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# Incorporating demographic information into spawner-recruit analyses alters biological reference point estimates for a western Alaska salmon population

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## 1 **Abstract**

2 Changes over time in age, sex, and length-at-age of returning Pacific salmon have been  
3 widely observed, suggesting concurrent declines in per capita reproductive output. Thus,  
4 assessment models assuming stationary reproductive output may inaccurately estimate  
5 biological reference points that inform harvest policies. We extended age-structured state-  
6 space spawner-recruit models to accommodate demographic time trends and fishery  
7 selectivity to investigate temporal changes in reference points using Kuskokwim River  
8 Chinook salmon (*Oncorhynchus tshawytscha*). We illustrate that observed demographic  
9 changes have likely reduced per capita reproductive output in an additive manner, for  
10 example, models including changes in both length-at-age and age composition showed  
11 larger declines than models incorporating only one time trend. Translated into biological  
12 reference points using a yield-per-recruit algorithm, we found escapement needed for  
13 maximum sustained catch has likely increased over time, but the magnitude further  
14 depended on size-selective harvest (i.e., larger increases for reference points based on  
15 larger mesh gillnets). Compared to traditional salmon assessments, our approach that  
16 acknowledges demographic time trends allows more complete use of available data and  
17 facilitates evaluating trade-offs among gear-specific harvest policies.

# 1 Introduction

18 Trends in demographic characteristics of Pacific salmon (*Oncorhynchus* spp.) have been  
19 widely observed throughout their range, particularly for Chinook salmon (*O. tshawytscha*).  
20 In many Chinook salmon populations, the average age and size at a given age of adult fish  
21 returning to their natal spawning grounds have declined since at least the 1970s (Ricker  
22 1981; Bigler et al. 1996), including populations that spawn in the rivers of Alaska (Kendall  
23 and Quinn 2011; Lewis et al. 2015) and along much of the west coast of North America  
24 (Ohlberger et al. 2018; Losee et al. 2019). The causes of these widespread demographic  
25 trends are largely unknown, but hypothesized drivers include competition with other  
26 species of Pacific salmon in the ocean (Oke et al. 2020), intensifying size-selective marine  
27 mammal predation (Ohlberger et al. 2019), climate factors influencing growth rates (Xu  
28 et al. 2020), and fisheries-induced evolution (Eldridge et al. 2010). Regardless of their  
29 cause, changes in the size-at-age and age composition of spawning populations have  
30 led to pronounced declines in the mean body size of individual spawners and are of  
31 concern because they likely reduce the per capita reproductive output (e.g., fecundity)  
32 of breeders (Forbes and Peterman 1994; Ohlberger et al. 2020) and possibly that of their  
33 progeny (Hankin et al. 1993). These changes may have long-term impacts on population  
34 productivity, fishery catches, and ecosystem benefits (Oke et al. 2020). Over the past  
35 decade, return abundances of many Chinook salmon populations in Alaska have declined,  
36 concurrent with the declines in mean size and age (Dorner et al. 2018; Schindler et al. 2013;  
37 Ohlberger et al. 2016).

39 Spawner-recruit analyses used in the management of Pacific salmon usually do not  
40 account explicitly for changes in demographic attributes of the spawning escapement  
41 and thus assume reproductive output is homogeneous among individuals and static over  
42 time. Population reference points derived from these spawner-recruit analyses are often  
43 used to configure fishery management strategies (Clark et al. 2009), e.g., estimates of the  
44 number of spawners required to achieve maximum sustained catch ( $S_{MSC}$ ; catch meaning

45 total numbers harvested, regardless of age, sex, or biomass). Traditional spawner-recruit  
46 analyses assume that the recruitment relationship is repeatable and stationary, i.e., that  
47 expected recruitment and its variability at a fixed number of spawners is constant over  
48 time (Walters and Martell 2004, Ch. 7). Using the number of spawners, regardless of  
49 demographic composition, as the sole predictor of recruitment may be overly simplistic if  
50 per capita reproductive output of those spawners (i.e., “escapement quality”) trends over  
51 time. For example, if per capita fecundity is a function of the size, age, or sex of the average  
52 spawner, then the aforementioned trends in these characteristics could alter population  
53 productivity even if spawner abundance remains the same.

54 Studies on other commercially important fish species suggest that trends in popu-  
55 lation age structure can affect recruitment (Shelton et al. 2015), and that incorporating  
56 information on demographic variation can improve the estimation of biological reference  
57 points (Murawski 2001; Wang et al. 2005). For fishes in general, large females are known to  
58 contribute more to population replenishment per unit body weight than small females, due  
59 to higher reproductive investment and resulting output (Barneche et al. 2018). It is known  
60 for Chinook salmon that large females produce more and larger eggs than their smaller  
61 (younger) counterparts (Healey and Heard 1984; Beacham and Murray 1993; Forbes and  
62 Peterman 1994; Ohlberger et al. 2020). Thus, failing to account for time trends that suggest  
63 increasing rarity of the most productive individuals may lead to biases in  $S_{MSC}$  and related  
64 escapement-based quantities relevant to setting harvest policies.

65 These issues warrant exploration of alterations to spawner-recruit models that accom-  
66 modate time trends in demography and heterogeneous reproductive output of different  
67 spawners, as suggested by an expert panel on declines of Chinook salmon in Alaska  
68 (Schindler et al. 2013). Variability in age composition has been incorporated into spawner-  
69 recruit models for Chinook salmon in Alaska as random fluctuations (e.g., Fleischman et al.  
70 2013; Hamazaki et al. 2012; Staton et al. 2017) or with estimated time trends (Fleischman  
71 and McKinley 2013; McKinley and Fleischman 2013; Reimer and DeCovich 2020), but only

72 as a means to explain variability in the data and not as an explicit link to escapement  
73 quality or productivity. Size-based escapement goals have been implemented for Chinook  
74 salmon in the Kenai River (Fleischman and Reimer 2017) to address assessment limitations  
75 (i.e., uncertainties in size-based sonar species apportionment) and in southeast Alaska  
76 (Heinl et al. 2014), but in general, escapement quality concerns have rarely been translated  
77 to changes in Pacific salmon management.

78 In this article, we translate time trends in demographic characteristics (sex structure,  
79 age composition, and size-at-age) to annual estimates of total reproductive output of  
80 the spawning escapement, expressed as either total egg or egg mass production. Such  
81 estimates serve as useful alternative metrics of reproductive output with which to inform  
82 spawner-recruit models that consider escapement quality. Using integrated state-space  
83 models augmented by a yield-per-recruit algorithm, we present an evaluation of the effects  
84 of demographic trends on Pacific salmon population dynamics and fishery biological  
85 reference points. We apply the model to data from Chinook salmon in the Kuskokwim  
86 River, western Alaska. Because many of the age and sex composition data originated  
87 from size-selective gillnet fisheries, we were compelled to include selectivity in the model  
88 to accurately quantify changes in demographic characteristics of the population. Demo-  
89 graphic time trends are long-term, and we do not attempt to attribute them to any cause;  
90 rather our objective is to quantify their magnitude and likely consequences for biological  
91 reference point estimates. However, incorporating size-selectivity enabled us to evaluate  
92 the effects of size-selective harvest on spawner composition and biological reference points  
93 and to provide helpful guidance on the risks and benefits of selective removal while jointly  
94 considering trending demographics.

## 95 **2 Methods**

### 96 **2.1 Study system**

97 The main-stem Kuskokwim River is approximately 1,500 km in length and contains a  
98 river network that drains approximately 130,000 km<sup>2</sup>. The Kuskokwim contains the

99 largest subsistence fishery for Chinook salmon in the state of Alaska: an average of 65,000  
100 Chinook salmon were harvested annually between 1995 and 2015 (range 15,000 – 104,000),  
101 composing 48% (range: 34 – 61%) of state-wide Chinook salmon subsistence harvests (Fall  
102 et al. 2018). Although limited bycatch occurs in offshore fisheries, targeted fishery harvests  
103 occur in-river during the spawning migration using drift gillnets, and have produced  
104 exploitation rates ranging from 13% (in 2017) to 74% (in 1982, 1976 – 2019 average: 40%,  
105 Larson 2020). Participants in subsistence and commercial fisheries are primarily native  
106 Alaskans, and the resource constitutes an integral part of the culture and lifestyle in the  
107 region (Wolfe and Spaeder 2009). Of the five species of anadromous Pacific salmon that  
108 return annually to the Kuskokwim River, Chinook salmon are favored by the subsistence  
109 fishery (Hamazaki 2008). Although Chinook salmon have been incidentally caught by the  
110 in-river commercial fishery, they have not been targeted since 1984 when a 6-inch (~15 cm)  
111 or less stretched mesh gillnet restriction was implemented with the intent of commercially  
112 targeting the more abundant stocks of chum (*O. keta*) and sockeye (*O. nerka*) salmon. The  
113 abundance of Chinook salmon returning to the Kuskokwim annually has oscillated on  
114 an approximately decadal scale, with the most recent peak abundance of approximately  
115 325,000 fish in 2006 (Larson 2020). Since that time, annual Chinook runs have averaged  
116 approximately 120,000 fish between 2010 and 2019 necessitating severe restrictions to the  
117 subsistence fishery (which requires 67,200 – 109,800 Chinook salmon annually to meet  
118 basin-wide harvest needs, Sheldon et al. 2016). The Chinook salmon stock is managed  
119 using a basin-wide fixed escapement goal policy of 65,000 – 120,000 fish annually, informed  
120 by a state-space spawner-recruit analysis that, as is traditional, models recruitment as a  
121 function of total spawners that escape harvest (Hamazaki et al. 2012). In order to meet this  
122 goal in recent years of below-average abundance, subsistence harvests have been limited  
123 primarily through mesh size restrictions (6-inch or less since 2014) and severely restricted  
124 fishing opportunities, especially in the lower river where the majority of the fishery is  
125 located (Staton 2018).

## 126 2.2 Analytical approach

127 Our approach to investigating the impacts of temporal changes in demographic attributes  
128 of the escapement on biological reference points involved multiple steps. First, we devel-  
129 oped an extension of state-space spawner-recruit analyses (i.e., akin to those documented  
130 in Fleischman et al. 2013) to accommodate (i) sex structure as well as age structure, (ii)  
131 terms that quantify time-trending probabilities of return by age and sex, (iii) estimation  
132 of age/sex-based selectivity by multiple fisheries using different gears and exploitation  
133 rates, and (iv) the use of alternative units of reproductive output (e.g., fecundity rather  
134 than total spawners) which may also have a time-trending nature resulting from changes  
135 in female size-at-age (model described in section 2.4). Next, we fitted 12 versions of this  
136 model that differed in the assumed units of reproductive output and assumptions about  
137 whether return by age, sex, or size are time-constant or time-trending (section 2.5, Table  
138 1). We then supplied estimates of population dynamics and demographic parameters to  
139 a yield-per-recruit algorithm (section 2.6) to estimate reference points (e.g., escapement  
140 and harvest at maximum sustained catch;  $S_{MSC}$  and  $H_{MSC}$ ) grouped into specific temporal  
141 strata to quantify changes in these quantities over time.

## 142 2.3 Data sources

143 The data spanned observations of Chinook salmon between 1976 and 2019 – nearly all  
144 sampling was conducted by the Alaska Department of Fish and Game (ADF&G). We used  
145 four information types: (i) annual age/sex composition by fate (harvested in commercial  
146 fishery, harvested in subsistence fishery, or sampled from the escapement), (ii) annual mean  
147 size-at-age, (iii) annual abundance assigned to each fate, and (iv) allometric relationships  
148 to translate female size to expected reproductive output by age.

