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A Simulation Study to Estimate the Unfished Biomass of Sitka Sound Pacific Herring

by

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Alaska Department of Fish and Game Division of Commercial Fisheries

Symbols and Abbreviations

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Weights and measures (metric)

centimeter	cm
deciliter	dL
gram	g
hectare	ha
kilogram	kg
kilometer	km
liter	L
meter	m
milliliter	mL
millimeter	mm

Weights and measures (English)

cubic feet per second	ft^3/s
foot	ft
gallon	gal
inch	in
mile	mi
nautical mile	nmi
ounce	oz
pound	lb
quart	qt
yard	yd

Time and temperature

day	d
degrees Celsius	°C
degrees Fahrenheit	°F
degrees kelvin	K
hour	h
minute	min
second	s

Physics and chemistry

all atomic symbols	
alternating current	AC
ampere	A
calorie	cal
direct current	DC
hertz	Hz
horsepower	hp
hydrogen ion activity (negative log of)	pH
parts per million	ppm
parts per thousand	ppt, ‰
volts	V
watts	W

General

Alaska Administrative Code	AAC
all commonly accepted abbreviations	e.g., Mr., Mrs., AM, PM, etc.
all commonly accepted professional titles	e.g., Dr., Ph.D., R.N., etc.
at	@
compass directions:	
east	E
north	N
south	S
west	W
copyright	©
corporate suffixes:	
Company	Co.
Corporation	Corp.
Incorporated	Inc.
Limited	Ltd.
District of Columbia	D.C.
et alii (and others)	et al.
et cetera (and so forth)	etc.
exempli gratia (for example)	e.g.
Federal Information Code	FIC
id est (that is)	i.e.
latitude or longitude	lat or long
monetary symbols (U.S.)	\$, ¢
months (tables and figures): first three letters	Jan,...,Dec
registered trademark	®
trademark	™
United States (adjective)	U.S.
United States of America (noun)	USA
U.S.C.	United States Code
U.S. state	use two-letter abbreviations (e.g., AK, WA)

Mathematics, statistics

all standard mathematical signs, symbols and abbreviations	
alternate hypothesis	H_A
base of natural logarithm	*e*
catch per unit effort	CPUE
coefficient of variation	CV
common test statistics	(F, t, χ^2, etc.)
confidence interval	CI
correlation coefficient (multiple)	R
correlation coefficient (simple)	r
covariance	cov
degree (angular)	°
degrees of freedom	df
expected value	*E*
greater than	>
greater than or equal to	≥
harvest per unit effort	HPUE
less than	<
less than or equal to	≤
logarithm (natural)	ln
logarithm (base 10)	log
logarithm (specify base)	log_2, etc.
minute (angular)	′
not significant	NS
null hypothesis	H_O
percent	%
probability	P
probability of a type I error (rejection of the null hypothesis when true)	α
probability of a type II error (acceptance of the null hypothesis when false)	β
second (angular)	″
standard deviation	SD
standard error	SE
variance	
population	Var
sample	var

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ABSTRACT

Allowable harvest levels of Pacific herring in Sitka Sound are prescribed using a threshold management strategy, wherein the fishery is closed if the estimated biomass falls below a certain threshold level, and a variable harvest rate is used at and above the threshold. The department last calculated a threshold level for Sitka Sound herring (16,759 short tons) in 1997 based on 25% of the estimated average unfished spawning biomass (B_0; 67,036 short tons) of the stock; although in response to subsistence concerns the threshold level in regulation was set at 20,000 short tons (1997) and later elevated to the current 25,000 short tons (2010 to present). The analysis contained in this report updates the estimate of average unfished spawning biomass of herring in Sitka Sound. In this report, data and parameter estimates from the integrated statistical catch-at-age 2023-forecast model are used to simulate the average biomass of the Sitka Sound Pacific herring stock under a no-fishing scenario with more rigorous statistical methods and a longer time series of data. Simulations were repeated 1,000 times and combined into a single nonparametric distribution of spawning biomass. The final estimate of average unfished spawning biomass of Sitka Sound herring based on the median simulated value is 85,576 short tons.

Keywords: *Clupea pallasii*, Pacific herring, sac roe, Sitka Sound, simulation, threshold level, average unfished spawning biomass

INTRODUCTION

The Sitka Sound Pacific herring (*Clupea pallasii)* stock is one of the largest in the North Pacific. It is both culturally and economically important and supports subsistence, personal use, and commercial fisheries (Thornton 2015; Moss 2016; Hebert 2021). Herring has been a vital subsistence food item for Tlingit peoples in Sitka Sound for centuries and still is to this day (Thornton 2015). Commercial harvests in Sitka Sound historically included bait, wild spawn-on-kelp, and sac roe fisheries (Davidson et al. 2013). Currently, the Sitka Sound commercial harvest is allocated to the purse seine sac roe fishery, with up to an additional 100 short tons (hereafter, all references to tons refer to short tons) provided for the bait pound fishery (5 AAC 27.160 (b) (2)). The Alaska Department of Fish and Game (ADF&G or department) manages the Sitka Sound herring fishery using a threshold management strategy, which requires the mature biomass forecast to exceed a minimum amount before commercial harvest is allowed. Additionally, the management of the Sitka Sound commercial sac-roe fishery must consider reasonable opportunity, quality, and quantity for the customary and traditional take (or use) of subsistence harvest spawn and sac roe (5 AAC 01.716 (b), 5 AAC 27.195 (a)(2), 5 AAC 27.195 (b)). Identifying an appropriate minimum mature biomass, or “threshold level”, is key to an effective threshold management strategy and may be defined as some fraction of the average unfished biomass of the stock. Average unfished spawning biomass (or equilibrium average unfished spawning biomass) refers to the long-term average of spawning biomass (B_0) under average environmental conditions, and in an unexploited fish population (Zheng et al. 1993). Estimating the average unfished spawning biomass of Sitka Sound herring is the objective of this report.

Methods for estimating and forecasting the herring stock size in Sitka Sound to sustainably manage the stock, have improved over time. Prior to 1993, the Sitka Sound herring stock was assessed using visual estimates from depth sounders and sonar preceding spawning or during winter (prior to 1970), computer-assisted hydroacoustic estimates (1971–1983), and/or spawn deposition dive surveys (1976 onwards; ADF&G 1995). Beginning with the 1994 forecast, ADF&G started using an age-structured analysis (ASA) model for stock assessment and forecasting purposes (Larson et al. 1994; Carlile 1996; Carlile et al. 1999). Along with the spawn deposition survey, the ASA model incorporates a time series of commercial fishery age composition and weight-at-age data from samples of the purse seine sac-roe harvest of pre-spawning herring, fishery-independent spawning age composition data from cast net sampling of spawning herring, and fecundity relationships. The ASA model currently incorporates data from 1976 onwards; hydroacoustic estimates are used from years when hydroacoustic surveys became operational (1976–1981; Blankenbeckler and Larson (1982, 1987)), and spawn deposition estimates are used from years when scuba surveys became operational (1982 on; Hebert 2020). Within a least squares procedure, deviations between the observed egg deposition, catch and spawning age compositions, and the model-based estimates of these variables are minimized. The model estimates initial abundance in 1976, initial abundance of recruits, and the key parameters of annual survival, age-specific maturity, and age-specific gear selectivity. The model-based estimates of recruits (or recruitment), maturation, and survival are applied to the prior year's spawning biomass to forecast the pre-fishery (mature) biomass (Hulson et al. 2018). "Recruitment" in this report refers to the abundance of mature and immature age-3 herring.

Mature biomass forecasts produced by the Sitka Sound herring stock assessment are used to set guideline harvest levels (GHLs) for the commercial sac roe fishery, which are currently determined using a 12-20% sliding scale harvest rate policy in concert with a 25,000-ton threshold level. Under this management regime, the commercial fishery is closed if the mature biomass is forecasted to be under the threshold level. Otherwise, if the mature biomass is forecasted at the threshold level or above, the GHL is set from 12% to 20% of the forecasted mature biomass, depending on the forecast size, with a maximum harvest rate of 20% (5 AAC 27.160 (g)). The department's management strategy of herring in Sitka Sound has changed several times since the 1970's. Beginning in 1977, the Sitka Sound herring sac roe fishery became limited entry with a minimum 6,000-ton biomass threshold below which no commercial sac roe fishery would open (Davidson et al. 2013). A 10% harvest rate was established in 1979, and by 1983, the harvest rate policy had changed to a sliding scale of 10-20% with increments of 2% for each forecast multiple of a 7,500 tons threshold level and with a maximum harvest rate of 20% (Davidson et al. 2013). A new harvest rate policy and threshold level were then established in 1997 by the Alaska Board of Fisheries (BOF): a 20,000-ton threshold level for a minimum 10% harvest rate increasing as a continuous linear function of the spawning biomass forecast (instead of 2% increments) to a maximum 20% harvest rate at 45,000 tons (Davidson et al. 2013). Finally, beginning in the 2010 sac-roe fishery season, the threshold level and minimum percent harvest rate at the threshold level were increased to the current 25,000 tons and 12%, respectively, but using the same sliding scale rule and maximum harvest rate (20%) established in 1997 (Davidson et al. 2011; Dupuis et al. 2022).

