,year} = \beta_{cohort} + I_{sex} * s_1(age_i,Temp_{lat,lon})$ | 271097 | 2736 | 0.927 |
| | | (1236) | | |
| 6 | $l_{i,cohort,lat,lon,year} = \beta_{year} + \eta_{cohort} + I_{sex} * s_1(age_i,Te$ | 269861 | | 0.927 |
| | $\eta_{cohort} \sim N(0, var = 13.68^2)$ | (0) | | |

663

664 **Table 2.** Statistical comparisons of GAM models applied to the restricted data set, used 665 to assess the mechanisms that drive a cohort effect on individual size at age (l). The 666 restricted data set only includes individuals from age 1 to age 5, and the 1993 to 2011 667 cohorts. All the models are additive, and they differ by i. whether year of capture (1st) or 668 year of birth (2nd) is included, ii. whether the cohort effect is hypothesized to covary with the bottom temperature experienced by the cohort at age-1($Temp_{age=1}, 3^{rd}$), iii. whether 669 the cohort effect is hypothesized to covary smoothly with the average location 670 671 experienced by the cohort at age-1($lon_{age=1}, 4^{th}$), iv. by an additive and smooth combination of both variables (5th), iv. or by an additive and smooth effect of temperature 672 and a threshold effect of location (6th). All symbols and table notations are explained in 673 Table 1. 674

- 675
- 676

| Model | Equation | AIC | GCV | R ² |
|-------|---|---------|------|----------------|
| | T | (d-AIC) | | |
| 1 | $l_{i,cohort,lat,lon,year} = \beta_{year} + \delta_{sex} + s_1(age_i) + s_2(lage_i) + s_2(lage$ | 171635 | 2283 | 0.900 |
| | | (0) | | |
| 2 | $l_{i,cohort,lat,lon,year} = \beta_{cohort} + \delta_{sex} + s_1(age_i) + s_2$ | 172123 | 2353 | 0.897 |
| | | (488) | | |
| 3 | $l_{i,cohort,lat,lon,year} = \delta_{sex} + s_1(age_i) + s_2(lat,lon)$ | 173279 | 2526 | 0.889 |
| | | (1644) | | |
| 4 | $l_{i,cohort,lat,lon,year} = \delta_{sex} + s_1(age_i) + s_2(lat,lon)$ | 173602 | 2577 | 0.887 |
| | | (1967) | | |
| 5 | $l_{i,cohort,lat,lon,year} = \delta_{sex} + lon_{age = 1} + s_1(age_i) + $ | 173070 | 2494 | 0.890 |
| - 7 | | (1435) | | |
| 6 | $l_{i,cohort,lat,lon,year} = \delta_{sex} + Temp_{age = 1} + s_1(age_i)$ | 173250 | 2521 | 0.889 |
| | | (1615) | | |

- 677
- 678

679 FIGURE LEGENDS

- 680 Figure 1. Top two panels: maps of the eastern Bering Sea shelf area with locations of
- sampled stations. The maps show the distribution of Pacific cod during a cold (1999, left)

- and a warm (2003, right) sampling year. Bubble size is proportional to natural log of the
- 683 catch per unit effort (number of individuals ha⁻¹) plus 1, at the sampled location. Grey
- scale image indicates bottom water temperature at time of sampling (units: °C). Bottom
- panel: time series of eastern Bering Sea middle shelf (50-100 m depth) average
- temperature from 1994 to 2016.
- 687

Figure 2. Predicted relationship between fish size and otolith age derived from the

reference GAM model (Table 1, first row). Model residuals are shown in black if they are

690 negative and grey if they are positive (left panel) and their average values at each location

are displayed on a map of the sampled area (right panel). Also shown are bottom

692 temperature isolines: 0, 1, 2, 3 °C.

693

Figure 3. Predicted length of 3-year-old males (left) and females (right). Isolines indicatethe standard length of the fish (mm) from Model 4 in Table 1.

Figure 4. Effect of bottom water temperature on Pacific cod spatial distribution for
different age groups. The grey-tone image indicates the estimated abundance (ln[1+n ha⁻
¹]), and the red bubbles indicate the increase of cod abundance due to 1°C variation of
bottom temperature at the target location.

700

Figure 5. Upper panel: anomalies of cod size at age in relation to the sampled year,
included as a factor in the Model 1 of Table 2. Lower panel: similar anomalies, but in
relation to cohort (birth year), included as a factor in the Model 2 of Table 2. Anomalies
are in reference to the 1994 year of sampling or 1993 year of birth. All analyses are

- conducted on the restricted data set, which only includes age groups from 1 to 5 and
- cohorts that are fully represented within the examined age range (1993 to 2011).
- 707

Figure 6. Estimated effects of location (left panel) and average temperature experienced
by each cohort during age-1 stage (right panel) on Pacific cod size-at-age. Effects are

- by each cohort during age-1 stage (right panel) on Pacific cod size-at-age. Effects are
- shown as the average size (mm) of an age 3 individual, and are estimated from Model 5
- in Table 2. See Fig. S5 for separation between east and west cohort locations.