149 For sources (i) and (ii), we extracted records of individual adults sampled from  
150 commercial fishery harvests, subsistence fishery harvests, and escapement sampled from  
151 eight weir projects for which the sex, age, and length (mid-eye to tail-fork; METF, mm)  
152 were measured. Sex was determined by internal inspection for harvest-related fates and

153 external inspection at weir projects; age was assigned using scale samples in all cases  
154 (Froning and Liller 2019). We discarded records with missing age or sex assignments. When  
155 calculating the average METF or age/sex composition for each year and fate, we used a  
156 within-year temporally stratified design to minimize bias resulting from any potentially  
157 non-representative sampling. We grouped samples into 2-week strata and calculated the  
158 composition or mean METF by age/sex for each stratum. We then averaged the resulting  
159 strata-specific estimates, weighted by stratum size (e.g., estimated weir passage in each 2-  
160 week stratum). For weirs, we applied the stratification design to each weir separately, then  
161 averaged the results across weirs weighted by the weir-specific annual passage estimates.  
162 Some imputation for missing values in the METF data was necessary given that the uses of  
163 these data required values each year; we used a linear interpolation rule for this purpose  
164 (see Online Supplement A, Section #1).

165 For data source (iii), we extracted aggregate basin-wide annual escapement estimates,  
166 commercial harvest estimates, and subsistence harvest estimates from Larson (2020). That  
167 report documents a run reconstruction model that estimates basin-wide annual run size  
168 (non-age/sex-specific) from a host of assessment projects. Although Brooks and Deroba  
169 (2015) caution against using model output as data in subsequent analyses, Staton et al.  
170 (2017) performed an investigation on the topic in the context of Kuskokwim River Chi-  
171 nook salmon spawner-recruit analyses. They found that an integrated approach which  
172 embedded the run reconstruction calculations within the observation model of state-space  
173 spawner-recruit analyses provided nearly identical estimates (and simulation-estimation  
174 performance) to a more “sequential” approach which treated aggregate escapement es-  
175 timates as observed data with associated observation variance. Given this finding, we  
176 constructed our model sequentially, where the estimation of these aggregate abundance  
177 quantities was performed external to the state-space model (i.e., by Larson 2020), and we  
178 fitted to them as though they were observed data.

179 Finally, for data source (iv) we required a relationship to predict year- and age-



180 specific reproductive output (e.g., fecundity) from female size. Although fecundity data  
181 for Kuskokwim River Chinook salmon have been collected, sampling has been highly  
182 opportunistic and primarily from size-selective fishery harvests. To avoid depending on  
183 these possibly unreliable data for our main analysis, we used samples of Canadian-origin  
184 Chinook salmon in the nearby Yukon River collected between 2008 and 2010 in Eagle, AK  
185 using multi-mesh gillnets and a more rigorous sampling design (Ohlberger et al. 2020).  
186 The data set included paired measurements of METF, egg count per female, and egg  
187 (ovary) mass per female from 140 individuals. We fitted power functions to these data  
188 to approximate the relative reproductive output of females of different ages based on  
189 observed mean METF from each year for the Kuskokwim River population. We analyzed  
190 six additional Alaska Chinook salmon fecundity data sets to assess the sensitivity of our  
191 conclusions to our choice of data set; our results regarding reference points were nearly  
192 identical regardless of which fecundity relationship we used (see Online Supplement A,  
193 Section #2).

#### 194 **2.4 State-space model to accommodate attributes of escapement**

195 The state-space model we developed was based on the age-structured framework of  
196 Fleischman et al. (2013) but extended to accommodate more demographic attributes of  
197 the escapement. Specifically, we included three extensions, all of which were age/sex-  
198 structured: heterogeneous reproductive output across ages and sexes, expected probability  
199 of return by age and sex, and size-selectivity of several fisheries. We constructed the model  
200 such that time trends in these factors may be included or can be assumed to be non-existent  
201 (as in the traditional approach to salmon stock assessment). The model tracks latent (i.e.,  
202 true, but partially or imperfectly unobserved) states of recruitment ( $R$ ), escapement ( $S$ ),  
203 and harvest ( $H$ ) by fishery, all on an age/sex-structured basis in a stochastic population  
204 dynamics process model, of which the parameters are estimated from available data.  
205 Multiple formulations of the state-space model were fitted in this analysis (12 in total, see  
206 section 2.5 and Table 1). Given that these alternative models are simplified generalizations

207 of a full model (symbology summarized in Table 2), we present the full formulation with  
 208 the subsequent section devoted to the specific treatment of demographic trends and units  
 209 of reproductive output in other models.

#### 210 2.4.1 Biological process model

211 Accounting of fish begins at the top-most level with the least amount of structure: total  
 212 adult recruitment ( $R_y$ ), indexed only by brood year indicating that it is the aggregate of all  
 213 adults that ever return from brood year  $y$ , regardless of age ( $a$ ) or sex ( $s$ ). In the absence of  
 214 process error, deterministic recruitment ( $\dot{R}_y$ ) by brood year was:

$$(1) \quad \log(\dot{R}_y) = \begin{cases} \log(\dot{R}_0) & \text{if } y \leq a_{\max} \\ \log(\alpha) + \log(Z_{t=y-a_{\max}}) - \beta Z_{t=y-a_{\max}} & \text{if } y > a_{\max} \end{cases}$$

215 where  $\alpha$  and  $\beta$  are Ricker (1954) parameters,  $a_{\max}$  is the maximum age of return (we  
 216 used  $a_{\max} = 7$  for Kuskokwim Chinook salmon),  $\dot{R}_0$  is the expected recruitment in the  
 217  $a_{\max}$  brood years prior to the first year of monitoring, and  $Z_{t=y-a_{\max}}$  is the total annual  
 218 reproductive output in calendar (i.e., observational or return year) year  $t$  and took on the  
 219 value of:

$$(2) \quad Z_t = \sum_s^{n_s} \sum_a^{n_a} S_{t,a,s} \cdot z_{t,a,s}$$

220 where  $S_{t,a,s}$  is year-, age-, and sex-specific escapement from eq. 11 below,  $n_s$  is the number  
 221 of sexes included in the model ( $n_s = 2$ ), and  $n_a$  is the number of possible ages adults  
 222 can return to spawn ( $n_a = 4$ ). The quantity  $z_{t,a,s}$  is the expected reproductive output per  
 223 individual in each year, age, and sex. Traditional spawner-recruit models can be expressed  
 224 by setting all elements of  $z_{t,a,s}$  to 1, in which case  $Z_t = S_t$ . For descriptive purposes, we also  
 225 calculated annual per capita reproductive output by dividing  $Z_t$  by  $S_t$ , which provided  
 226 an index of reproductive output by the average spawner regardless of age or sex. We  
 227 treated latent recruitment states (i.e., realized, with process error,  $R_y$ ) as lognormal random  
 228 variables around the deterministic  $\dot{R}_y$ , and included lag-1 autoregressive errors:

$$(3) \quad \begin{aligned} \log(R_y) &\sim N\left(\log(\hat{R}_y) + \omega_y, \sigma_R^2\right), \\ \omega_y &= \phi\left(\log(R_{y-1}) - \log(\hat{R}_{y-1})\right), \end{aligned}$$

229 where  $\phi$  is the lag-1 autoregressive coefficient and  $\sigma_R^2$  is the variance of white noise process  
 230 variability. We used two separate  $\sigma_R^2$  terms: one for the period where  $\hat{R}_y$  was constant ( $\sigma_{R_0}^2$ ),  
 231 and one for the period that included the reproductive link in eq. 1.

232 For linkage to observations made on a calendar year basis,  $R_y$  must be apportioned  
 233 to the year, age, and sex at which these adults make the spawning migration. We used  
 234 probability vectors ( $\pi_{y,a,s}$ ) to represent the marginal probability of return at age  $a$  by sex  $s$   
 235 and brood year  $y$  to perform this apportionment as shown in eq. 7. We chose to model  
 236 return probabilities as separate sex and age processes to allow investigation of time trends  
 237 separately with respect to these two demographic quantities. We used linear models to  
 238 capture time trends in probabilities of return by sex and age to enable expressing time-  
 239 constant or time-varying demographic quantities – had we used a stochastic expression  
 240 such as a white noise model (e.g., as in Fleischman et al. 2013) or a random walk model,  
 241 the random deviates would attempt to follow the trend and prevent us from evaluating  
 242 the consequences of failing to account for certain trends. We modeled the probability that  
 243 recruits  $R_y$  would return as female ( $\psi_y$ , regardless of age) as a logit-linear model:

$$(4) \quad \text{logit}(\psi_y) = \delta_0 + \delta_1 y,$$

244 where  $\delta_1$  is an additive effect of year on the log odds of returning as a female. A time-  
 245 constant version can be expressed by fixing  $\delta_1$  at zero, in which case  $\delta_0$  is the log odds of  
 246 female return averaged across all brood years. We apportioned total recruitment to each  
 247 sex:

$$(5) \quad R_{y,s} = \begin{cases} R_y \psi_y & \text{if } s = \text{female} \\ R_y (1 - \psi_y) & \text{if } s = \text{male} \end{cases}.$$

248 We obtained sex-specific return-at-age probability vectors ( $\pi_{y,a,s}$ ) for each brood year using

249 a baseline-category logit model (Agresti 2012, Ch. 7):

$$(6) \quad \eta_{y,a,s} = \begin{cases} \gamma_{0,a,s} + \gamma_{1,a,s}y & \text{if } a \leq n_a - 1 \\ 0 & \text{if } a = n_a \end{cases}$$

$$\pi_{y,a,s} = \frac{e^{\eta_{y,a,s}}}{\sum_{b=1}^{n_a} e^{\eta_{y,b,s}}}$$

250 where  $\eta_{y,a,s}$  represents the log ratio of return probabilities at age  $a$  and age  $n_a$  in year  $y$   
 251 for sex  $s$ . As in the binary logit-linear model in eq. 4, the  $\gamma_{1,a,s}$  coefficients can be fixed at  
 252 zero to express time-constant probability vectors  $\pi_{y,a,s}$ . Regardless, the  $\gamma_{0,n_a,s}$  and  $\gamma_{1,n_a,s}$   
 253 coefficients were always fixed at zero because we used the last return age as the baseline  
 254 group in eq. 6. We then apportioned recruits to abundance ( $N_{t,a,s}$ ) in the appropriate  
 255 calendar year, age, and sex in which they would return to spawn and be observed:

$$(7) \quad N_{t,a,s} = R_{y=t+n_a-a,s} \cdot \pi_{y=t+n_a-a,s}$$

256 The year indexing maps the brood year index  $y$  in which the adults of age  $a$  returning in  
 257 calendar year  $t$  were spawned (see Online Supplement A, Section #3 for more details).