Threshold management strategies have been used throughout the North Pacific to manage Pacific herring stocks. The current maximum harvest rate of Sitka Sound herring is 20% of the forecasted mature biomass and a 20% harvest rate has been historically used along with thresholds in herring management throughout Alaska (e.g., Prince William Sound area (5 AAC 27.365 (b)), Togiak district (5 AAC 27.865 (b) (4); 5 AAC 27.865 (b) (6)), Southeast Alaska (5 AAC 27.190 (4)) and for British Columbia stocks (Cleary et al. 2010). This maximum harvest rate was originally based on studies in the 1980's and 1990's concluding that a 20% harvest rate is sufficiently conservative to maintain s herring stocks when paired with a threshold level (Doubleday 1985; Fried and Wespestad 1985; Hall et al. 1988; Zheng et al. 1993). Specifically, Hall et al. (1988) and Zheng et al. (1993) recommended a 20% harvest rate paired with a threshold level (also referred to as a cutoff) equal to 25% of average unfished biomass for stocks in British Columbia and Alaska. More recent simulations have suggested that when population productivity is high, a 20% harvest rate paired with a threshold level equal to 25% of average unfished biomass is sufficient to avoid stock declines to critical levels with greater than 95% probability (Cleary et al. 2010). However, a 20%

harvest rate may not be adequate in preventing long-term declines for herring stocks in low productivity states (Schweigert et al. 2007) or rebuilding seriously depleted stocks (Cleary et al. 2010). Indeed, during the mid-2000s 3 of the 5 herring stocks in British Columbia entered states of “low production, low biomass” despite having been managed with a 20% maximum harvest rate and 25% threshold level for over a decade (Kronlund et al. 2018). Department of Fisheries and Oceans (DFO) has been aligning their herring management with the precautionary approach (DFO 2006, 2009) and in 2018 first established limit reference points of 30% of estimated average unfished biomass for 3 of their herring stocks (Kronlund et al. 2018). “Limit reference point” refers to a population biomass level which should be avoided with high probability to prevent serious harm to a stock, and DFO manages BC herring stocks with a conservation objective to maintain spawning biomass at or above the limit reference point with at least 75% probability for at least 3e herring generations (Forrest et al. 2023). For 2024 forecasts, DFO research (Fisheries and Oceans Canada Pacific Science Branch) explored numerous harvest rate strategies with their most plausible model (density-dependent process model) for British Columbia herring stocks. These included strategies with a sliding scale harvest rate from a 30% unfished biomass threshold (referred to as lower operational control point) to a 60% unfished biomass inflection point where the maximum harvest rate is attained. Sliding scale harvest rates with the following maximum harvest rates were identified by DFO research as meeting their conservation objective: 0% for Haida Gwaii, up to 20% for Prince Rupert, up to 10% for Central Coast (15% and 20% were not explored), up to 15% for Strait of Georgia, and up to 15% for the West Coast of Vancouver Island (20% was not explored; DFO 2024a; Jaclyn Cleary, Fisheries Biologist, Fisheries and Oceans Canada [DFO], fall 2023, personal communication). The fisheries policy as reported in the 2023/2024 Integrated Fisheries Management Plan (DFO 2024b) was more conservative. Currently, for the 2023–2024 season, the Minister of Fisheries, Oceans, and the Canadian Coast Guard, set the harvest rate at a maximum of 4% for the Central Coast management area, 5% for the Prince Rupert District management area, and 10% for the Strait of Georgia, while the Haida Gwaii and West Coast of Vancouver Island management areas were closed to commercial harvest (DFO 2024b).

The department last calculated a proposed threshold level for Sitka Sound herring in 1997 (16,759 tons) that was based on a 25% average unfished spawning biomass criterion (Carlile 1998). Thresholds for the Sitka Sound herring fishery prior to 1997 were based on historical estimates of abundance, and professional judgement regarding the minimum amount of harvest that could be managed and controlled (Carlile 1998). Carlile (1998) implemented a more formal analysis. To estimate the average unfished spawning biomass of the stock, Carlile (1998) simulated the spawning stock’s biomass trajectory under a no-harvest scenario (the unfished spawning biomass) and then calculated the average unfished spawning biomass after 2,500 simulation years using parameter estimates from the 1996 ASA (1997 forecast) Sitka herring model in a similar approach to Funk and Rowell (1995). Recruitment, the number of immature and mature age-3 fish, was sampled with replacement from 3 strata for 2,500 simulation years. The strata were chosen based on perceived natural breaks in the number of herring recruits spawned from 10,000 and 30,000 tons of biomass. After allowing for model stabilization and excluding the first 500 simulation years, the mean unfished spawning biomass estimate was 67,036 tons which, after multiplying by 25%, resulted in a proposed threshold level of 16,759 tons (Carlile 1998). Carlile’s (1998) use of this “25% criterion” was based on past work concluding that a threshold level of 25% of a herring stock’s average unfished spawning biomass (combined with an 20% maximum harvest rate) would provide adequate protection from overfishing (Zheng et al. 1993). The 25%

criterion had been previously implemented in British Columbia herring stocks (Schweigert 1993) and recommended by department staff, but not adopted by the Alaska BOF, for the Togiak herring stock (Funk and Rowell 1995).

The current analysis, which provides an update to the estimate of average unfished spawning biomass from Carlile (1998), is being undertaken due to the number of years since the last analysis and the increase in mature biomass (indicating increased productivity) since that time. Furthermore, the hindcasted estimates for spawning stock size from the current 2023-forecast ASA model exceed the average unfished spawning biomass estimate from Carlile (1998) for 14 of the 26 Sitka Sound herring sac roe seasons since the Alaska BOF decision in 1997 (i.e., from the 1997 to the 2022 sac-roe fishery season), despite an active fishery in most of those years. While fished biomass can exceed an average unfished spawning biomass in one or more years and not indicate that the carrying capacity of the ocean has changed, if estimates of annual fished biomass persistently exceed average unfished spawning biomass over many years, then an analysis with updated data like that provided here is valuable to assess whether the carrying capacity of the ocean has changed. Our analysis updates the estimated average unfished spawning biomass of herring in Sitka Sound based on parameter estimates from the most recent (2023–forecast) ASA model, more rigorous statistical methods, and a longer time series. In the analysis, 1,000 simulations of the biomass trajectory of the spawning stock are run under a no-harvest scenario, and the resulting median biomass is reported as the equilibrium average unfished spawning biomass (i.e., the expected, long-term dynamics of the Sitka Sound herring stock in the absence of fishing; B_0) of the Sitka Sound herring stock.

OBJECTIVES

Estimate the average unfished spawning biomass of Sitka Sound herring.

METHODS

STATISTICAL CATCH-AT-AGE (SCAA) MODEL

The statistical catch at age model (SCAA) used for Sitka Sound herring, previously known by the more general term of the ASA model, is a standard implementation of an age-structured assessment model (Quinn and Deriso 1999, chapter 8), with time-dependent parameterizations, using least squares minimization. A detailed description of the general model structure and equations are found in Hulson et al. 2018. The observed data that were fit by the 2023-forecast model included an egg deposition index, commercial fishery age composition data (from samples of the purse seine sac-roe harvest of pre-spawning herring), and fishery-independent spawning age composition data (from cast net sampling of spawning herring). Egg estimates used in the model for 1982 to 2022 were based on a two-stage sampling design (aerial surveys followed by scuba dive surveys) to estimate egg deposition as described in Hebert (2020). To extend the egg index back further in time, hydroacoustic estimates of herring biomass for 1976 to 1981 (1976–1980 estimates from Blankenbeckler and Larson (1982); 1981 estimate from Blankenbeckler and Larson (1987)) were converted to eggs assuming 100 million eggs per ton of spawners (Blankenbeckler and Larson 1987). The egg deposition index was fit by assuming log-normally distributed observation uncertainty and an among-dataset weighting of 1.0. The fishery and spawning age compositions were fit using the normal distribution with variance (i.e., sum of squares, SSQ) fixed at 1.0 (among-data set weighting). The objective function also included the model fit to a Ricker spawner-recruit function. The Ricker spawner-recruit function was weighted low (0.0001; among-data set weighting) in the objective function so had virtually no influence on the model fit but kept estimates of recruitment positive and was used for forecasting the number of recruits in the upcoming year. For within-data set weighting, there was equal weighting among years for both age composition data sets (each year is set to 1.0). For the egg index, individual years were weighted with an inverse of the estimated variance (or approximated inverse-variance). For 1991 to 2022 (years for which spawn deposition dive survey raw data were available), the variance for the egg index was estimated with a bootstrap procedure of the egg deposition observations in each year according to the two-stage survey sampling design (Thompson 2002). For 1982–1990 (years in which spawn deposition dive surveys were the basis for the egg estimate, but raw data were not available), variance (standard deviation squared) is estimated using the egg estimate for each year and a linear regression of log-transformed egg estimates and associated standard deviations from 1991–2022. For 1976 to 1981 (hydroacoustic biomass estimates converted to eggs), a CV of 0.29 (measurement error estimated from Prince William Sound herring acoustic surveys; Muradian et al. 2017) was used to calculate the variance where: $variance = (egg\ estimate * CV)^2$. Parameters (e.g., instantaneous natural mortality, logistic parameters for maturity and selectivity, initial abundance of age-4 to 8+, recruitment of age-3 fish, Ricker spawner-recruit parameters; Hulson et al. 2018) were estimated within the model to maximize the objective function (i.e., to produce a model that best described the data that was collected).

To ensure the best possible fit to the data, a suite of alternative model structures with different time-dependent parameterizations were compared to determine the recommended model for the 2023-forecast. Time blocks, between which the survival, maturity, and gear selectivity parameters were allowed to differ within the Sitka herring forecast models, were based on breakpoints in the mean monthly Pacific Decadal Oscillation (PDO) index (Appendix A). Breakpoints were defined as the point in time in which positive PDO anomalies switch to negative PDO anomalies, or vice versa. The "Sequential t-Test Analysis of Regime Shifts" (STARS) method (Rodionov and Overland 2005) was used to identify the breakpoints in the mean PDO index (Appendix A). Based on the STARS method, 3 potential time blocks (1976–2007, 2008–2014, and 2015–2022) were considered in the 2023-forecast model; years in which model-estimated survival, maturity, and gear selectivity were allowed to change corresponded with these time blocks. The selection of the recommended model was then based on the Akaike Information Criterion corrected for small sample sizes (AICc; Burnham and Anderson 1998), biologically realistic estimation of parameters, inspection of residuals, and consistency with prior structures (i.e., similar time blocks of change for survival, maturity, and selectivity as prior years' forecast models). The recommended 2023-forecast model had 3 survival time blocks (1976–2007, 2008–2014, 2015–2022), one maturity time block (1976–2022), and one selectivity time block (1976–2022).

AVERAGE UNFISHED SPAWNING BIOMASS SIMULATIONS

Data

Data used in this simulation-based approach included inputs to, and outputs from, the 2023-forecast SCAA model for Sitka Sound herring for years 1980–2022. The SCAA model input data used in the simulations consisted of annual weight-at-age samples from the Sitka Sound herring purse-seine fishery (Table 1). The annual weight-at-ages input to the SCAA model were averaged over 1980–2022[1]. The SCAA model's outputs, fed into the simulations, included key parameter estimates such as recruitment (the number of immature and mature age-3 fish in millions), spawning stock biomass (tons; Figure 1), the age-invariant annual survival fraction (proportion) averaged across the 3 time blocks (63% survival for 1976–2007, 77% survival for 2008–2014, and 69% survival for 2015–2022) in the model time series (0.6645), and the time-invariant age-specific proportion of mature herring from the estimated logistic maturity function (Tables 1–2).

The SCAA model data and parameter estimates that were used in the simulation included the years 1980–2022, although the SCAA model includes years back to 1976. This range (1980–2022) was determined based on having enough years for a simulation-type analysis and a year-range that comprises a reasonable environmental regime of the Northeast Pacific over which carrying capacity can be assumed (post-1976 conditions). Many year-ranges can be, and have been, used to describe environmental regimes in the Northeast Pacific. The 1980–2022 year range was chosen for this study because there was a notable and widely substantiated climatic (Trenberth 1990; Ebbesmeyer et al. 1991; Graham 1994; Miller et al. 1994) and ecological (Beamish 1993; Beamish et al. 1997; Francis and Hare 1994; Francis et al. 1998; McGowan et al. 1998) regime shift in the winter of 1976/1977 across the Northeast Pacific. Although other potential regime shifts have been identified in the Northeast Pacific within the model time series (1976 on) of the Sitka Sound herring stock, such as 1988/1989 (Beamish et al. 1999; Watanabe and Nitta 1999; McFarlane et al. 2000; Welch et al. 2000; Benson and Trites 2002), 1998/1999 (McFarlane et al. 2000; Bond et al. 2003; Chavez et al. 2003; Batten and Welch 2004), and 2007/2008 (Overland et al. 2012; Hatch 2013), the 1976/1977 regime shift remains the most widely recognized climatological and ecological shift. Only the 1976/1977 regime shift has been identified as a "new climate state" (Litzow and Mueter 2014) with a "significant transformation in ocean conditions and their associated ecosystems" (Wooster and Zhang 2004) in the North Pacific. The first herring eggs laid during this new climate state hatched in spring of 1977 and contributed to the age-3 population starting in 1980. Therefore, the time series used to perform the average spawning biomass simulations was based on herring recruitment from 1980 through 2022.

Algorithms

The average unfished spawning biomass (B_0) simulations consisted of two different, but similar, algorithms (Figure 2). Firstly, a numbers-at-age matrix is initialized by sampling SCAA-estimated recruitment and populating older age classes using the mean annual survival fraction (Appendix B). Secondly, the spawning biomass for the numbers-at-age matrix is calculated and used to simulate new recruits via stratified sampling, wherein older age classes are again populated, spawning biomass calculated, and so on. This procedure iterates until 30,000 years after the cumulative mean of spawning biomass converges (Appendix C). To account for stochastic effects from the initial conditions of the simulation, these algorithms were performed 1,000 times with different initial population sizes. The final estimate for B_0 was the median simulated biomass across all 1,000 simulations. All calculations and analysis were performed in the R programming language[2] and is reproducible using code available at www.github.com/commfish/sitka-herring-unfished-biomass. Details of the simulation are as follows.

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[1] There was no purse seine fishery in 2019 and 2020; the weight-at-age used for 2019 and 2020 was the average weight-at-age from 2017 and 2018.

[2] R Core Team. 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Initialize numbers-at-age matrix

The numbers-at-age matrix is initialized during years 1 through 8 of the simulation ($t \in [1,8]$). $N_{t,a}$ denotes the numbers-at-age matrix of mature and immature fish, where $a \in [3, 8]$ is age class and t is the year of the simulation (t ranges from 1 through 30,000 years after convergence). The plus age-group (i.e., 8+) in the SCAA model and in this simulation included all fish age-8 or older. The numbers-at-age matrix is initialized by sampling SCAA-estimated age-3 recruitment (R_y, where y indexes years in the SCAA model time series, 1980–2022) with replacement. That is, for year $t \in [1,8]$ of the simulation $N_{t,3}$ is sampled from the column of recruits in Table 2. All older age classes are calculated using

$$N_{t+1,a+1} = S \cdot N_{t,a} \tag{1}$$

where S is the mean annual survival fraction (Table 1). All age classes in the numbers-at-age matrix are populated beginning in year 6 of the simulation since that is the first year in which the initial cohort ($N_{1,3}$) appears in the plus age-group. For example, in year one, only age-3 appears in the numbers-at-age matrix, in year 2 that age-3 cohort becomes age-4, and so forth until the plus age-group is populated in year 6. When the numbers-at-age matrix contains all age classes (t = 6, 7, 8), the spawning biomass for year t is calculated as

$$B_t = \sum_{a=3}^{8+} \rho_a \cdot W_a \cdot N_{t,a} \tag{2}$$

where ρ_a is the proportion of mature herring at age a, and W_a is the weight-at-age (Table 1). Since recruitment is defined as the abundance of immature and mature age-3 fish, there is a three-year lag between simulated recruitments and the biomass from which they spawned. And, because spawning biomass is first calculated in year 6, density-dependent recruitment can first be simulated in year 9. Hence, the initialization algorithm iterates for 8 years and the main simulation procedure begins in year 9. See Appendix B for pseudocode implementing the initialization algorithm.

Simulation Procedure

After the numbers-at-age matrix is initialized, the rest of the simulation is an iterative procedure in which new recruits are sampled conditional on their spawning biomass, older age-classes are populated in the age-matrix, spawning biomass is projected forward, and convergence is checked. Beginning in year 9 of the simulation (t = 9), a stratified sampling approach with 3 sampling blocks (i.e., three-strata sampling) is taken to simulate new recruits (pseudocode implementation in Appendix C). This 3-strata sampling approach enables the incorporation of spawning stock information into the simulation of age-3 herring cohorts without the use of a traditional spawner-recruit relationship such as a Ricker (Ricker 1954) or Beverton-Holt (Beverton and Holt 1957) model (Appendix D). The stratified sampling works by delineating the coordinate pairs of the spawner-recruit SCAA parameter estimates into 3 strata, based on the *k*-means cluster analysis (Hartigan and Wong 1979; Figure 3), and then sampling (with replacement) new age-3 herring cohorts from the available SCAA age-3 estimates within one of the 3 different strata, conditional on spawning biomass (B_{t-3}) from 3 years prior (i.e., the size of the spawning stock). For example, in 2019 there were an estimated 3,472 million recruits spawned from a biomass of 63,890 tons of fish in 2016 (B_{y-3}) (Table 2, Figure 3). Hence, (63890, 3472) is one example of an SCAA parameter estimate coordinate pair used to delineate sampling strata. When sampling new recruits over the course of the simulation, the following rules are applied:

- if $B_{t-3} < l_1$ sample $N_{t,3}$ from stratum 1,

- if $l_1 \leq B_{t-3} < l_2$ sample $N_{t,3}$ from stratum 2, and
- if $l_2 \leq B_{t-3}$ sample $N_{t,3}$ from stratum 3.

The strata boundaries (l_1 and l_2) were the mean between the minimum and maximum values of B_{t-3} in adjacent clusters; $l_1 = 39{,}182$ tons and $l_2 = 78{,}706$ tons (Figure 3). Due to stochasticity in the initialization of the k-means algorithm, the cluster analysis was repeated 100 times prior to the unfished spawning biomass simulations. Of the 100 repeated cluster analyses, the most frequently chosen clusters were the sampling strata used in the unfished spawning biomass simulation. During the repeated cluster analysis, there were always 3 strata.

After the age-3 recruits are sampled with replacement from the column of recruits in Table 2, beginning in year 9 of the simulation, the abundance of older age classes is calculated using Equation 1 and total spawning biomass is calculated using Equation 2. The last step in each simulation iteration is to check for convergence (Appendix B). Arbitrary convergence criteria are applied to provide a consistent rule to determine when to stop the simulations. Convergence is defined using a sliding window of root mean squared deviations (RMSD) in the spawning biomass cumulative mean series, where "window" refers to a subset of the spawning biomass cumulative mean series for which a statistic is calculated (i.e., RMSD) and iterated sequentially over the series. For a window i of size n, the RMSD is calculated as

$$\mathrm{RMSD}_i = \sqrt{\frac{1}{n-1} \sum_{t=I_0}^{I_0+n} \left(B_{i,t} - \bar{B}_i\right)^2} \tag{3}$$

where I_0 is the initial year of window i, $B_{i,t}$ is the spawning biomass in year t and window i, and $\bar{B}_i$ is the mean spawning biomass in window i. After RMSD_i is calculated, Equation 3 is applied again to obtain a RMSD for window $i+1$ beginning in year $I_0 + 1$, and so forth. As the spawning biomass cumulative mean series tends towards convergence, the associated RMSD_i statistics tend towards zero. Convergence in the spawning biomass cumulative mean series is defined as the year in which $\mathrm{RMSD}_i < 0.05$ for 100 consecutive windows The simulation iterates for 30,000 more years after the spawning biomass cumulative mean converges. To ensure robustness towards the initial conditions of the simulation, the simulation was repeated 1,000 times with varying start states, resulting in a combined distribution of 3×10^7 iterations of post-convergence spawning biomass from the 1,000 simulations. To address any potential skewness in the distribution of spawning biomass estimates, the median was used as the final estimate for B_0 and the 0.025 and 0.975 quantiles made up an associated 95% confidence interval.

SENSITIVITY ANALYSIS

Since a large recruitment event, like the one in 2019, may or may not occur again in the future, a sensitivity analysis was performed to check the robustness of the biomass simulations to infrequent (once every 43 years) large recruitments. The 2019 abundance of age-3 recruits in the Sitka Sound stock was estimated by the 2023-forecast SCAA to be the largest in the model time series by a wide margin. The recruitment in the Sitka Sound stock in 2019 (3,472 million immature and mature age-3 fish; Table 2) was estimated to be approximately 3.5 times larger than the next largest recruitment (987 million in 2003; Table 2), and almost 18 times larger than the median of the time series (196 million; 1980–2022). This sensitivity analysis was performed by repeating the 1,000 simulations with the same simulation procedure, but with the large 2019 recruitment omitted.

RESULTS

UNFISHED SPAWNING BIOMASS SIMULATIONS

Based on the simulation procedure in this study, the estimated B_0 for Sitka Sound herring was 85,576 tons (Figure 4). An example of one of the 1,000 biomass simulations is shown in Figure 5. In this example, the cumulative mean series converged in year 768 of the simulation, after which the simulation continued for 30,000 more years (Figure 2). The 30,000 iterations for the one simulation created a right-skewed distribution (Figure 6). When results of the 1,000 simulations were combined, they formed a single right-skewed distribution of 3×10^7 iterations (Figure 4). The median spawning biomass of this distribution was 85,576 tons. Based on the 0.025 and 0.975 quantiles, the lower and upper bounds of the 95% confidence interval were 47,282 tons and 288,768 tons (Table 3). That is, 95% of all simulated unfished spawning biomasses for Sitka Sound herring were between 47,282 tons and 288,768 tons. Note that the median, 95% confidence bounds, and right-skewness of the distribution of simulated biomasses in the overall results (Figure 4) were all very similar to the example simulation shown in Figure 6, indicating that the initial conditions of individual simulations likely had little effect on the results.