#### 258 2.4.2 Fishery process model

259 Total abundance (age/sex-specific or otherwise) is rarely ever observed (i.e., censused).  
 260 Instead, fish are counted (or estimated) according to their fate, either as harvest or as escape-  
 261 ment and a subset is sampled for age and sex characteristics. Due to size-selective fishery  
 262 harvest, individuals of different ages and sexes have unequal probabilities of capture by  
 263 fisheries using different gillnet mesh sizes and exploitation rates, which could result in the  
 264 age/sex composition signal differing among fates. To build an observation model that can  
 265 accommodate this among-fate variability, we further apportioned the modeled abundance  
 266  $N_{t,a,s}$  according to fate by age and sex using a size-selectivity function embedded within  
 267 the state-space model. Both the commercial and subsistence fisheries have primarily used  
 268 drift gillnets to harvest salmon and both have experienced an unrestricted mesh period  
 269 (typically 7.5- or 8-inch [ $\sim 20$ cm] stretched mesh) and a restricted mesh period (6-inch mesh

270 or less). We modeled size-selection using the Pearson gillnet selectivity model (Bromaghin  
 271 2005), which has the advantage of expressing selectivity as a function of the ratio between  
 272 fish length to mesh perimeter (RLM). This allowed a single set of parameters to explain  
 273 size-selectivity regardless of the mesh size used by each fishery each year. The Pearson  
 274 gillnet selectivity model has the form:

$$(8) \quad V(x) = \left(1 + \frac{\lambda^2}{4\theta^2}\right)^\theta \times \left(1 + \frac{\left(x - \frac{\sigma\lambda}{2\theta} - \tau\right)^2}{\sigma^2}\right) \times \exp\left(-\lambda \left(\tan^{-1}\left(\frac{x - \frac{\sigma\lambda}{2\theta} - \tau}{\sigma}\right) + \tan^{-1}\left(\frac{\lambda}{2\theta}\right)\right)\right),$$

275 as presented by Bromaghin (2005), where  $x$  is the fish size:mesh perimeter ratio and  $\tau$ ,  
 276  $\sigma$ ,  $\theta$ , and  $\lambda$  are parameters controlling the location and shape of the selectivity function  
 277 subject to the constraints  $\sigma > 0$  and  $\theta > 0$ . We used estimates of  $\tau$ ,  $\sigma$ ,  $\theta$ , and  $\lambda$  from a lower  
 278 Kuskokwim River multi-mesh test fishery project (operated for species apportionment of  
 279 sonar counts, methods described in Birchfield and Smith 2019) to formulate weak priors  
 280 on these parameters. We used independent normal prior distributions (zero-truncated  
 281 where necessary) with mean equal to those provided by ADF&G (N. Smith, personal  
 282 communication) but with variance equal to  $(SE \times 10)^2$  to reduce the information content  
 283 of the prior (Table 3). We compared the marginal posterior and prior density functions for  
 284 these parameters to verify that minimal information was introduced. More vague uniform  
 285 priors resulted in excessively poor mixing that was remedied to some extent by these weak  
 286 priors.

287 We standardized the Pearson selectivity function such that one age/sex class was  
 288 fully selected by each mesh size ( $m$ ) each year:

$$(9) \quad v_{t,a,s,m} = \frac{V(\text{RLM}_{t,a,s,m})}{\max(V(\text{RLM}_{t,1:n_a,1:n_s,m}))},$$

289 which allowed for the annual intensity of fishing pressure to be identifiably expressed as  
 290 the fishing mortality of the fully selected age/sex class. We calculated the input  $RLM_{t,a,s,m}$   
 291 values using the mean METF by age, sex, and year from the escapement data set assuming  
 292 two mesh sizes: 8-inches and 6-inches. We chose to use escapement METF data because  
 293 sampling can be assumed to be non-size-selective, this source had the longest and most  
 294 complete data set, and any missing values had already been imputed for populating  $Z_{t,a,s}$   
 295 (reproductive output see section 2.5 and Online Supplement A, Section #1 therein for more  
 296 details).

297 We modeled harvest by the commercial and subsistence fisheries separately, given  
 298 that total harvest estimates were available for each and they have different manage-  
 299 ment and monitoring histories. Each fishery had an estimated fishing mortality of  
 300 the fully selected age/sex class ( $F_{sub,t}$  and  $F_{com,t}$ ), allowing us to model harvest on a  
 301 fishery/year/age/sex-specific basis by using the appropriate value of  $m$  (mesh size index):

$$\begin{aligned}
 F_{tot,t,a,s} &= F_{sub,t}v_{t,a,s,[sub,t]} + F_{com,t}v_{t,a,s,[com,t]}, \\
 H_{sub,t,a,s} &= N_{t,a,s} \frac{F_{sub,t}v_{t,a,s,[sub,t]}}{F_{tot,t,a,s}} \left(1 - e^{-F_{tot,t,a,s}}\right), \\
 H_{com,t,a,s} &= N_{t,a,s} \frac{F_{com,t}v_{t,a,s,[com,t]}}{F_{tot,t,a,s}} \left(1 - e^{-F_{tot,t,a,s}}\right),
 \end{aligned}
 \tag{10}$$

302 where  $v_{t,a,s,[sub,t]}$  denotes age/sex-specific selectivity of mesh size type  $m$  used by the  
 303 subsistence fishery in year  $t$  and likewise for  $v_{t,a,s,[com,t]}$  and the commercial fishery. We  
 304 then obtained age/sex-structured escapement ( $S_{t,a,s}$ ) as:

$$S_{t,a,s} = N_{t,a,s} - H_{sub,t,a,s} - H_{com,t,a,s}.
 \tag{11}$$

305 As is common in salmon stock assessment models, we did not include terms for natural  
 306 sources of post-harvest mortality (e.g., predation) in eqs. 10 or 11 since very little, if any,  
 307 data exist to inform them and the time period between passing through the primary harvest  
 308 areas in the lower main-stem Kuskokwim River and reaching the spawning grounds in  
 309 the tributaries is relatively short (i.e., several weeks or months).

### 310 2.4.3 Observation model

311 We summarized the values of  $H_{\text{sub},t,a,s}$ ,  $H_{\text{com},t,a,s}$ , and  $S_{t,a,s}$  to fit to the observed data. The  
312 observed abundance of escapement and harvest each year were available as aggregate  
313 estimates, not partitioned into age or sex. Thus for fitting to (e.g.,)  $S_{\text{obs},t}$ , we calculated the  
314 expectation  $S_t$  as  $\sum_s^{n_s} \sum_a^{n_a} S_{t,a,s}$  and used it in a lognormal likelihood with assumed known  
315 observation variance  $\sigma_{S,t}^2$ . We used the same likelihood expression for aggregate harvest  
316 from each fishery separately. Similarly, we obtained modeled age/sex composition from  
317 (e.g.,)  $S_{t,a,s}$  by calculating the proportion in each unique age/sex category ( $j$ , of which there  
318 were eight elements: four ages by two sexes) each year  $t$  and used it as the expectation in  
319 a multinomial likelihood, linking the expected fate-specific age/sex composition to their  
320 observed frequencies (e.g.,  $x_{S,t,j}$ ). We used the same likelihood expression for age/sex  
321 composition from each fishery.

322 The observation variance terms for abundance states (e.g.,  $\sigma_{S,t}^2$ ) were in-  
323 formed using the estimated coefficient of variation (CV) provided by ADF&G:  
324 ( $\sigma^2 = \log((\text{CV}/100)^2 + 1)$ ), which characterizes assessment uncertainty. Observation  
325 CVs were generally higher for escapement [average: 12%, range: 5 – 27%; Larson (2020)]  
326 than for subsistence harvest (average: 5%, range: 1 – 10%; e.g., Sheldon et al. 2016) or  
327 commercial harvest (all year CV = 2%, estimated annually via mandatory trip tickets,  
328 Hamazaki et al. 2012). Although the CVs may seem low (e.g., for aggregate escapement),  
329 they were estimated by the same models that produced the estimates we used as data and  
330 were the best expressions of observation uncertainty available to us, and we preferred to  
331 use these estimated values instead of applying arbitrary rules that would increase their  
332 value. See Online Supplement A, Section #4 for details on how we obtained effective  
333 sample size (set lower than observed sample size, Maunder 2011) for multinomial  
334 likelihoods and a sensitivity analysis to the specific method we used.

## 335 2.5 Alternative assumptions for state-space model

### 336 2.5.1 Unit of reproductive output

337 We assessed three sets of alternative assumptions for the unit of reproductive output for an  
338 average spawner of age  $a$  and sex  $s$  returning in calendar year  $t$ . Traditional Pacific salmon  
339 spawner-recruit analyses assume that all spawners contribute equally to production of  
340 progeny, thus expressing the  $\alpha$  (productivity) parameter in terms of maximum recruits-per-  
341 spawner, regardless of age or sex. Our state-space model can accommodate this assumption  
342 by setting all elements of  $z_{t,a,s}$  equal to 1, which results in  $Z_t = S_t$  in eq. 2. However,  
343 larger (older) females generally produce more eggs (Healey and Heard 1984; Ohlberger  
344 et al. 2020), and it is thus reasonable to expect that they should produce more progeny  
345 than females of younger, smaller age classes. We used the aforementioned fecundity data  
346 from the Yukon River (2008 – 2010) to fit a power function of the form  $\text{eggs} = a \cdot \text{METF}^b$ ,  
347 then calculated “expected” fecundity of the average (Kuskokwim) female spawner in  
348 each year, by age, using mean METF from Kuskokwim River escapement sampling (see  
349 Online Supplement A, Section #2 for a sensitivity analysis using other Chinook salmon  
350 fecundity data sets). We used the expected eggs per female year and age to populate the  
351 elements of  $z_{t,a,s}$  for females while setting male elements to zero. This assumes that male  
352 abundance is sufficient to ensure all (or a constant fraction of) eggs are fertilized and that  
353 there is no survival benefit for eggs fertilized by older males. Further, not only do larger  
354 females produce more eggs but their eggs also tend to be larger (Beacham and Murray  
355 1993; Ohlberger et al. 2020), implying a possible survival benefit to the progeny resulting  
356 from more resources at the embryo and alevin stages (Forbes and Peterman 1994). Thus,  
357 we fitted another power function with total egg mass as the response variable (from the  
358 same Yukon River data set) and used its predictions to populate the  $z_{t,a,s}$  elements for a  
359 third assumption about how relative reproductive output varies with age and year. Note  
360 that all future uses of egg number and egg mass in the context of Kuskokwim Chinook  
361 salmon refer to these expectations derived using Kuskokwim River METF data in Yukon



362 River allometric relationships. We denote these models as N-\* (all  $z_{t,a,s}$  elements equal to  
 363 one), E-\* ( $z_{t,a,s}$  based on eggs per female), and EM-\* ( $z_{t,a,s}$ ) based on total egg mass per  
 364 female; Table 1).

### 365 2.5.2 Included time trends

366 We designed the state-space model specifically to investigate the influence of trends in  
 367 sex composition, age composition, and length-at-age on biological reference points: by  
 368 comparing the output from models that include these trends to those that do not (Table  
 369 1), we were able to quantify these influences. We expressed time-trending probability  
 370 of return-by-sex by estimating  $\delta_1$  from eq. 4 and expressed the time-constant version by  
 371 fixing  $\delta_1$  at zero. Likewise, we expressed time-trending probabilities of return-at-age by  
 372 estimating the  $\gamma_{1,a,s}$  terms from eq. 6 and fixing their values at zero for the time-constant  
 373 version. To incorporate time-varying length-at-age (and thus expected reproductive output  
 374 for models E-\* and EM-\*), we used annual values of  $z_{t,a,s}$  obtained from the Yukon River  
 375 power functions and Kuskokwim River METF data in eq. 2, and implemented the time-  
 376 constant version by averaging  $z_{t,a,s}$  across years for each age  $a$  and sex  $s$ . All models  
 377 included selectivity terms following eqs. 8, 9, and 10 in which  $RLM_{t,a,s,m}$  varied each year  
 378 depending on the value of METF for each age and sex. We denote models with none of  
 379 these time trends (regardless of reproductive unit) by \*-0, return-at-age trends by \*-A,  
 380 return-by-sex trend by \*-S, and length-at-age trends by \*-L; we denote models with more  
 381 than one trend included by, e.g., \*-ASL (Table 1).