SENSITIVITY ANALYSIS

To explore the impact of the exceptional 2019 recruitment, this year was omitted from biomass simulations and the results were compared to the full simulation. The simulation procedure without the 2019 recruits resulted in a median unfished spawning biomass of 81,794 tons (Figure 7). Based on the 0.025 and 0.975 quantiles, the lower and upper bounds of a 95% interval were 46,384 tons and 146,850 tons, respectively (Figure 7). Although removing the large 2019 recruitment from the analysis had little effect on the median point estimate and lower confidence bound (2% and 4% lower, than the full simulation), the upper confidence bound was much lower (49%) than the full simulation and the overall distribution of simulated biomasses was more symmetric. This indicated that the median point estimate for B_0 was robust to the magnitude of extreme recruitment events, but the large uncertainty in B_0 was partially driven by the 2019 abundance estimate.

DISCUSSION

Updating the average unfished spawning biomass estimate of herring in Sitka Sound with more current data, more rigorous statistical methods, and a longer time series resulted in a 28%increase compared to Carlile’s (1998) estimate. In the prior analysis, the mean estimate for average unfished spawning biomass was 67,036 tons and, by applying the 25% criterion, the suggested threshold level was 16,759 tons (Carlile 1998). Based on the simulation procedure in our study, the median estimate of unfished spawning biomass for Sitka Sound herring was determined to be 85,576 tons and, if a 25% criterion is applied, a harvest threshold level of 21,394 tons would result. This higher estimate for B_0 is consistent with the increase in spawning stock biomass since the mid-2000’s, according to the 2023-forecast SCAA model. Of note is that Carlile (1998) calculated the average unfished spawning biomass (67,036 tons) using the mean because the distribution of the simulated biomasses was not skewed; the mean and median would be very similar in a non-skewed distribution. Due to the skewed distribution in the updated analysis, the calculated average unfished spawning biomass was based on the median point estimate, not the mean point estimate.

Basing thresholds on a percent of average unfished spawning biomass (B_0) has been shown to provide an effective basis for threshold management strategies, but there are numerous approaches to estimating B_0. For unfished stocks, methods for estimating B_0 are often derived from a first-order approximation of current biomass estimates from remote, unfished areas (e.g., coral reef habitats or established marine protected areas with limited to no fishing; Heyer and Samhouri 2017; McClanahan 2018). For fished stocks, B_0 is sometimes calculated from the estimated parameters of stock assessment models. One way to estimate average unfished spawning biomass from the estimated parameters of stock assessment models is to find the product of the estimate of unfished spawning biomass-per-recruit by the estimated average recruitment when the stock's biomass is relatively high (e.g., Goethel et al. 2021). This method is conditional on the availability of fishery independent data during periods of light fishing pressure (Haltuch et al. 2008). Alternatively, analytical solutions exist for calculating B_0 from estimates of MSY and the fishing mortality rate (F_{MSY}) that would result in MSY (Martell et al. 2008). These calculations are contingent on models parameterized such that MSY and F_{MSY} are directly estimated as well as information about stock productivity. Furthermore, an estimate for the steepness parameter from a spawner-recruit relationship is necessary and may be integrated within the stock assessment model or estimated outside of it (Haltuch et al. 2009). Unfortunately, in practice, spawner-recruit models often suffer from poor fit resulting in their parameters being estimated with low precision (Quinn and Deriso 1999, chapter 3).

A simulation-based approach to estimate B_0, as done in this report, may be performed in lieu of the calculations described above (e.g., Quinn et al. 1990; Zheng et al. 1993; Funk and Rowell 1995; Carlile 1998). Specifically for Sitka Sound herring, neither method for calculating B_0 directly from estimated parameters of stock assessment models (i.e., calculating B_0 from unfished spawning biomass-per-recruit, or from MSY and F_{MSY}) is appropriate. Firstly, the Sitka Sound herring stock has a long history of fishing pressure, which predates the time series modeled by the stock assessment (i.e., 1976). Thus, calculating B_0 from unfished spawning biomass-per-recruit is not feasible. Secondly, calculating B_0 from MSY and F_{MSY} is not possible since the 2023-forecast SCAA model is not currently parameterized to estimate those quantities due to the current weighted least-squares structure of the model. In addition, although a Ricker spawner-recruit relationship is integrated into the model, its parameters are not expected to be estimated with high precision and thus weighted low in the objective function.

Setting a threshold level at 25% of B_0 has an established history in exploited Pacific herring stocks. After the 20% harvest rate was introduced for the 1983 forecasts of British Columbia herring stocks (Stocker et al. 1983), an arbitrary threshold level ("cutoff"; 25% of B_0) was introduced to the British Columbia harvest strategy to protect endangered stocks (Hall et al. 1988), and first implemented in the 1986 forecasts (Haist et al. 1986; Schweigert and Ware 1986). This management decision was later validated by research suggesting a 20% harvest rate coupled with a 25% threshold level would sustain all British Columbia herring stocks even during periods of low productivity (Hall et al. 1988). Zheng et al. (1993) similarly found that a threshold level set to 25% of B_0 (coupled with a 20% harvest rate) would protect Pacific herring stocks in Prince William Sound and the Eastern Bering Sea, while balancing population size, average harvest, variation in harvest, and the frequency of fishing closures and recognizing multiple users of the resource and species interactions. Zheng et al. (1993) estimated that the 20% harvest rate was nearly half of that which would occur at maximum sustainable yield (MSY) and did not recommend harvesting at MSY or maximum economic yield due to the importance of herring to multiple users of Alaska herring resources. Carlile (1998) estimated B_0 for Sitka Sound herring and applied the 25% criterion recommended by Zheng et al. (1993) for management of the Sitka

Sound sac roe fishery (16,759 tons). In 1997, the BOF used the results of Carlile (1998) and elevated the threshold level to 20,000 tons (~30% of B_0) to account for subsistence concerns for the fishery, and later raised it to 25,000 tons (~37% of B_0) for the 2010 fishery season and on (Hebert 2022).

Recent studies, though, have recommended a more conservative approach to setting threshold levels and harvest rates than Hall et al. (1988) and Zheng et al. (1993), particularly for key prey species (e.g., Sainsbury 2008; Pikitch et al. 2012; Froese et al. 2016). Kronlund et al. (2018) and Forrest et al. (2023), for example, recommended a limit reference point of 30% of unfished spawning biomass for Pacific herring stocks in the British Columbia management areas of Central Coast, Haida Gwaii, and the West Coast of Vancouver Island. The production analysis by Kronlund et al. (2018) noted that 3 of the 5 major British Columbia Pacific herring stocks (Central Coast, Haida Gwaii, West Coast of Vancouver Island) entered states of "low production, low biomass" even when managed with threshold management strategies implementing the 25% criterion and recommended increasing to a limit reference point of $0.3B_0$. Although similar analyses were not performed for either the Prince Rupert District or the Strait of Georgia management areas, Kronlund et al. (2018) also recommended the limit reference point of 30% of unfished spawning biomass for these areas due to common life history traits and recent states of persistent "low production, low biomass" of herring stocks in the surrounding geographic vicinity. This value ($0.3B_0$) is consistent with a "best practice" limit reference point recommended to the Australian Fisheries Management Authority (Sainsbury 2008), and harvest advice for British Columbia herring stocks by DFO research (Fisheries and Oceans Canada Pacific Science Branch) is based on management strategy evaluations using the limit reference point of $0.3B_0$ (DFO 2024a). Taking a broader view, other authors have advocated considering the quality and quantity of available information of a fish stock when setting harvest control rules. Pikitch et al. (2012) suggest classifying forage fish stocks into "information tiers" and recommend a threshold level of $0.8B_0$ for stocks in the low information tier, $0.4B_0$ for stocks in the intermediate information tier, and $0.3B_0$ for stocks in the high information tier. Based on the criteria in the Pikitch et al. (2012) report, the Sitka herring stock might fall in the intermediate information tier.

Average unfished spawning biomass in this analysis is simulated from parameter estimates from the 2023-forecast SCAA model; hence, all relevant assumptions of the model (and key data) are propagated to the methods of this report. That is, the validity of the reported estimate for B_0 of Sitka Sound herring relies on the ability of the 2023-forecast SCAA model to accurately describe the spawning stock biomass over time as well as to estimate maturity and survival parameters. Although all fisheries models contain assumptions, error within a fish assessment model (e.g., model misspecification, observation error, confounding of parameters, natural variation within the environment that is unaccounted for) where common model assumptions are violated, or data is biased or imprecise, can result in substantial assessment errors (NRC 1998) and inaccurate estimates of population abundance (as spawning stock biomass). Some key model (and data) assumptions include: 100 million eggs per ton of spawner to unite data from hydroacoustic biomass surveys (1976–1981); spawning herring are 100% vulnerable to fishery-independent cast net sampling and these fish represent the proportion of the population by age class in the spawning stock; observation error of the egg deposition index is log-normally distributed; age compositions are multinomially distributed; harvest in the purse-seine fishery is observed without error; the stock-specific fecundity-to-weight relationships over time are representative of the stock; the egg loss between spawning and dive surveys (correction factor applied to the dive survey estimate) is

10% and does not vary annually; assumptions applied in the two-stage sampling design (Hebert 2022); survival and maturity of herring are affected by changes in the mean PDO index; survival is age-invariant; and maturity is time-invariant. As the unfished spawning biomass simulations are conditional on these model assumptions, if the assumptions or model formulation change (e.g., a Bayesian stock assessment model; Muradian et a. 2017; Trochta and Branch 2021) then the estimate for average unfished spawning biomass may also need to be updated in the transition to reflect improved understanding of the stock dynamics.

Our calculation for average unfished spawning biomass was based on simulations of herring stock dynamics under average conditions in Sitka Sound since 1980 and, hence, implicitly assumes constant carrying capacity over that time. For our estimate of B_0 to be relevant for stock management, the constant carrying capacity assumption must also be valid in the future. This is likely a reasonable assumption for the near future; long-term directional trends in the North Pacific climate are generally expected to occur on time scales greater than decadal (King and McFarlane 2006; Hollowed et al. 2013; Litzow et al. 2014). The simulation start year (1980) was chosen (a priori to the analysis) as broad changes in oceanic and ecological conditions in the Northeast Pacific and a perceived shift in the long-term recruitment pattern occurred after the regime shift in winter 1976/77, and 1980 was the first year that an age-3 cohort, which was spawned after the regime shift in winter 1976/1977, joined the spawning stock. Simulating unfished spawning biomass using the time series based on regime shifts other than the 1976/1977 shift were also considered. The 2007/2008 regime shift (Overland et al. 2012; Hatch 2013; Litzow and Mueter 2014), for example, has been proposed as a significant ecological shift, similar in magnitude to the 1976/1977 shift. A simulated estimate for B_0 based on data from 2011 (recruitment year of the first post-2007/2008 year-class) to 2022 would likely be higher than the value in this report, since herring in those years had the highest survival (77% survival for 2008–2014 and 69% survival for 2015–2022, compared to 63% for 1976–2007) and the stock experienced its largest spawn events as estimated by the 2023-forecast SCAA model. However, using a longer time series (1980 on) "averages" across multiple conditions (low biomass and high biomass), which may be more applicable for future unknown conditions, as long as directional trends such as climate change are not the predominant environmental factor affecting herring. In addition, using a shorter time series (2011 on) would not provide enough data to perform the recruitment forecasting comparison analysis in Appendix D. Moving forward, the estimate for average unfished spawning biomass will be most accurate if future recruitment patterns mirror past estimates due to the recruitment sampling techniques used in the unfished spawning biomass simulations. Specifically, the B_0 estimate in this report is expected to be closest to true B_0 if a large recruitment event, similar to the 2019 event, occurs approximately once every 43 years. If large recruitment events happen more frequently, then the true B_0 is likely higher than currently estimated. Conversely, if large recruitment events happen less frequently, then the true B_0 may be lower than estimated. Given the results shown in the sensitivity analysis, however, the magnitude of influence that the frequency of large recruitment events has on the estimate for B_0 is likely low due to calculating average unfished spawning biomass using the median instead of the mean. Indeed, when the 2019 recruitment was omitted from the analysis the B_0 estimate only lowered from 85,576 tons to 81,794 tons (Figure 4, Figure 7). The influence of these large age-3 abundance events, though, is still reflected in the variability around the point estimate of B_0.

The updated estimate of average unfished spawning biomass of Pacific herring in Sitka Sound provides a basis for setting a threshold that includes recent data, a long time series of data, and rigorous methods. These are considered a necessary update and valuable methodological improvements to the Sitka Sound herring harvest strategy. Future work should emphasize further improving the calculation of biological reference points as well as the effectiveness of the harvest rate strategy for Sitka Sound herring. Potential projects that might achieve these goals could include utilizing maximum likelihood estimation in the SCAA model's objective function rather than least squares minimization, reformulating the model to directly calculate MSY and F_{MSY}, incorporating more robust assumptions regarding the error structure of data sources, implementing a Bayesian formulation of the model, or implementing a management strategy evaluation within the modeling framework.

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TABLES AND FIGURES

Table 1.–Inputs to unfished biomass simulations. Mean weight (g) is an unweighted average of 1980–2022 annual mean weight-at-age estimates used as input data to the 2023-forecast statistical catch-at-age model and comes from field samples of the spring commercial purse seine catch. Maturity proportion is an age-specific model estimate over 1980–2022. Annual survival fraction is a weighted average of the 1980–2007, 2008–2014 and 2015–2022 time block estimates from the 2023-forecast model (65%, 77%, and 69%, respectively), where the weights are proportional to the number of years in each time block.

Age	Mean weight (g)	Maturity proportion	Annual survival fraction
3	77.1	0.34	0.66
4	99.9	0.95	0.66
5	121.7	1.00	0.66
6	141.8	1.00	0.66
7	158.9	1.00	0.66
8+	177.5	1.00	0.66

Table 2.–Annual outputs from the 2023-forecast statistical catch-at-age (SCAA) model for Sitka Sound herring 1980–2022, including spawning biomass (short tons) and the number of age-3 recruits (millions). Note that the recruits were spawned from the biomass shown 3 years prior. For example, in year 2019, there were an estimated 3,472 million recruits spawned from a biomass of 63,890 short tons in 2016 (bolded values). Hence, (63890, 3472) is one example of an SCAA parameter estimate coordinate pair used to delineate sampling strata. Also shown is the implemented threshold level (short tons) in each year.

Year	Spawning biomass (short tons)	Age-3 recruits (millions; immature and mature)	Threshold level (short tons)
1980	44,902	93	6,000
1981	42,319	48	6,000
1982	29,005	59	6,000
1983	36,045	460	7,500
1984	44,424	172	7,500
1985	34,686	42	7,500
1986	27,327	175	7,500
1987	45,021	952	7,500
1988	56,172	109	7,500
1989	32,459	8	7,500
1990	23,212	3	7,500
1991	30,582	774	7,500
1992	47,371	20	7,500
1993	25,061	1	7,500
1994	17,858	63	7,500
1995	28,421	372	7,500
1996	31,756	180	7,500
1997	35,814	335	20,000
1998	49,225	391	20,000
1999	49,882	149	20,000
2000	50,031	315	20,000
2001	54,729	384	20,000
2002	58,798	261	20,000
2003	83,900	987	20,000
2004	103,989	184	20,000
2005	85,790	245	20,000
2006	73,512	296	20,000
2007	70,554	328	20,000
2008	85,667	415	20,000
2009	102,566	297	20,000
2010	96,429	269	25,000
2011	88,185	88	25,000
2012	63,311	49	25,000
2013	68,355	196	25,000
2014	54,583	46	25,000
2015	55,365	760	25,000
2016	**63,890**	37	25,000
2017	48,823	265	25,000
2018	53,106	256	25,000
2019	155,440	**3,472**	25,000
2020	274,801	110	25,000
2021	233,137	386	25,000
2022	176,906	145	25,000

Note: The recruits were spawned from the biomass shown 3 years prior. For example, in year 2019, there were an estimated 3,472 million recruits spawned from a biomass of 63,890 short tons in 2016 (bolded values). Hence, (63890, 3472) is one example of an SCAA parameter estimate coordinate pair used to delineate sampling strata. Also shown is the implemented threshold level (short tons) in each year.

Table 3.–Selected quantiles for the combined distribution of all unfished spawning biomass simulations of Sitka Sound herring.

Quantile	Unfished spawning biomass (short tons)
0.000	6,177
0.005	38,549
0.025	47,282
0.250	69,542
0.500	85,576
0.750	111,738
0.975	288,768
0.995	347,701
1.000	662,980

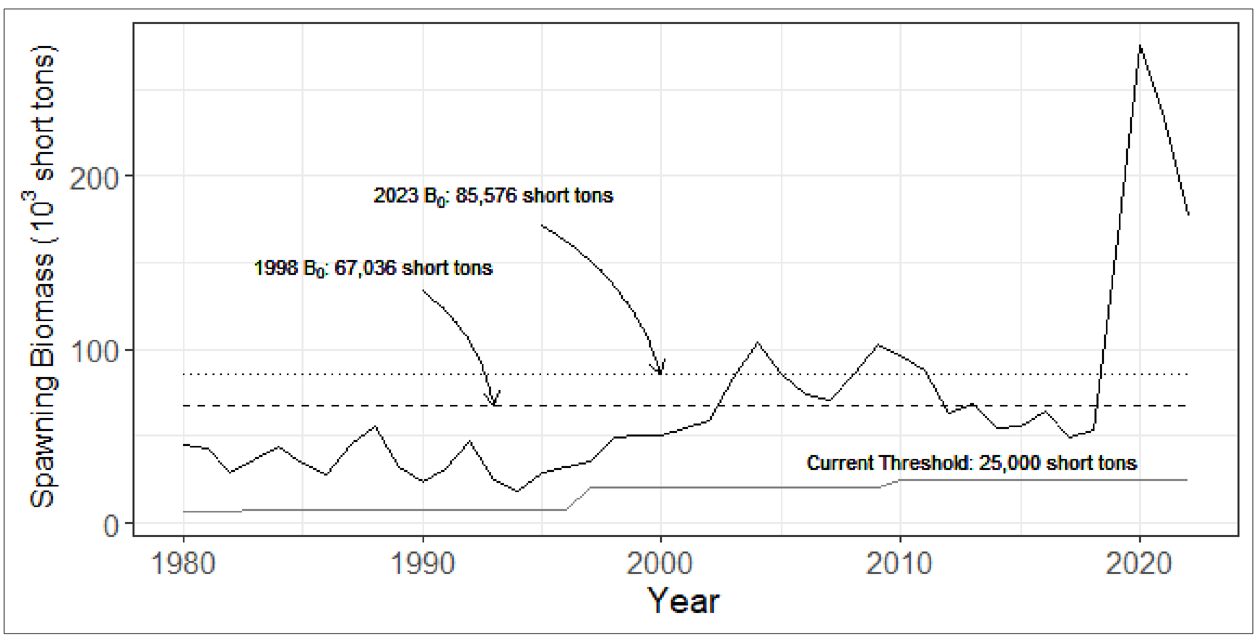

Figure 1.–Spawning biomass estimates from the 2023-forecast statistical catch-at-age (SCAA) model for Sitka Sound herring 1980–2022 (black solid line). The estimate of average unfished spawning biomass from 1998 (Carlile 1998) is shown as a dashed line (67,036 short tons) and the estimate of average unfished spawning biomass from this simulation is shown as a dotted line (85,576 short tons). The light grey line gives the threshold levels implemented for 1980–2022.