## 382 2.6 Equilibrium calculations

383 Traditional calculations (Scheuerell 2016) and approximations (Hilborn 1985) for  $S_{MSC}$  and  
 384  $H_{MSC}$  and other equilibrium quantities assume all spawning individuals contribute equally  
 385 to future generations. Because some of our models relaxed this assumption and because  
 386 the probability of escaping harvest by age/sex was a function of fishing mortality and  
 387 mesh size, a yield-per-recruit approach was required to obtain estimates of these biological  
 388 reference points. To find  $S_{MSC}$  and  $H_{MSC}$ , we constructed an optimization algorithm that

389 iteratively searched for the fishing mortality of the fully selected age/sex class ( $F_{\max}$ ) such  
 390 that total harvest (regardless of age or sex) was maximized, and the corresponding value  
 391 of escapement at that  $F_{\max}$  level was taken as  $S_{MSC}$ , also regardless of age or sex. To  
 392 evaluate whether our findings were general to other biological reference points, we used  
 393 the same approach to calculate the spawner abundance ( $S_{R_{MAX}}$ ) and harvest ( $H_{R_{MAX}}$ ) at  
 394 maximum recruitment by setting total recruitment as the objective to maximize instead  
 395 of catch. We conducted the calculations that follow externally to the fitting of state-space  
 396 models, but for each posterior sample from each model to propagate parameter uncertainty.  
 397 Further, we summarized state-space model output into temporal strata: all years (1976 –  
 398 2019), the first 10 years (1976 – 1985), and the last 10 years (2010 – 2019) for equilibrium  
 399 calculations. To isolate the temporal effects of demographic trends from size-selective  
 400 harvest, we evaluated a scenario that was not size-selective (all  $v$  terms set to 1) in addition  
 401 to the 6-inch and 8-inch mesh size scenarios. Required outputs from state-space models  
 402 for yield-per-recruit analyses were  $\alpha$ ,  $\phi$ ,  $\sigma_R^2$ ,  $\beta$ ,  $\bar{\pi}_{i,j}$ ,  $\bar{v}_{i,j,m}$ , and  $\bar{z}_{i,j}$ ; the bar denotes averages  
 403 over some time period (indexed by  $i$ ) and  $j$  represents a unique age/sex class.

404 We calculated reproductive output-per-recruit ( $z_{PR}$ ) under fishing mortality  $F_{\max}$  for  
 405 a fishery using mesh  $m$  as a function of the age/sex class-specific reproductive output ( $\bar{z}_{i,j}$ )  
 406 weighted by the probability of returning by age/sex ( $\bar{\pi}_{i,j}$ ) and the probability of escaping  
 407 harvest ( $1 - U_{i,j}$ ):

$$(12) \quad z_{PR,i,m} = \sum_j (1 - U_{i,j,m}) \bar{z}_{i,j} \bar{\pi}_{i,j},$$

408 where  $U_{i,j,m} = 1 - e^{-F_{\max} v_{i,j,m}}$ . Following Walters and Martell (2004), we then calculated  
 409 total equilibrium recruitment as:

$$(13) \quad R_{eq,i,m} = \frac{\log(\alpha_c z_{PR,i,m})}{\beta z_{PR,i,m}},$$

410 We used the corrected version of  $\alpha$  ( $\alpha_c$ ) to adjust for auto-correlated lognormal process  
 411 errors, where:

$$(14) \quad \alpha_c = e^{\log(\alpha) + \sigma_R^2 / (2(1-\phi^2))}.$$

412 Once the scale of the equilibrium population fished at  $F_{\max}$  was obtained from eq. 13, we  
 413 calculated the age/sex structured abundance, harvest, and escapement:

$$(15) \quad \begin{aligned} N_{\text{eq},i,j,m} &= R_{\text{eq},i,m} \bar{\pi}_{i,j}, \\ H_{\text{eq},i,j,m} &= N_{\text{eq},i,m} U_{i,j,m}, \\ S_{\text{eq},i,j,m} &= N_{\text{eq},i,m} (1 - U_{i,j,m}), \end{aligned}$$

414 and calculated totals for harvest and escapement by summing over ages and sexes:

$$(16) \quad \begin{aligned} H_{\text{eq},i,m} &= \sum_j H_{\text{eq},i,j,m}, \\ S_{\text{eq},i,m} &= \sum_j S_{\text{eq},i,j,m}. \end{aligned}$$

415  $H_{\text{eq},i,m}$  was treated as the objective value to maximize via iterative numerical search on  
 416 the quantity  $F_{\max}$  for  $S_{\text{MSC}}$  calculations and the objective value was  $R_{\text{eq},i,m}$  for  $S_{R_{\text{MAX}}}$   
 417 calculations.

## 418 2.7 Computation and model fit

419 State-space model parameters were estimated with Markov chain Monte Carlo (MCMC)  
 420 methods implemented in JAGS (Plummer 2003) invoked through R (R Core Team 2019)  
 421 using the package “jagsUI” (Kellner 2018). We selected prior distributions to be as mini-  
 422 mally informative as possible, while preventing the sampler from considering biologically  
 423 implausible or invalid areas of the parameter space (Table 3). Long MCMC chains were  
 424 necessary to ensure convergence (checked visually and using the  $\hat{R}$  statistic, Brooks and  
 425 Gelman 1998) and adequate information content for posterior inference (checked using the  
 426 effective MCMC sample size). We used posterior predictive checks to verify model ade-  
 427 quacy for the data (Kéry 2010; Gelman et al. 2014) and the Wantanabe-Akaike information  
 428 criterion (WAIC) as a measure of model parsimony (Hooten and Hobbs 2015).

429 We summarized all posterior distributions using the median and 95% equal-tailed

430 credible intervals unless otherwise stated. In all cases where a quantity was derived from  
431 estimated parameters, (e.g.,  $S_{MSC}$  derived from  $\alpha$  and  $\beta$ ), we performed the calculation  
432 for each sample from the joint posterior for that model, then summarized the resulting  
433 marginal posterior. All code for data preparation, JAGS models, making use of High  
434 Performance Computing resources, and output summarization is documented in Staton  
435 (2020).

436 No models displayed egregious lack of MCMC convergence or inadequacy for the  
437 data, though posterior predictive checks did suggest aggregate escapement estimates with  
438 assumed-known lognormal observation variance were over-dispersed relative to model  
439 fitted values (more details in Online Supplement A, Section #5 therein and model-specific  
440 Online Supplements B – I). WAIC tended to favor models that included trends in the  
441 probabilities of returning by age and sex – suggesting patterns in the data justified the  
442 additional model complexity (Table 1). Among models that used fecundity as the unit  
443 of reproductive output, the model with time trends for age and sex was the top model,  
444 but the model also including length time trends came in close second (Table 1); we think  
445 the similarity is due to these two models having the same number of parameters and  
446 the lack of a length-based likelihood function like those for age and sex composition.  
447 Regardless of this finding that some models had more statistical support than others,  
448 we present inferences from multiple models to illustrate the contrast among different  
449 assumptions about how time trends in demography affect population productivity and  
450 biological reference points.

## 451 **3 Results**

### 452 **3.1 Fishery selectivity**

453 The estimated selectivity function from all models indicated a dome-shaped pattern with  
454 fish of intermediate size relative to the perimeter of the mesh (RLM) being those most  
455 selected (Figure 1). The curve was nearly identical for all models, regardless of the assumed  
456 unit of reproductive output or included time trends. Fish with RLM values equal to 1.88

457 were estimated to be most selected, (~760 mm and ~570 mm METF for 8-inch and 6-inch  
458 mesh, respectively). Across ages, the consequence of this estimated function for both sexes  
459 was a dome-shaped pattern for 8-inch mesh (Figure 2a), and a declining pattern for 6-inch  
460 mesh (Figure 2b). Due to changes in mean length-at-age over time, we would not expect  
461 the relative selectivity of different ages and sexes to be static, and indeed when stratified  
462 into early (first 10 years; 1976 – 1985) and late (last 10 years; 2010 – 2019) time blocks, we  
463 found this to be the case. The most pronounced temporal shifts in selectivity were for  
464 age-5 and age-6 males fished with 8-inch mesh: the model suggested increasing relative  
465 selectivity for age-6 and decreasing relative selectivity for age-5 in recent years (Figure 2a).

466 Selectivity parameters were estimable because (i) we fitted to fate-specific age/sex  
467 composition data, (ii) these were weighted by the aggregate abundance of fish in each  
468 fate, and (iii) the two fisheries did not use the same mesh size each year. From 1976  
469 – 1983, both fisheries used mostly 8-inch mesh and showed similar fitted age and sex  
470 composition, namely that they were made up of fewer age-4 and more age-5 fish than  
471 the escapement (Figure 3). Starting in 1984, the commercial fishery was restricted to  
472 using 6-inch mesh while the subsistence fishery continued to use 8-inch mesh, and at  
473 this point the composition of the two fisheries experienced a pronounced separation: the  
474 commercial fishery was comprised of more age-4 males than either the escapement or  
475 subsistence composition time series and the subsistence fishery was comprised of more age-  
476 5 and age-6 females (especially after 2000) and age-6 males than either the escapement or  
477 commercial harvest (Figure 3). Starting in 2014, the subsistence fishery was also restricted  
478 to 6-inch mesh, at which point the subsistence and commercial fisheries again showed  
479 similar composition time series. Although the patterns displayed in Figure 3 are posterior  
480 medians, they agreed well with the raw age and sex composition data from scale counts  
481 sampled throughout the basin (Online Supplements B – I; Figure 2 in each document).

## 482 3.2 Estimated demographic trends

### 483 3.2.1 *Return-by-sex*

484 For models with  $\delta_1$  fixed at zero (thus assuming probability of return-by-sex is time-  
485 constant), the posterior median probability of returning as a female from any brood year  
486 was 0.34 (0.32 – 0.36; all intervals in parentheses are 95% credible limits). For models that  
487 freely estimated  $\delta_1$  (thus allowing time-trending probability of return-by-sex), the posterior  
488 probability ranged from 0.41 (0.36 – 0.46) in the first tracked brood year (1969) to 0.29 (0.26  
489 – 0.32) in the last brood year (2015), and these values were nearly identical among models  
490 that varied in other aspects. The median value of the  $\delta_1$  coefficient was -0.012 (-0.018 –  
491 -0.005), meaning that in each brood year, recruits were 98.9% (98.2 – 99.5%) times as likely  
492 to return as female than in the previous brood year.

### 493 3.2.2 *Return-at-age*

494 For models that allowed return-at-age probabilities to vary with respect to brood year,  
495 clear patterns were identified in which returning at younger ages has become more likely  
496 over time for both sexes (Figure 4). Among females, the probability of returning at age-4  
497 continued to be as low as in the beginning of the time series (less than 5% of all female  
498 recruits), however the probability of returning at age-5 has increased, while returning at  
499 age-6 and age-7 has declined (Figure 4). For example, in the first brood year, the posterior  
500 median probability of returning at age-6 for females was 0.76 (0.69 – 0.82) compared to  
501 0.59 (0.52 – 0.66) in the last brood year, whereas for age-5 this change went from 0.12 (0.08 –  
502 0.17) to 0.36 (0.3 – 0.43). For males, the largest temporal changes occurred for age-4 and  
503 age-6, with the former becoming approximately twice as common and the latter becoming  
504 approximately half as common over the time frame included in the model (Figure 4).