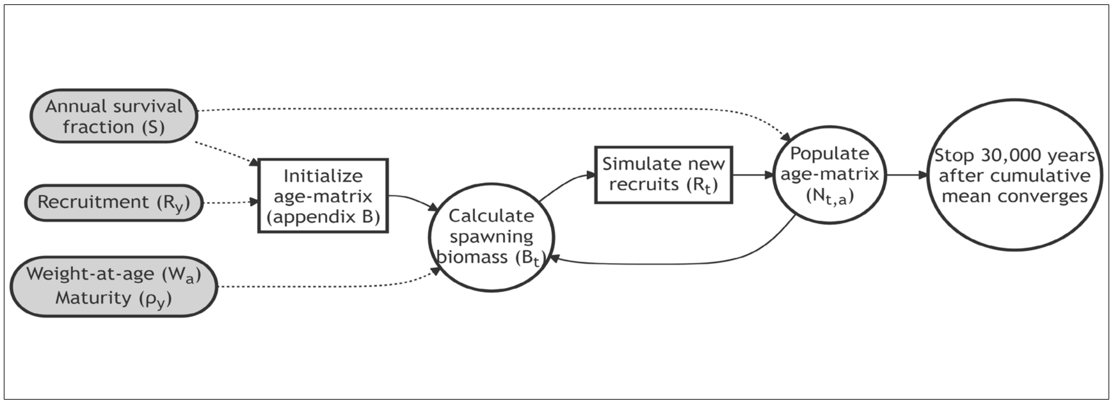

Figure 2.–A flowchart representing the algorithm used to estimate the average unfished spawning biomass (B_0) of Sitka Sound herring. Shaded nodes represent inputs to the simulation. Rectangular nodes show stochastic processes of the simulation, whereas round nodes show deterministic calculations. The simulation algorithm was repeated 1,000 times, resulting in a distribution of 3×10^7 iterations of simulated spawning biomass. The median spawning biomass from the 1,000 simulations (3×10^7 iterations) with no fishing was then determined to be the average unfished spawning biomass. The subscript *y* represents year in the input data time series (i.e., 1980–2022), the subscript *t* represents simulation year (i.e., from year one until 30,000 years after convergence in the cumulative mean series), and the subscript *a* represents age group (i.e., 3–8+). See Appendix C for more details.

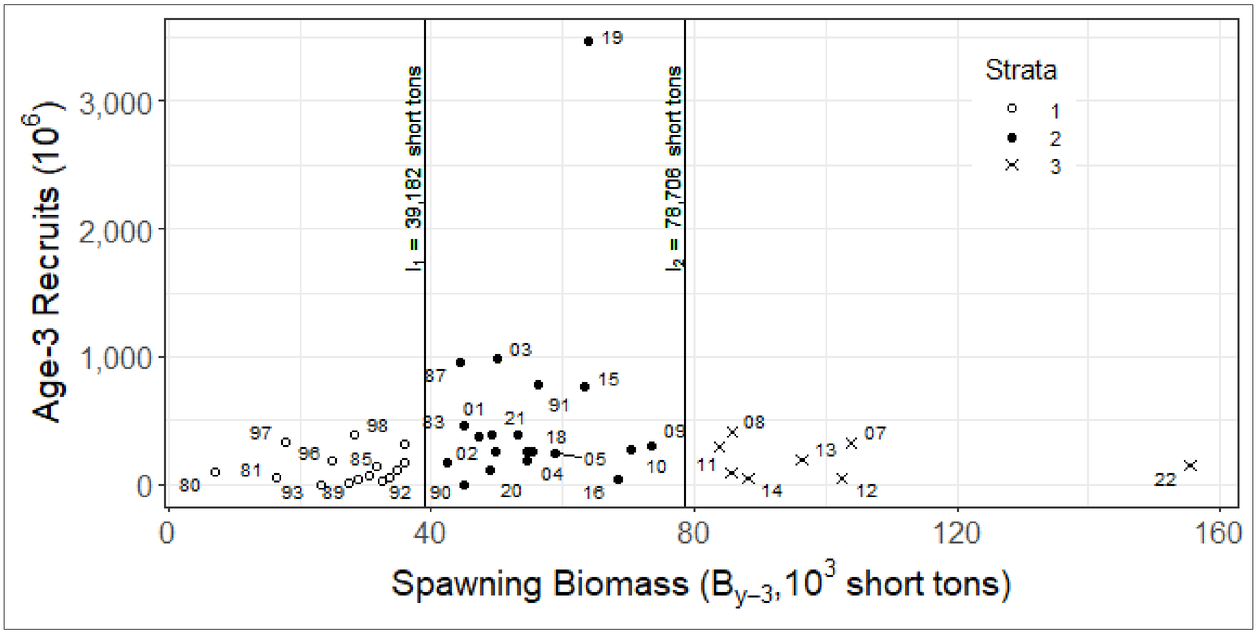

Figure 3.–Estimates of age-3 recruits (millions) for 1980–2022 and the biomass from which they were spawned (short tons) from the 2023-forecast statistical catch-at-age (SCAA) model for Sitka Sound herring; labeled coordinate pairs are by year of recruitment. For example, in 2019 (labeled year on strata symbols is 19) there were an estimated 3,472 million recruits spawned from a biomass of 63,890 short tons of fish in 2016 (y-3). Hence, (63890, 3472) is one example of an SCAA parameter estimate coordinate pair used to delineate sampling strata. The strata were chosen by the k-means algorithm and are delineated by l_1 and l_2 (vertical black lines). For ease of viewing, only some of the stratified coordinate pairs are labeled by year. The strata are used to sample new recruits in the Sitka Sound herring unfished spawning biomass simulations.

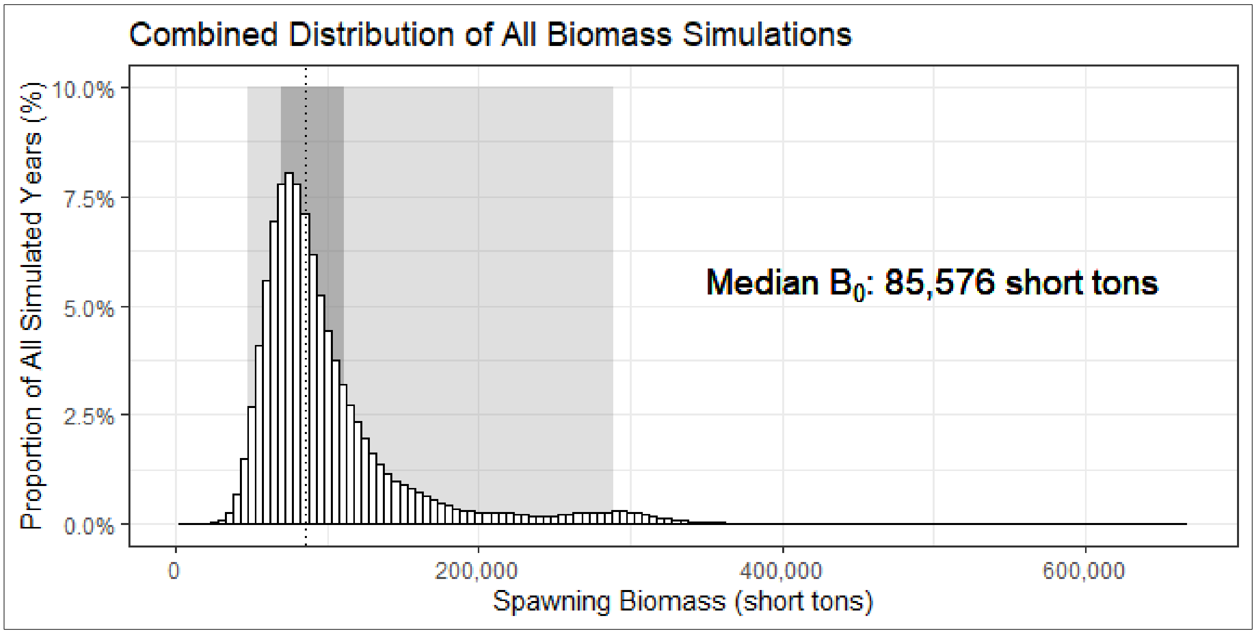

Figure 4.–Combined distribution of 30,000,000 iterations of the 1,000 simulations of Sitka Sound herring unfished spawning biomass. The light grey interval denotes the middle 95% of spawning biomass estimates, and the dark grey interval denotes the middle 50%. The dotted vertical line is the median.

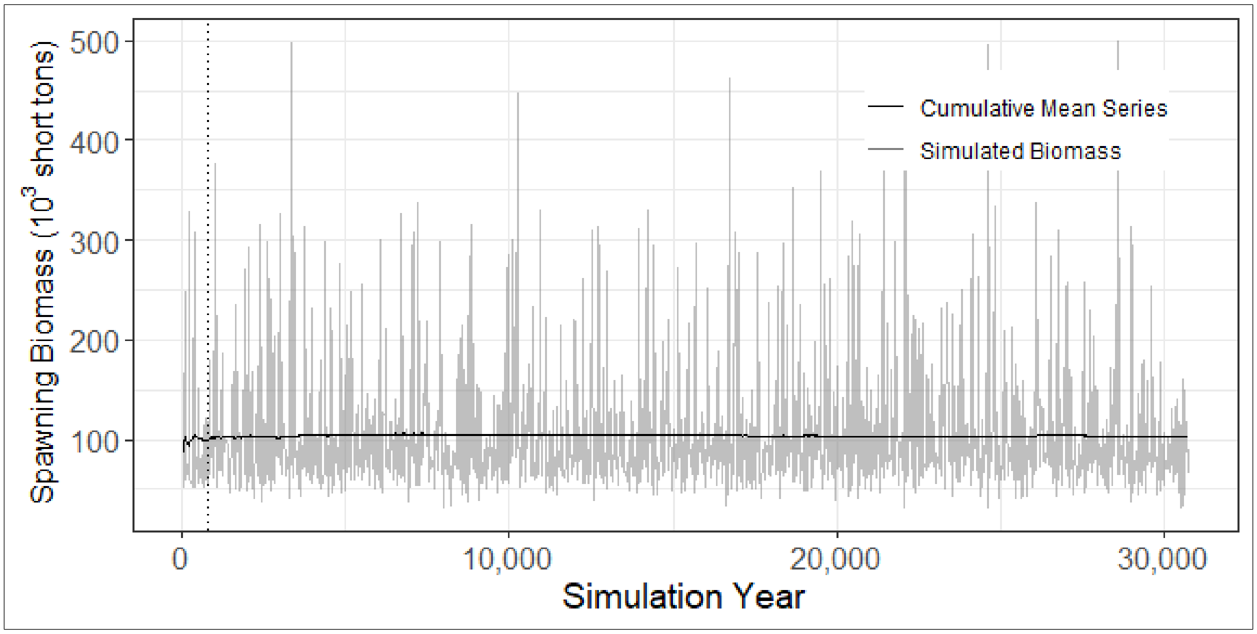

Figure 5.–An example of one Sitka Sound herring unfished spawning biomass simulation, an implementation of the procedure shown in Figure 2. The noisy light grey series shows the spawning biomass (short tons) in each simulation year and the dark grey horizontal line shows the spawning biomass cumulative mean series. The cumulative mean series converged in year 768 of this simulation (dotted vertical line). The B_0 estimate for this single simulation was taken to be median biomass from year 769 to year 30,768 of the simulation. This resulted in an example estimate of B_0 of 86,102 short tons.