### 505 3.2.3 *Assumed reproductive output*

506 Both alternative measures (egg number and egg mass) indicated that reproductive output  
507 increases sharply and disproportionately with fish size. The egg number per female spawner  
508 relationship obtained from the Yukon River population sampled at Eagle, AK was  $9.3 \times$

509  $10^{-4} \cdot \text{METF}^{2.36}$  and for egg mass (g) per female spawner it was  $8.7 \times 10^{-12} \cdot \text{METF}^{4.83}$   
510 (Figure 5) – these relationships enabled modeling how relative reproductive output from  
511 individual female spawners may have changed over time with observed trends in female  
512 length-at-return by age. The egg mass relationship suggested a steeper increase in relative  
513 reproductive output with increasing length (age) than the egg number relationship. For  
514 example, using the average METF-at-age in the first 10 years of the data set in the equations  
515 above, age-5 females produced 69% as many eggs as an age-7 female, but only 46% of  
516 the egg mass (Figure 5a). In comparing the first 10 years to the last 10 years, moderate  
517 changes in female length-at-return (5-10% depending on age) resulted in comparatively  
518 large changes in reproductive output (Figure 5b), especially when egg mass rather than  
519 egg number was considered. For example, average METF for age-6 females has decreased  
520 by 7% (first 10 years versus last 10 years), but this is expected to have resulted in a 17%  
521 reduction in the number of eggs produced by age-6 females, and a 31% reduction in total  
522 egg mass (Figure 5b). Females of all ages showed reductions in mean size and expected  
523 fecundity measures except for age-4 females, which have increased in mean length by 5%  
524 – though considering they make up less than 5% of all female recruits (Figure 4), these  
525 increases are unlikely to offset the decreases for the other ages.

#### 526 3.2.4 *Per capita reproductive output*

527 We found that per capita reproductive output has likely changed over time as a result of  
528 these demographic changes, but that the extent depended on which trends were included  
529 in the model (Figure 6), and only for models that used heterogeneous reproductive output  
530 across ages (models N-0 and N-ASL assumed per capita reproductive output was time  
531 invariant and constant across individuals). When only one trend was included in the  
532 model at a time (models E-L, E-A, and E-S), the model with a trend included for return-  
533 by-sex (model E-S) exhibited the largest change in per capita reproductive output: the  
534 early period was approximately 15% higher and the later period was approximately 15%  
535 lower than the mean across all years (21% overall decline; Figure 6). For two-trend models,

536 the model with both sex-at-return and length-at-return (model E-SL) exhibited the largest  
537 per capita shift (31% overall), but it was similar in magnitude to that suggested by model  
538 E-AS (29% overall). The change over time was larger still for the three-trend models and  
539 was more exaggerated for the model treating egg mass as the unit of reproductive output  
540 (EM-ASL) rather than egg count (E-ASL). Model EM-ASL suggested that the average  
541 spawner in the early third of the time series produced 30% more reproductive output  
542 than the average of the whole time series, and that spawners in the later third produced  
543 approximately 25% less reproductive output (49% decline overall). Models using eggs or  
544 fewer trends than model EM-ASL exhibited smaller declines in per capita reproductive  
545 output: models E-ASL, E-AL, E-L, and E-A showed overall declines of 39%, 23%, 15%, and  
546 11%, respectively.

### 547 **3.3 Equilibrium values**

548 Models that expressed reproductive output in terms of fish units (models N-0 and N-ASL,  
549 collectively denoted N-\*) were insensitive to the mesh size, time period, and incorporated  
550 trends in equilibrium calculations (Figure 7). This is because N-\* models assumed all  
551 fish contributed equally to producing the next generation, i.e., age/sex composition and  
552 selective harvest had no bearing on per capita reproductive output. However, when either  
553 eggs (models denoted E-\*) or egg mass (EM-\*) were used, we found sensitivity in the  
554 equilibrium values of  $S_{MSC}$  and  $H_{MSC}$ , which depended strongly on fishery selectivity,  
555 considered time period, and included demographic trends. The equilibrium quantities  
556 associated with maximum recruitment rather than maximum catch ( $S_{R_{MAX}}$  and  $H_{R_{MAX}}$ )  
557 showed similar patterns as those described below (Online Supplement A, Section #6).

#### 558 *3.3.1 Large mesh gillnets*

559 Assuming large (8-inch) mesh would be used exclusively by the fishery, models E-0 and  
560 EM-0 suggested a median increase of approximately 30% in  $S_{MSC}$  from model N-0 (90,000  
561 versus 69,000 total spawners) considering all years of demographic information (Figure  
562 7a). Incorporating trends in age- (A), sex- (S), and length-at-return (L) resulted in similar



563 percent increases ranging from 25% (model E-A) to 42% (model EM-ASL). The time period  
564 of information used in equilibrium calculations had a large effect on these changes, with  
565 the earlier period having values of median  $S_{MSC}$  closer to the N-0 model, and the late  
566 period having larger values. Further, the extent of this time dependency was influenced by  
567 which trends were accounted for: models with only one trend (models E-A, E-S, and E-L)  
568 were less sensitive to the considered time period than the models that accounted all three  
569 trends simultaneously (models E-ASL and EM-ASL), and there was not a strong tendency  
570 for any one trend (A, S, or L) to be driving this pattern. Notably, the assumed reproductive  
571 unit did not have a major impact on the inference (Figure 7a), i.e., the scale and shift over  
572 time in  $S_{MSC}$  was similar for models E-ASL (86% temporal increase) and EM-ASL (100%  
573 temporal increase).

574 Increases in the spawning abundance needed to maintain a maximum sustainable  
575 catch were accompanied by decreases in the level of  $H_{MSC}$  achieved. This pattern was  
576 driven mostly by increased  $S_{MSC}$  and not reduced recruitment when fished at MSC. Models  
577 E-\* and EM-\* showed a range (across models) of 10-17% declines in median  $H_{MSC}$  relative  
578 to model N-0 when all years of demographic information were considered, and 15-45%  
579 declines when only the most recent 10 years were considered (Figure 7b).

### 580 3.3.2 *Smaller mesh gillnets*

581 Unlike for the large mesh scenario, median  $S_{MSC}$  was suggested to be lower for the E-\* and  
582 EM-\* models than for the N-\* models by a range (across models) of 15 – 30% when all years  
583 were considered (Figure 7e), which resulted in increases of  $H_{MSC}$  that ranged between 10 –  
584 17% across models (Figure 7f). This resulted from the ability to exert a higher exploitation  
585 rate on young males, which are abundant yet were assumed to contribute no reproductive  
586 output and are mostly invulnerable to capture by the larger mesh. Maximizing catch with  
587 small mesh under models E-\* and EM-\* involved an exploitation rate of approximately 80%  
588 for the entire population (70% for females and 85% for males overall), but for age-4 males  
589 the rate was 97% and 85% for age-5 males, which collectively make up approximately 50%

590 of all returning adults. When fished at these levels, the yield-per-recruit model suggested  
591 that the post-harvest sex composition would switch from being male dominated (~65%  
592 males) to being approximately evenly split between sexes. As for the larger mesh scenario,  
593 there was still a tendency to need to allow more total spawners (29% increase for model  
594 E-ASL) and lower  $H_{MSC}$  (12% decrease for model E-ASL) when considering the most  
595 recent 10 years relative to the earliest 10 years, but the difference was far less exaggerated  
596 than in the larger mesh scenario.

### 597 3.3.3 *Non-selective mesh gillnets*

598 In comparison to the large mesh scenario, the analysis involving a hypothetical gear  
599 combination that could exert no size-selectivity suggested less pronounced effects of  
600 demographic changes on  $S_{MSC}$  (Figure 7c) and  $H_{MSC}$  (Figure 7d). Though it would be  
601 difficult to construct a non-selective gillnet, this alternative provides a way to isolate the  
602 effects of trending demography from those of fishery selectivity. Note that, in the absence  
603 of size-selectivity, the E-0 and EM-0 models provided nearly the same estimates of  $S_{MSC}$   
604 and  $H_{MSC}$  as the N-0 model, indicating that, for this stock, the choice of reproductive unit  
605 alone had little effect on the reference points. However, when the demographic trends  
606 were included (models E-ASL and EM-ASL), reference point estimates (and their changes  
607 over time) were intermediate between those from the large and small mesh scenarios.

## 608 4 Discussion

609 We have illustrated that the estimation of biological reference points is sensitive to as-  
610 sumptions regarding the reproductive contribution of different spawners (i.e., fecundity  
611 rather than simple spawner units) and which demographic changes are acknowledged  
612 in spawner-recruit analysis. Most importantly, we found that  $S_{MSC}$  increased and  $H_{MSC}$   
613 decreased when we incorporated demographic time trends based on empirical field data  
614 (fewer females, younger age-at-return, and smaller size-at-age). Further, we showed a  
615 strong dependence of both the scale of  $S_{MSC}$  and  $H_{MSC}$  and the magnitude of temporal  
616 changes on the selectivity of the gear used to harvest the population – our analysis sug-

617 gests fisheries using smaller mesh sizes require fewer escaping fish because they target  
618 smaller and less productive individuals. Although these results make intuitive sense,  
619 the state-space approach we used enabled their rigorous quantification based on robust  
620 statistical methods and transparent assumptions.

621 Concerns about declining Pacific salmon escapement quality are often expressed  
622 by fisheries managers and stakeholders, however, they are rarely explicitly accounted  
623 for in stock assessments or management strategies. A notable exception is the example  
624 of the “big fish goal” for Kenai River Chinook salmon (Fleischman and Reimer 2017),  
625 which although it was motivated by sonar assessment limitations (i.e., overlap in length  
626 distributions among species make size-based species apportionment difficult for smaller  
627 salmon), may have benefits for long-term population productivity. We think the discrep-  
628 ancy between concern and action is a result of two main factors: (i) it is not always clear  
629 how to leverage available data to formulate a defensible stock assessment model that  
630 accounts for escapement quality and (ii) lack of a transparent way to develop and imple-  
631 ment management strategies based on escapement quality rather than total number of fish  
632 harvested or escaped. To our knowledge, ours is the first Pacific salmon spawner-recruit  
633 model to explicitly link estimated demographic trends from observed data to population  
634 production feedback. By developing the yield-per-recruit model to provide estimates of  
635 management reference points, we made a first attempt at translating demographic changes  
636 into reference points relevant to fishery managers.

637 By incorporating demographic time trends into the assessment model, we identified  
638 evidence for declines in per capita reproductive output for Kuskokwim River Chinook  
639 salmon. Expressed as total annual egg production divided by total spawner abundance,  
640 we estimated an average decline in per capita reproductive output of 39% when all  
641 demographic time trends were included in the model. Calculating per capita reproductive  
642 output this way accounts for changes in fecundity at a given age weighted by changes in  
643 female prevalence and age composition, thus is a more comprehensive expression than

644 quantifying changes in any one demographic quantity in isolation of the others. It is  
645 likely that a change in per capita reproductive output of this magnitude is a contributor  
646 to the observed non-stationarity in productivity and declines in abundance in recent  
647 years (Dorner et al. 2018; Schindler et al. 2013; Ohlberger et al. 2016). Although we  
648 performed our analysis with only the Kuskokwim River Chinook salmon population,  
649 it is not unique in exhibiting demographic time trends (Lewis et al. 2015; Ohlberger  
650 et al. 2018; Oke et al. 2020) and we expect that this is a much broader issue than solely  
651 the Kuskokwim River population or even western Alaska as a whole. However, our  
652 focus was to investigate sensitivity of assessment models and biological reference point  
653 estimates to the incorporation of demographic time trends, not to quantify evidence for the  
654 relative contribution of different causal factors for observed non-stationary productivity.  
655 Investigations wishing to address this latter topic must consider demographic time trends  
656 alongside a suite of other hypothesized mechanisms such as climate forcing, inter-specific  
657 interactions, and habitat changes.

658 In addition to the incorporation of demographic trends that feed back into population  
659 dynamics, the other aspect of our model that is not generally included in Pacific salmon  
660 stock assessments is the selectivity function. With the addition of only four parameters  
661 plus length-at-age observations, our model was able to accommodate multiple sampling  
662 processes that differed in selectivity. The more realistic observation model enabled more  
663 complete use of the available data and made it possible to obtain a representation of  
664 the unharvested run age composition. This separation of latent versus external factors  
665 highlights a distinct advantage of our analytical approach over other studies that analyze  
666 demographic trend data in isolation of fisheries management or sampling regimes (e.g.,  
667 Lewis et al. 2015; Ohlberger et al. 2018). Furthermore, incorporation of the selectivity  
668 function enabled quantification of size-selective harvest effects on suggested reference  
669 points. We identified a clear trade-off between gear restrictions and the value of  $S_{MSC}$   
670 that suggested fewer fish need to escape the fishery if a smaller mesh size is used. This

671 was largely due to the selective removal of younger, less productive spawners by smaller  
672 mesh (Figure 2b). This finding implies that escapement goal ranges that acknowledge  
673 escapement quality should perhaps be on a “sliding scale” depending on the selectivity of  
674 the gear used by the fishery. Further, although we designed our equilibrium calculations  
675 to estimate biological reference points for a single fishery (i.e., one  $F_{\max}$  and mesh size  
676 combination), reference points based on multiple simultaneous fisheries could be obtained  
677 if the algorithm was supplied with a proportional allocation and the mesh size used by  
678 each fishery (e.g., Goethel et al. 2018).

679 Our equilibrium approach to estimating biological reference points was useful in  
680 that it translated observed demographic trends into changes in measures from which  
681 harvest policies are commonly developed. However, this approach is admittedly not  
682 likely the optimal way to evaluate candidate escapement levels that take into account  
683 escapement quality concerns. Salmon fisheries management has multiple objectives (e.g.,  
684 inter-annual stability in catch may be more relevant than its long-term maximization), and  
685 the equilibrium approach we used only maximized one objective at a time (total catch or  
686 total recruitment) and it did not acknowledge inter-annual variability in harvest outcomes.  
687 Future analyses could express utility in terms of value measures other than numbers of  
688 fish harvested, such as total biomass harvested, total eggs deposited, or age diversity  
689 in the spawning escapement in an attempt to better characterize attainment of harvest-  
690 and conservation-based objectives. Further, our assumption that males contribute no  
691 reproductive output made sense for model fitting (e.g., allowed  $\alpha$  to represent maximum  
692 expected recruits-per-egg), but produced some unrealistic results when used to calculate  
693 reference points (i.e., inflated exploitation rates, particularly for young males). We think the  
694 ideal way to evaluate harvest policies (e.g., escapement goals) in this context would be to  
695 use stochastic simulation. Using this approach, one would sample from the joint posterior  
696 from our state-space models, simulate the population forward through time under a range  
697 of candidate escapement goals and mesh sizes, and calculate performance metrics that

698 better-encompass the breadth of objectives relevant to managers and stakeholders. In this  
699 case, it would be possible to address some of the weaknesses of our equilibrium approach  
700 (e.g., incorporating inter-annual variability, assigning male spawners some reproductive  
701 value, and evaluating more objectives).

702 Our approach required some noteworthy assumptions to arrive at our results. First,  
703 in calculating biological reference points, we made important assumptions about the  
704 reproductive utility of males. Specifically, we assumed that total reproductive output is  
705 limited by females and that male abundance is always sufficient to fertilize all eggs (or  
706 at least a time-constant fraction of them). Overall we believe this assumption is valid,  
707 however the small mesh equilibrium scenario did suggest that when fished at MSC,  
708 the sex composition of the escapement would shift close to 50% females (relative to the  
709 unfished composition of ~35%) – which may reduce the validity of this assumption if the  
710 population was ever fished hard enough to maximize sustained catch. Second, our annual  
711 fecundity predictions were not directly measured but rather were expanded from length  
712 measurements. Thus, we assumed that the allometric egg number/mass relationships  
713 were time-constant, i.e., that on average, a female of a given size produced the same  
714 number and mass of eggs in every year from 1976 to 2015. If factors have selectively  
715 pressured females to become more or less fecund at a given size, then our estimates of how  
716 reference points have changed would be biased. The limited availability of fecundity data  
717 prevented us from evaluating this assumption quantitatively, but given its importance  
718 we suggest that fecundity relationships be quantified with greater temporal regularity.  
719 Third, similar to the previous caveat, we assumed that the expected maximum survival  
720 from egg to recruit ( $\alpha$ ) is time-constant – violations in this assumption would also render  
721 our estimates incorrect. Fourth, we assumed that non-retention mortality from small  
722 mesh gillnets is negligible, i.e., larger fish that interact with but are not captured by small  
723 mesh gillnets are not injured to an extent that would prevent successful spawning. Non-  
724 retention mortality has been shown to be potentially important, for example, Baker and

725 Schindler (2009) estimated that sockeye salmon in Bristol Bay with gillnet injuries had  
726 pre-spawn mortality rates of 8-100%, depending on the severity of injury and the assumed  
727 threshold for stream residence time for successful spawning. If gillnet injury is a major  
728 factor affecting spawning success in Kuskokwim Chinook salmon, then our estimates  
729 of  $S_{MSC}$  for the small mesh scenario would be underestimated. Fifth, our treatment of  
730 age/sex composition data assumed that no biases in age or sex assignment exist. In  
731 general, based on the sampling methods used to collect the data we used, we are confident  
732 this assumption is valid. External sex assignment is most difficult early in the upstream  
733 migration, before fish display external cues of sexual dimorphism. Fish sampled during  
734 this part of the migration were examined internally because they were harvested. For  
735 fish sampled at weir locations, however, sex assignment bias is possible. If this bias is  
736 strongly size-dependent, then it is possible that our sex composition/trend is incorrect. For  
737 example, if small females are frequently assigned as males, then their increased prevalence  
738 over time could be perceived as declining female composition. Sixth, by freely exchanging  
739 reproductive units between numbers of spawners, numbers of eggs, and egg mass, we  
740 made simplifying assumptions about the mechanisms that underlie density-independent  
741 and density-dependent processes. For example, density-dependent survival probably  
742 operates both within individual redds (reflecting competition among progeny) and among  
743 redds (reflecting competition among spawners); thus there may be important trade-offs  
744 between small numbers of large females and large numbers of small females that we have  
745 not accounted for in this work. Finally, our use of egg mass as the unit of reproduction  
746 assumes that fish from larger eggs survive better to adulthood than fish from smaller eggs,  
747 if this is not indeed true, then inferences from the EM-\* models would be identical to  
748 inferences from the E-\* models.

## 749 5 Conclusions

750 Salmon stock assessments are most often expressed in terms of adult recruits being pro-  
751 duced by adult spawners, which make important assumptions about the relative value

752 of each spawner to producing the next generation. In the absence of demographic trends  
753 that would reduce per capita reproductive output, these assumptions should be valid.  
754 However, time trends in return-by-age/sex and size-at-age have been widely observed  
755 for Chinook salmon, leading to concerns about long-term population productivity if left  
756 unaddressed. The alterations we made to the traditional recruit-per-spawner approach  
757 suggest that accounting for demographic attributes of the escapement alters the interpreta-  
758 tion of the available data and changes estimates of biological reference points. Namely,  
759 we illustrated that since the average fish is likely less fecund now than in the past, more  
760 spawners are also likely required to produce the same number of eggs and surviving  
761 recruits. Importantly, through incorporation of the selectivity function in equilibrium  
762 calculations to derive biological reference points, we showed that at high exploitation rates  
763 that would maximize sustained harvest, fishing gear may play a central role in controlling  
764 per capita reproductive output of fish surviving the fishery. This result suggests that  
765 management targets (e.g., escapement goals) should perhaps be adjusted based on which  
766 gear is used (i.e., higher escapement necessary when large mesh is used). Surely other  
767 factors, environmental and anthropogenic, unaccounted for by our analysis, influence the  
768 survival of progeny post-spawning, but here we identified gear-specific escapement levels  
769 as a potential mechanism for managers to explicitly address escapement quality concerns.  
770 We advise that future work with Kuskokwim River Chinook salmon harvest policies  
771 use estimates of population dynamics parameters from our models to build stochastic  
772 evaluations of candidate escapement levels and mesh sizes that acknowledge changes in  
773 escapement quality. We believe more salmon stock assessment models should move in  
774 this direction of incorporating demographic attributes, and our approach should serve as  
775 a useful example and starting point for practitioners with a desire to formulate similar  
776 models for other specific cases.



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**TABLE 1.** Summary of state-space models fitted for this study showing the notation for how models are referenced and results of WAIC calculations. Cells with ■ indicate that particular trend was included in the model, those with □ indicate the demographic quantity was time-constant. Inclusion/exclusion of trends and alternative units of reproductive output are described in section 2.5. Supplements B – I show detailed model output from select models, including convergence summaries, model fit, posterior predictive checks, and model code.  $\Delta$ WAIC values were calculated relative to the lowest value within each reproductive unit type.

Rep. Unit	Model	Demographic Trends			Supplement	$\Delta$ WAIC
		Age	Sex	Length		
Spawners	N-0	□	□	□	B	106.1
	N-ASL	■	■	■		0.0
Egg Count	E-0	□	□	□	C	104.1
	E-A	■	□	□	D	10.5
	E-S	□	■	□	E	90.9
	E-L	□	□	■	F	104.5
	E-AS	■	■	□	G	0.0
	E-AL	■	□	■		11.0
	E-SL	□	■	■		91.8
	E-ASL	■	■	■	H	0.6
Egg Mass	EM-0	□	□	□		103.5
	EM-ASL	■	■	■	I	0.0

TABLE 2. Symbology used in the presentation of the state-space model.

Symbol	Description	Eqs.
<b>Dimensional Constants</b>		
$n_t$	Number of calendar years included in the model	
$n_y$	Number of brood years included in the model	
$n_s$	Number of sexes of return	
$n_a$	Number of ages of return	
$a_{\min}, a_{\max}$	Minimum and maximum age of return, respectively	
<b>Indices</b>		
$y, t$	Brood and calendar year, respectively	
$a, s$	Age and sex, respectively	
$j$	Unique age/sex class	
$m$	Mesh size	
$i$	Time block	
<b>Parameters</b>		
$\alpha$	Ricker productivity parameter	1,14
$\beta$	Ricker capacity parameter	1,13
$\phi$	Lag-1 autoregressive coefficient	3,14
$\sigma_R^2$	White noise recruitment process variance	3,14
$\delta_0, \delta_1$	Logit-scale coefficients for sex-at-return	4
$\psi_y$	Probability a recruit from brood year $y$ is female	4,5
$\gamma_{0,a,s}, \gamma_{1,a,s}$	Baseline logit-scale coefficients for age-at-return	6
$\pi_{y,a,s}$	Year- and sex-specific probability of return-at-age	6,7
$\tau, \sigma, \theta, \lambda$	Parameters of the Pearson gillnet selectivity function	8
$v_{t,a,s,m}$	Selectivity in year $t$ for age $a$ and sex $s$ using mesh $m$	9,10
$F_{\text{com},t}$	Fishing mortality of the commercial fishery in year $t$	10
$F_{\text{sub},t}$	Fishing mortality of the subsistence fishery in year $t$	10
<b>States</b>		
$\hat{R}_y$	Expected recruitment for brood year $y$	1,3
$\hat{R}_0$	Expected recruitment for brood years without spawner-link	1
$R_y$	Realized recruitment for brood year $y$	3,5,7
$N_{t,a,s}$	Run abundance in calendar year $t$ of age $a$ and sex $s$	7,10
$H_{\text{com},t,a,s}$	Commercial harvest in calendar year $t$ of age $a$ and sex $s$	10
$H_{\text{sub},t,a,s}$	Subsistence harvest in calendar year $t$ of age $a$ and sex $s$	10
$S_{t,a,s}$	Escapement in calendar year $t$ of age $a$ and sex $s$	2,11
$Z_t$	Total reproductive output in calendar year $t$	1,2
<b>Assumed Known Quantities</b>		
$z_{t,a,s}$	Reproductive output of a spawner in year $t$	2
$S_{\text{obs},t}, H_{\text{com},t}, H_{\text{sub},t}$	Observed (estimated) aggregate escapement, commercial harvest, and subsistence harvest in year $t$	
$\sigma_{S,t}^2, \sigma_{\text{com},t}^2, \sigma_{\text{sub},t}^2$	Observation variances for aggregate escapement, commercial harvest, and subsistence harvest in year $t$	
$x_{S,t,j}, x_{\text{com},t,j}, x_{\text{sub},t,j}$	Adjusted scale frequencies for fish with different fates and unique age/sex class $j$	
$\text{RLM}_{t,a,s,m}$	Mean length of fish in year $t$ of age $a$ and sex $s$ relative to mesh perimeter $m$	9