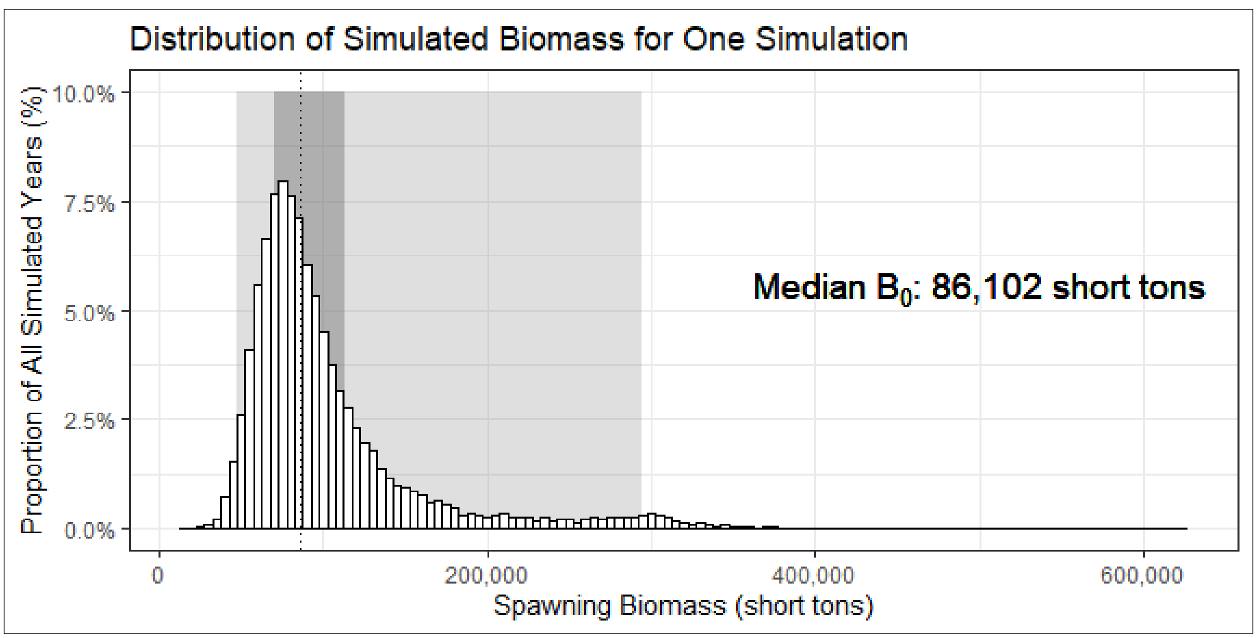

Figure 6.–Distribution of the single 30,000-year simulation of Sitka Sound herring spawning biomass is shown in Figure 5. The light grey interval denotes the middle 95% of spawning biomass estimates, and the dark grey interval denotes the middle 50%. The dotted vertical line is the median.

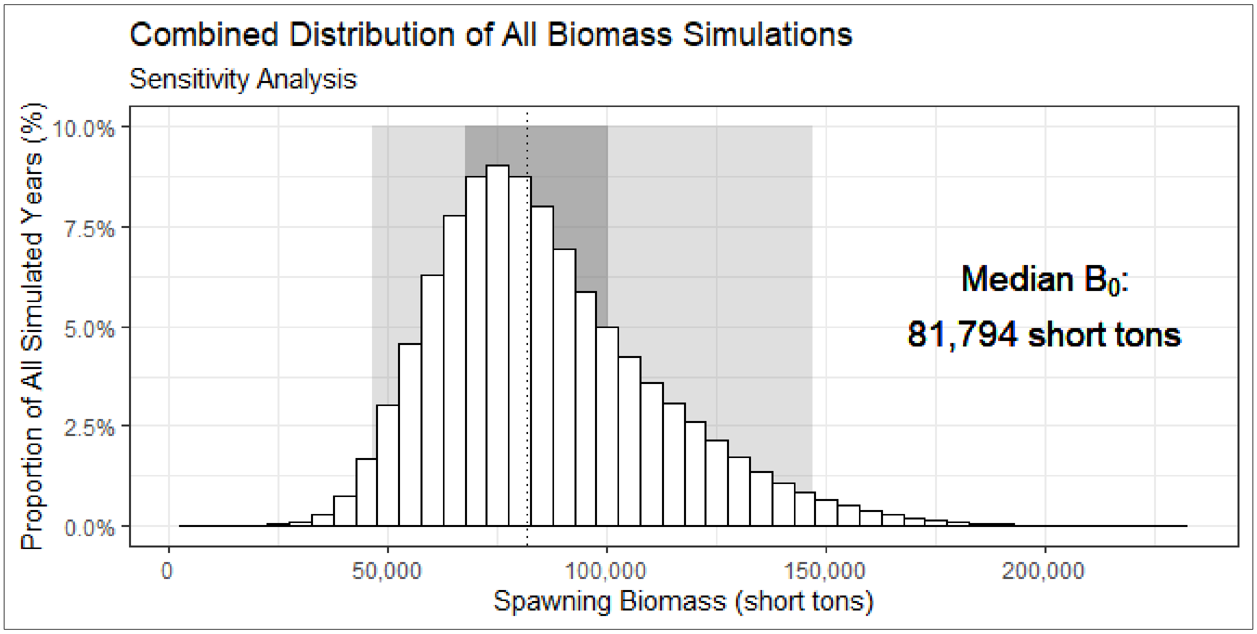

Figure 7.–Combined distribution of 30,000,000 iterations from the 1,000 Sitka Sound herring unfished spawning biomass simulations when the large 2016 year-class (2019 recruitment) was omitted. The light grey interval denotes the middle 95% of spawning unfished biomass estimates and the dark grey interval denotes the middle 50%. The dotted vertical line is the median.

APPENDIX A.–DESCRIPTION OF THE PACIFIC DECADAL OSCILLATION AND THE SEQUENTIAL T-TEST ANALYSIS OF REGIME SHIFTS

Appendix A1.–Description of the pacific decadal oscillation and the sequential *t*-test analysis of regime shifts.

Fisheries stock assessments often model life history parameters as varying over time (e.g., Thorson 2011; Johnson et al. 2014; Jacobsen et al. 2019). Sometimes data, or theory, suggest that model parameters shift between discrete time blocks in response to regime shifts in oceanic conditions. To model such dynamics, it is helpful to identify time blocks within which oceanic conditions relevant to life history parameters are relatively constant but are delineated by temporal changes in those conditions. The statistical catch-at-age (SCAA) model for Southeast Alaska herring stocks allows for fitting of time varying parameters by utilizing such time blocks, between which the survival, maturity, and gear selectivity parameters are allowed to differ. Gear selectivity (availability plus fishing selectivity) is only allowed to vary if there are similar time period changes in maturity or if there are known and obvious changes in selectivity/fishing. Alternative models based on different time blocks used for each life history parameter are evaluated during stock assessments on an annual basis, and it is a best practice in fisheries assessments to apply a range of diagnostics to select a "best" model (e.g., convergence diagnostics, residual diagnostics, retrospective analysis; Punt 2023). The recommended model each year is selected by considering Akaike Information Criterion corrected for small sample sizes (AICc; Burnham and Anderson 1998), biologically realistic estimation of parameters, inspection of residuals, consistency with prior structures (i.e., similar time period blocks for survival, maturity, and gear selectivity as prior years), and parsimony. The difference in AICc between a given model and the model with the lowest AICc value (Δ_i) was one factor used for choosing a "best" model. For biologically realistic models, those with $\Delta_i \leq 2$ have substantial support, those in which $4 \leq \Delta_i \leq 7$ have considerably less support, and models with $\Delta_i > 10$ have essentially no support for being chosen (Burnham and Anderson 2004).

Pacific Decadal Oscillation (PDO)

Sea-surface temperature anomalies are often leading indicators and important drivers of ecosystem fluctuations (Stock et al. 2015) and temperature indices have shown to be important for herring population dynamics (Stocker et al. 1985; Zebdi and Collie 1995; Williams and Quinn 2000). Temperature has been identified as affecting the recruitment (Stocker et al. 1985; Zebdi and Collie 1995; Williams and Quinn 2000), growth (Moores and Winters 1982; McGurk 1984; Haist and Stocker 1985), survival (McGurk 1984; Gregg et al. 2011), and maturity (Moores and Winters 1982) of herring species. The mechanism by which temperature affects herring may be direct (e.g., changes in metabolism) or indirect, as temperature often does not drive ecosystem changes and processes through direct physiological effects, but serves as a proxy for other physical (e.g., mixed layer depth, stratification, horizontal transports; Stock et al. 2015) and biological factors (e.g., prey quality and availability, predation, spawn timing; Benson and Trites 2002; Tojo et al. 2007; Andrews et al. 2016).

The Pacific Decadal Oscillation (PDO) is a basin-wide oceanographic index of sea surface temperatures that has been linked to productivity of lower trophic levels and Pacific salmon production in the North Pacific (Mantua et al. 1997; Mantua and Hare 2002). Models incorporating the mean PDO index as environmental information, whether through time-blocks or as a covariate, have shown to have better model fits to available data compared to the model in which these parameters were time-invariant (Hulson et al. 2018). Due to the importance of temperature to the

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population dynamics of herring, an annual index, based on temperature anomalies (mean monthly PDO values; Mantua et al. 1997; Zhang et al. 1997; Newman et al. 2016), is used as an annual PDO index to determine time period blocks in the forecast models for Southeast Alaska herring stocks. Time period blocks, within which the survival, maturity, and gear selectivity parameters were allowed to differ within the Southeast Alaska herring forecast models, were based on the defined breakpoints between years with predominantly positive PDO anomalies and years with predominantly negative PDO anomalies.

For Southeast Alaska herring assessments, a "mean PDO index" was constructed to coincide with herring growth and herring data collection. Annual herring growth, based on growth rings on the scale, slows overwinter and accelerates after spawning when spring and summer feeding occurs. The mean PDO index was, therefore, based on the annual average of PDO values from April of one year through March of the next year. For example, the 'mean PDO index' value for 1990 is the average monthly PDO value from April 1989 through March 1990. The natural mortality (or maturity or gear selectivity) time-dependent parameter that is estimated for a given year is based on the natural mortality experienced by herring during the year from the previous spring spawning event, the last time data was collected.