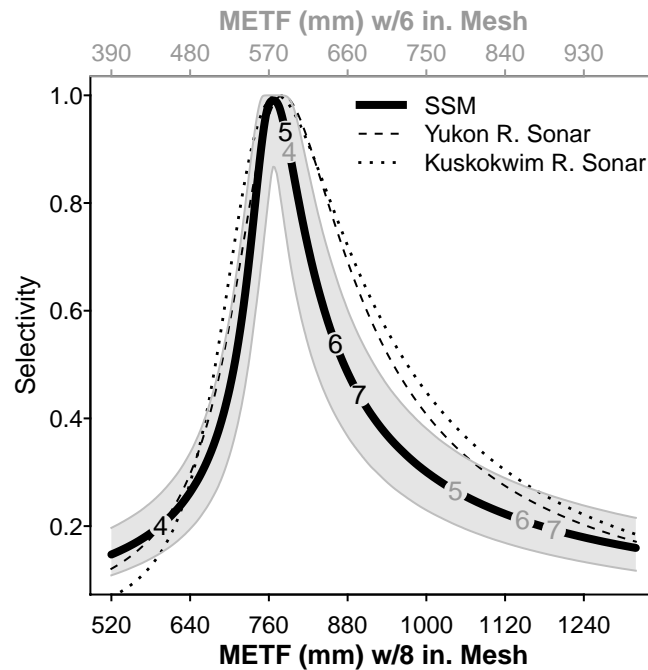
**TABLE 3.** Prior distributions used for all estimated parameters state-space models. Identical priors were used for all models except where noted by the footnote. Normal distributions were parameterized as (mean, precision) and gamma distributions as (shape, rate) just as in the JAGS language.

Parameter	Prior	Bounds
$\alpha$	<sup>a</sup> Uniform(0, X)	
$\beta$	Uniform(0, 0.5)	
$\phi$	Uniform(-1, 0.99)	
$\log(\dot{R}_0)$	Normal(0, $1 \times 10^{-4}$ )	
$1/\sigma_R^2$	Gamma(0.01, 0.01)	
$1/\sigma_{R_0}^2$	Gamma(0.01, 0.01)	
$R_y$	see eq. (3)	
$\delta_0$	Normal(0, $1 \times 10^{-6}$ )	
$\delta_1$	<sup>b</sup> Normal(0, $1 \times 10^{-6}$ )	
$\gamma_{0,a,s}$	Normal(0, $1 \times 10^{-6}$ )	
$\gamma_{1,a,s}$	<sup>b</sup> Normal(0, $1 \times 10^{-6}$ )	
$\tau$	<sup>c</sup> Normal(1.897, $1/0.46^2$ )	
$\sigma$	<sup>c</sup> Normal(0.236, $1/0.81^2$ )	[0, $\infty$ )
$\theta$	<sup>c</sup> Normal(0.756, $1/1.86^2$ )	[0, $\infty$ )
$\lambda$	<sup>c</sup> Normal(-1.049, $1/3.82^2$ )	
$F_{\text{com},t}$	Uniform(0, 10)	
$F_{\text{sub},t}$	Uniform(0, 10)	

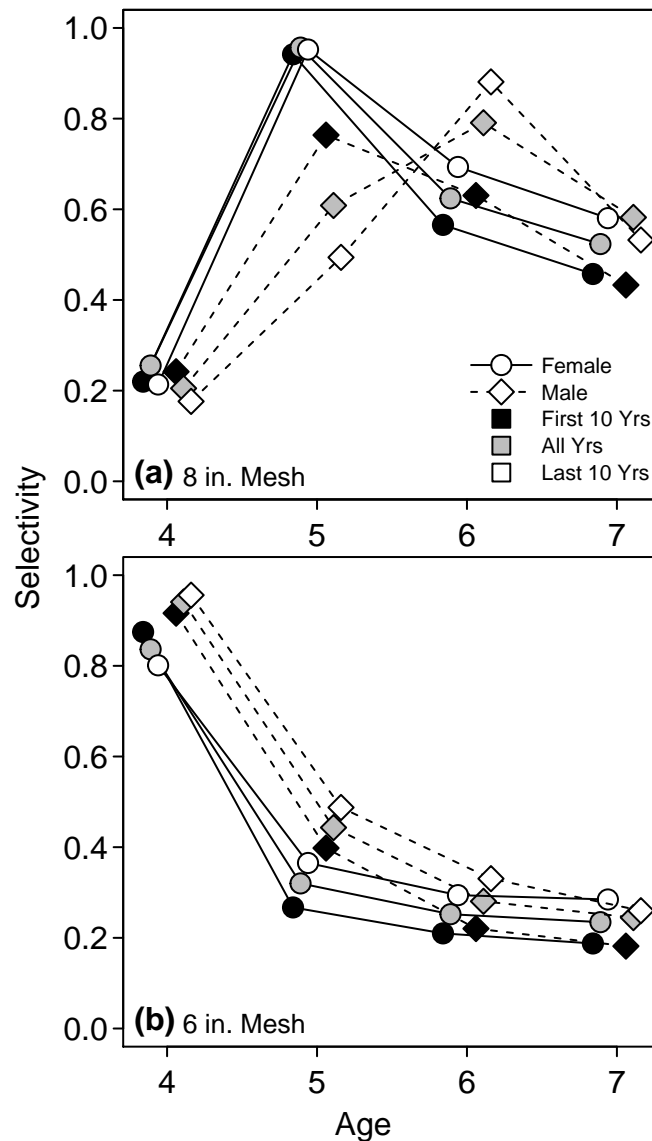
#### Notes

- <sup>a</sup> Value of X was 20 for models assuming spawners were the unit of reproductive output (i.e., N-\* models) and 0.1 for non-spawner units (i.e., E-\* and EM-\* models)
- <sup>b</sup> In models that assumed time-constant return-by-sex and return-by-age, these priors were replaced with fixed zero values
- <sup>c</sup> Estimates provided by N. Smith (ADF&G; methods in Birchfield and Smith 2019), point estimate used as mean,  $(\text{SE} \times 10)^2$  used as variance

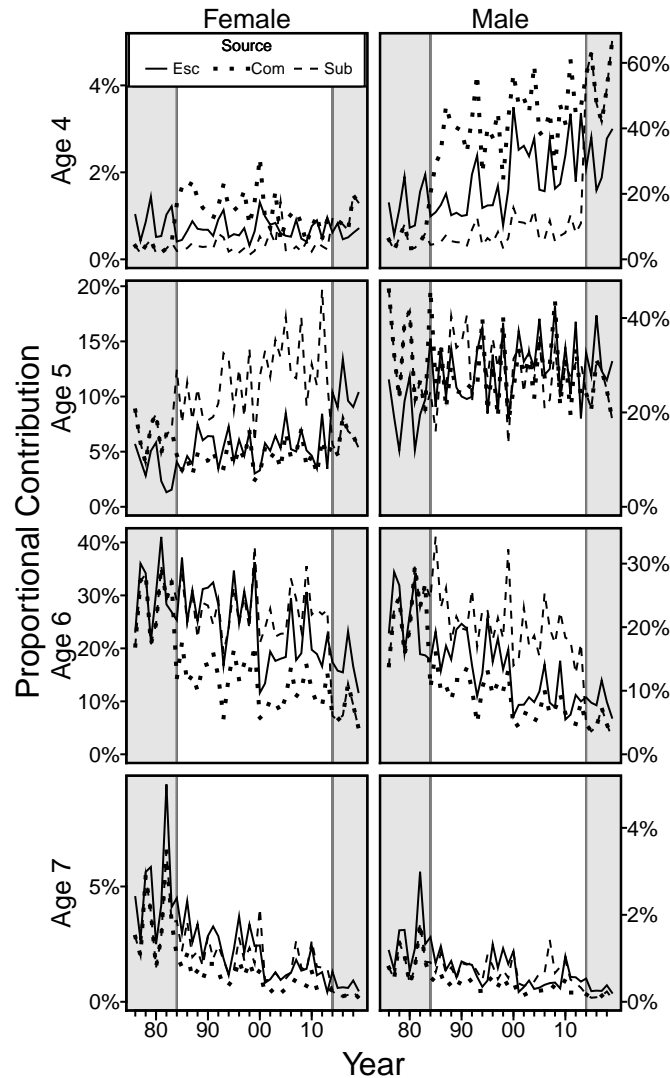




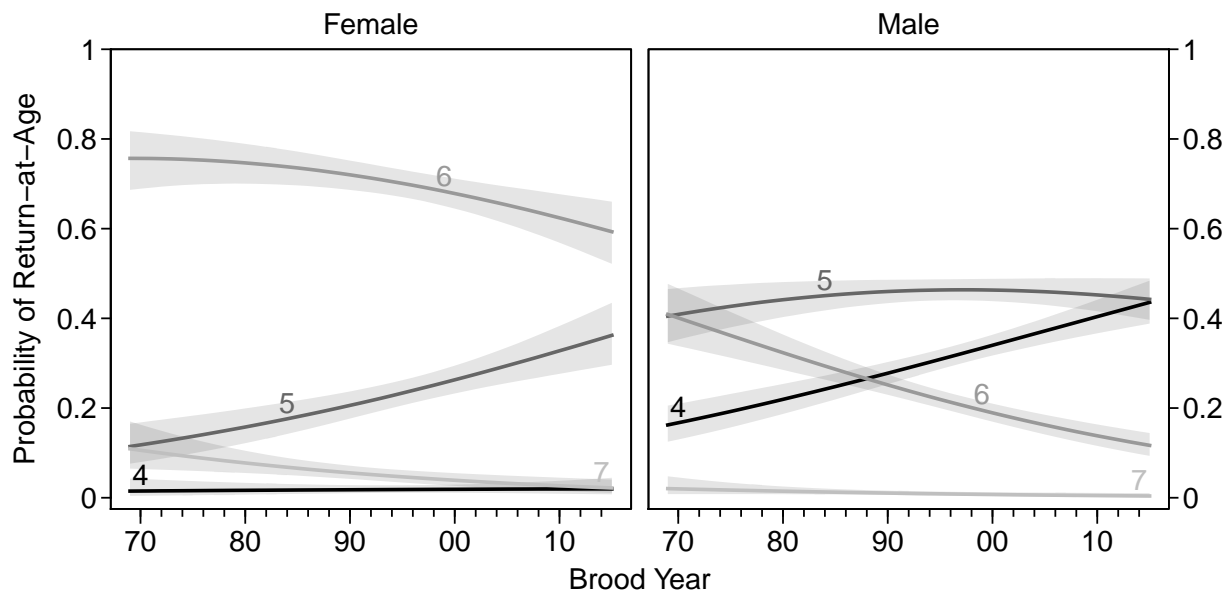
**FIGURE 1.** Estimated Pearson gillnet selectivity function for Kuskokwim River Chinook salmon. Numbers along the curve indicate the selectivity of females at each age based on the average length across the whole time series according to two mesh sizes: 8-inch (black) and 6-inch (grey). The length (mid-eye to tail-fork; METF) for each mesh size are displayed on the horizontal axes. The grey band represents the 95% credible region for Kuskokwim River Chinook salmon as estimated by the state-space model E-ASL (other models looked identical). For comparative purposes only, Pearson functions are shown for Chinook salmon sampled for sonar-based species apportionment models from the Yukon River (Bromaghin 2005) and Kuskokwim River (N. Smith, personal communication).



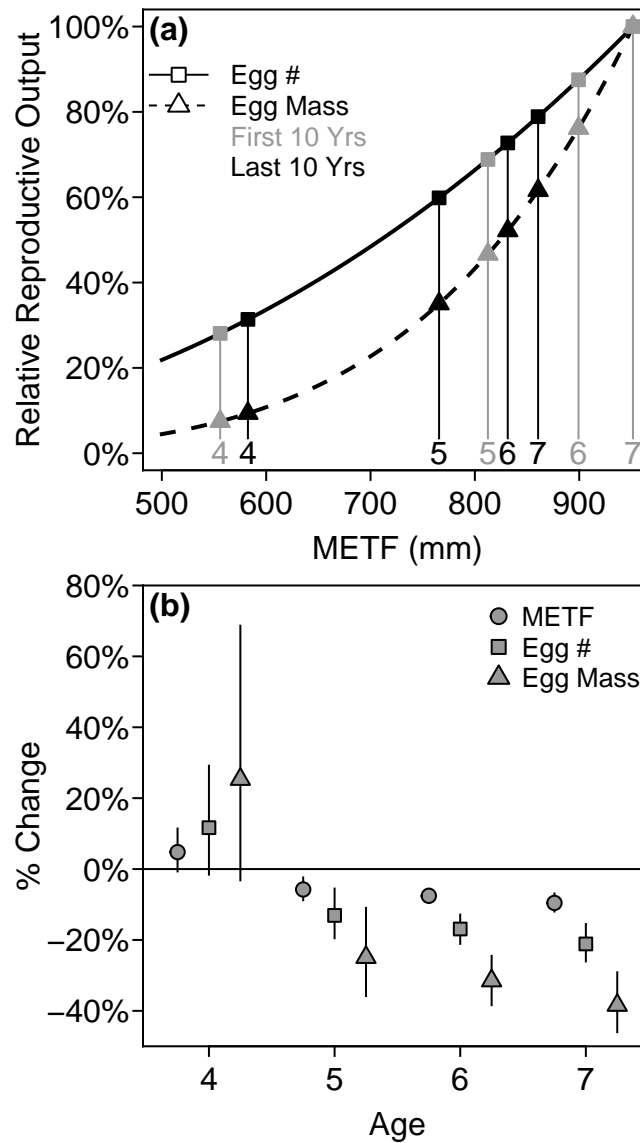
**FIGURE 2.** Relative selectivity on an age-, sex-, and time period-specific basis for fisheries using (a) 8-inch mesh and (b) 6-inch mesh. Points connected by lines represent the average posterior median for the years included in each time period. Posterior estimates are from model E-ASL; other models looked nearly identical.



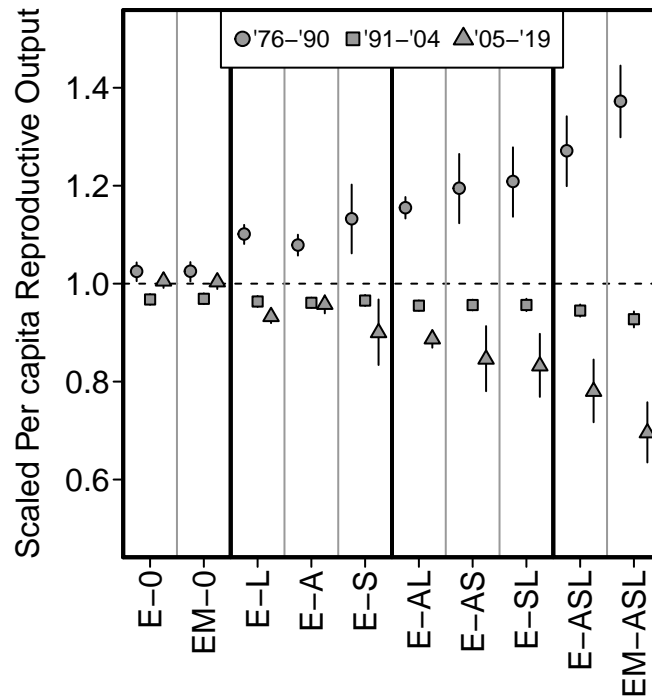
**FIGURE 3.** Calendar year composition for each age and sex class through time according to three different fates: escapement (solid line), commercial fishery (dotted lines), and subsistence fishery (dashed lines). Lines represent posterior medians from model E-ASL; within a fate and year, all panels sum to one. Grey regions represent the periods when the two fisheries used the same mesh size: 1976 – 1983 both used 8-inch mesh, 1984 – 2011 commercial was restricted to 6-inch mesh, and 2014 – 2019 both were restricted to 6-inch mesh.



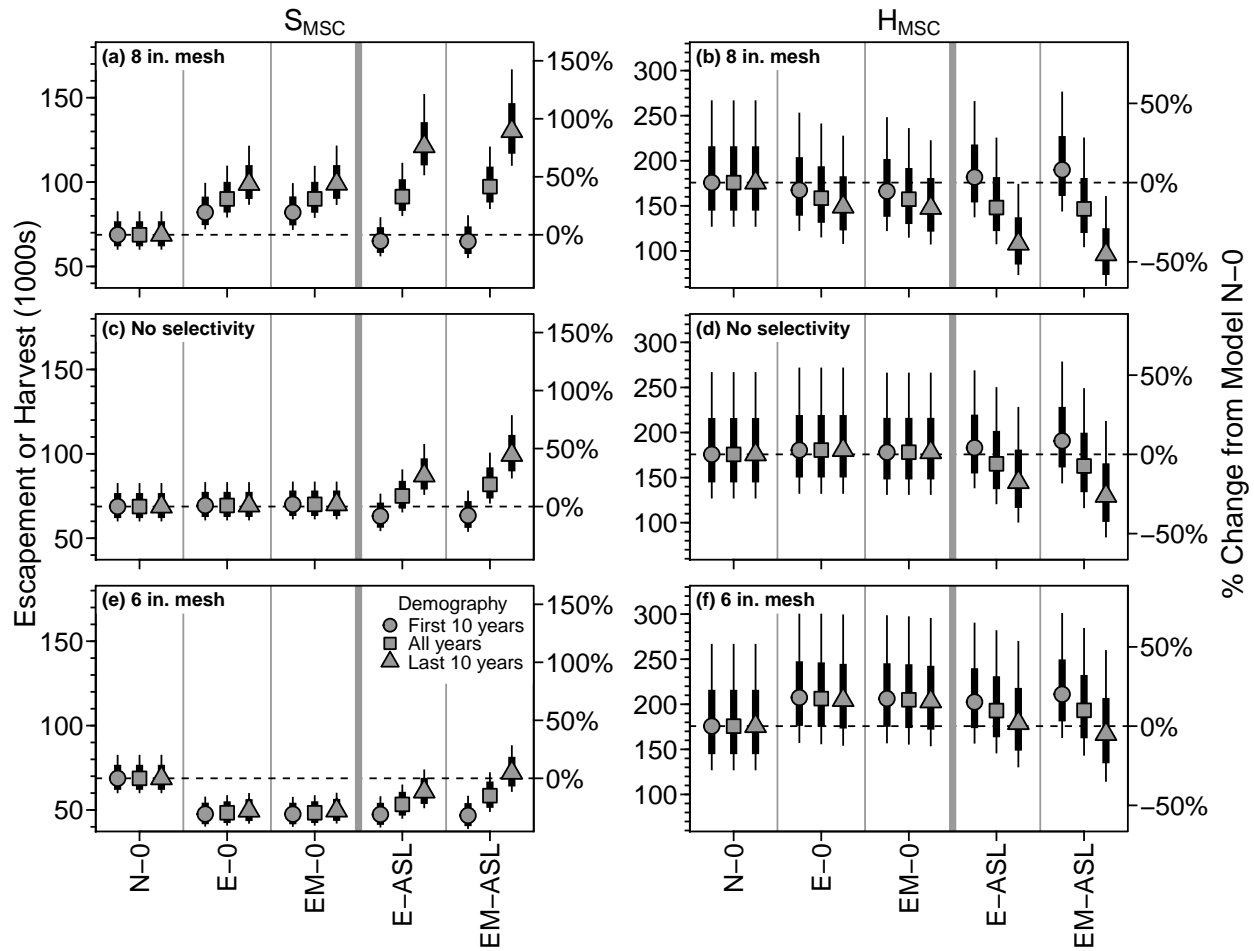
**FIGURE 4.** Brood year- and sex-specific probability of returning as an adult recruit at each age for models that allowed age-at-return to trend over time (posterior summaries are shown from model E-ASL; but all models with this age component showed the same pattern). The four lines on each panel represent the possible ages of maturity (as indicated by the numerical labels), shaded areas are 95% credible regions, and thick lines are posterior medians. The  $x$ -axis spans brood years 1969 – 2015.



**FIGURE 5.** Panel (a) shows assumed relationships between female Chinook salmon length (mid-eye to tail-fork; METF) and relative reproductive output expressed as total fecundity (Egg #) or total egg mass per female. Relationships scaled to the reproductive output for age-7 females in the first 10 years of Kuskokwim River mean length data. Numbers and symbols represent METF and relative reproductive output of females at age using METF averaged over the first and last 10 years in the data set. Relationships were fitted to samples taken the Yukon River at Eagle, Alaska between 2008 – 2010 (Ohlberger et al. 2020). Panel (b) shows percent change in METF, egg number, and egg mass per average female spawner of each age between the last and first 10 years of the Kuskokwim data set. Error bars represent 95% bootstrapped confidence limits, obtained by resampling with replacement the mean length values for the years in each time block. Note that although age-4 females are predicted to have increased in size and reproductive output, they make up less than 5% of total female recruits (Figure 4).



**FIGURE 6.** Posterior per capita reproductive output ( $Z_t/S_t$ , scaled to the mean across all years) averaged for three time periods for each model in the analysis (excluding models N-0 and N-ASL). Larger shifts from the early period (circles) to the later period (triangles) indicate steeper suggested declines in the reproductive output of the average spawner. Points represent posterior medians and error bars represent central 95% credible limits. This measure integrates over age and sex composition while taking into account relative reproductive output.



**FIGURE 7.** Estimated equilibrium values of  $S_{MSC}$  (panels a, c, and e) and  $H_{MSC}$  (panels b, d, and f) using 8-inch mesh (panels a and b), non-selective (panels c and d), and 6-inch mesh (panels e and f) gillnet gear for a subset of models. The time period (symbol type) represents which years were used to calculate the average demographic qualities used in equilibrium calculations. The percent change from the posterior median for model N-0 is displayed on the secondary  $y$ -axis for reference. Points are posterior medians, thick lines are the posterior central 50% limits, and thin lines are the posterior central 80% limits.