The current method of determining time period blocks uses the Sequential *t*-Test Analysis of Regime Shifts method. Model-estimated survival, maturity, and gear selectivity parameters were allowed to change with perceived shifts in the PDO following 3 consecutive years of mean PDO index change from positive to negative values, or from negative to positive values. Because consistently defining meaningful shifts in the PDO is not necessarily obvious, the Sequential *t*-Test Analysis of Regime Shifts method (STARS; Rodionov 2004; Rodionov and Overland 2005; Rodionov 2006) is now used as a way to more objectively determine the breaks in the 'mean PDO index'.

Sequential *t*-Test Analysis of Regime Shifts (STARS) method

The STARS method identifies discontinuity in a time-series and allows for early detection of a regime shift and subsequent monitoring of changes in its magnitude over time (Rodionov 2004). Detection of discontinuity is accomplished by sequentially testing whether a new mean PDO value within a time-series represents a statistically significant deviation from the mean value of the current 'regime.' As data are added to the time-series, the hypothesis of a new 'regime' (i.e., time period block) is either confirmed or rejected based on the Student's *t*-test (Rodionov and Overland 2005). The STARS method is well documented in the literature and has been applied previously to physical and biological indices (Mueter et al. 2007; Howard et al. 2007; Marty 2008; Conversi et al. 2010; Lindegren et al. 2010; Blamey et al. 2012; Menberg et al. 2014; Reid et al. 2016).

Several parameters within the STARS method need specification prior to application to determine the breaks in the mean PDO index; *p*-value, cutoff length, Huber's weight parameter, and autocorrelation with an associated subsample size. Two parameters, the *p*-value (the probability level for significance between 'regime' means) and the cutoff length (the approximate minimum number of years within a regime) control the magnitude and scale of the regimes to be detected, or how strong a change in the mean PDO index needs to be detected. There is a reduced probability of detection for regimes shorter than the cutoff length, but the regimes may still be detected if the

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shift is of sufficient magnitude (Rodionov 2004). Regime shifts are known to be associated with relatively rapid changes in climate, oceanic conditions, or the ecosystem (King 2005) and the most important scale of variability for fisheries management has been identified in some literature as decadal-scale (King and McFarlane 2006). Climate variability over decadal-scale timeframes, as described in climate indices such as the PDO, continues to be an important mode of ocean and atmospheric change (Francis et al. 1998; Miller et al. 2004; Wang et al. 2023). Therefore, a cutoff value of ten years was specified within the STARS method. For this study, a p-value of 0.10 was chosen, which is well within the range of other studies that have applied the STARS method (e.g., Mueter et al. 2007; Blamey et al. 2012). Huber's weight parameter determines the weight assigned to outliers and thus the magnitude of the average values of each regime (Huber 1964); the STARS method's default value of one for Huber's weight parameter was used. Finally, the user determines whether to account for autocorrelation and specifies the associated subsample size needed. Two frameworks are available within the STARS method to estimate autocorrelation (Rodionov 2004): the Marriott-Pope and Kendall (MPK) and the Inverse Proportionality with 4 corrections (IPN4). The 2 frameworks break the time series into subsamples, estimate bias corrected first-order autocorrelation for each subsample and then use the median value of all estimates. The 2 frameworks produce very similar results and only in certain instances (small subsample size) does the IPN4 method significantly outperform the MPK method (Rodionov 2004). Therefore, autocorrelation in the PDO (Newman et al. 2003) was accounted for using the IPN4 method was used in this analysis with the suggested subsample size of $m = (l+1)/3$, where l is the cutoff length.

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APPENDIX B.–PSEUDOCODE IMPLEMENTATION OF NUMBERS-AT-AGE MATRIX INITIALIZATION

Appendix B1.–Pseudocode implementation of numbers-at-age matrix initialization.

Initialization algorithm: The following pseudocode implements the first 8 years of the unfished spawning biomass simulation. Age-3 herring are simulated by sampling (with replacement) 1980–2022 recruitments estimated by the 2023-forecast statistical catch-at-age (SCAA) model. Older age classes are calculated using an SCAA-estimated annual survival fraction. All age classes are populated by year 6; 2 more years are simulated to allow for the year 6 spawning stock to start simulating age-3 recruits in year 9.

Input: The inputs are mean weight-at-age (W_a), age-specific maturity (ρ_a), annual survival fraction (S), SCAA estimated age-3 recruitment (number of mature and immature fish) for years 1980–2022 (R_y). The subscript *y* represents year in the input data time series (i.e., 1980–2022); the subscript *t* represents simulation year (i.e., from year 1 to 8); and the subscript *a* represents age group (i.e., 3–8+).

Output: The output is initialized numbers-at-age matrix (N_t).

1. **Define** $N_{t,a}$ to be a 8×6 matrix
2. **For** $t \in [1,8]$
    a) $N_{t,3}$ is sampled from R_y
    b) **for** $a \in [4,8]$
        - **if** $N_{t-1,a-1}$ exists **then** $N_{t,a} = S \cdot N_{t-1,a-1}$
        - **if** $N_{t-1,a-1}$ does not exist **then** $N_{t,a} = 0$

    c) **if** $N_{t,8}$ exists **then** compute total spawning biomass as $B_t = \sum_{a=3}^{8+} \rho_a \cdot W_a \cdot N_{a,t}$
3. **Return** $N_{t,a}$

APPENDIX C.–PSEUDOCODE IMPLEMENTATION OF SIMULATION ALGORITHM

Simulation algorithm: The following pseudocode implements the remainder of the unfished spawning biomass simulation starting in year 9. Age-3 herring are simulated by sampling 1980–2022 recruitments estimated by the 2023-forecast statistical catch-at-age (SCAA) model. Samples are drawn (with replacement) from 1 of 3 strata, depending on spawning biomass. Older age classes are calculated using an SCAA-estimated annual survival fraction. The simulation ends 30,000 years after its cumulative mean series converges.

Input: The inputs are initialized numbers-at-age matrix (N_t), mean weight-at-age (W_a), annual survival fraction (S), age-specific maturity (ρ_a), and number of recruits in 1980–2022 estimated by SCAA model and grouped into k strata ($R_y^k,\ y \in [1980,\ 2022],\ k \in [1,\ 3]$). The subscript *y* represents year in the input data time series (i.e., 1980–2022), the subscript *t* represents simulation year (i.e., from year 9 until 30,000 years after convergence in the cumulative mean series), and the subscript *a* represents age group (i.e., 3–8+).

Output: The output is 30,000 simulated years of unfished spawning biomass (B_t). This excludes years before convergence of the cumulative mean series.

1. **Define** $t = 9$
2. **Define** strata boundaries
   a) $l_1 = \frac{1}{2}\left(\max\left(R_y^1\right) + \min\left(R_Y^2\right)\right)$
   b) $l_2 = \frac{1}{2}\left(\max\left(R_y^2\right) + \min\left(R_Y^3\right)\right)$
3. Simulate spawning biomass (B_t)
   a) identify spawning biomass for recruits in year *t*, B_{t-3}
      - **if** $B_{t-3} < l_1$ **then** $N_{t,3}$ is sampled from R_y^1
      - **if** $l_1 \leq B_{t-3} < l_2$ **then** $N_{t,3}$ is sampled from R_y^2
      - **if** $l_2 \leq B_{t-3}$ **then** $N_{t,3}$ is sampled from R_y^3
   b) compute the number of fish in age classes 4–8 in year *t*
      - **for** $a \in [4,7], N_{t,a} = S \cdot N_{t-1,a-1}$
      - **for** $a = 8$, $N_{t,a} = S \cdot N_{t-1,a-1} + S \cdot N_{t-1,a}$
   c) compute total spawning biomass for year *t*; $B_t = \sum_{a=3}^{8+} \rho_a \cdot W_a \cdot N_{t,a}$
   d) *t* = *t*+1
   e) check convergence of $\frac{1}{t-1}\sum_1^{t-1} B_t$
      - **if** convergence false repeat steps 3a through 3e
      - **if** convergence true define $T_c = t$ and repeat steps 3a through 3d 30,000 more times
4. **Return** B_t for $t > T_c$

APPENDIX D.–RECRUITMENT SIMULATION METHOD COMPARISON

BACKGROUND

Recruitment in fish stocks (defined for Sitka Sound Pacific herring as the abundance of immature and mature age-3 fish) is a notoriously variable vital rate that drives population dynamics and presents a particular challenge when estimating and forecasting abundance or biomass within stock assessments. The practical application of stock assessment and management generally includes the mature portion of recruitment forecasts as part of forecasted spawning stock biomass from which allowable harvest and fisheries opening and closures are determined. There are many different methods used by fisheries researchers to forecast recruitment. Recruitment forecasting methods can include classical spawner-recruit models such as Ricker (Ricker 1954; e.g., Sitka Sound Pacific herring (*Clupea pallasii)* statistical catch-at-age (SCAA) model) and Beverton-Holt (Beverton and Holt 1957; e.g., British Columbia Pacific herring stocks [DFO 2024a]); environmentally-conditioned stock recruit models (e.g., Pacific sardine in the US West Coast (*Sardinops sagax*) prior to 2005 (Hill 2007)); sampling algorithms (e.g., in Atlantic cod (*Gadus morhua*) research (Paz and Larrañeta 1993)); time series methods (e.g., in Atlantic herring (*Clupea harengus*) in the North Sea [Noakes et al. 1987]); and modern machine learning algorithms (e.g., walleye (*Sander vitreus*) in Wisconsin lakes [Hansen et al. 2015]).

In a recent paper, Van Beveren et al. (2021) suggested a framework for comparing different recruitment forecasting methods used in stock assessments. The general idea is to use the population dynamics in the early years of an age-structured model to make a series of predictions for spawning biomass in the later years of the model, and these predictions differ only in how recruitment is forecasted. Then, the different recruitment forecasting methods are compared by their ability to accurately predict spawning biomass in the model. This approach was adapted to choose a recruitment forecasting method for application in biomass simulations for the Sitka Sound Pacific herring stock. In this appendix, nine methods were evaluated by their ability to predict spawning biomass of Sitka Sound Pacific herring in the 2023-forecast statistical catch-at-age (SCAA) model after accounting for harvest. Recruitment forecasting methods were compared using the performance metrics mean percent error (MPE) to evaluate for bias and mean absolute percent error (MAPE) to evaluate for precision. The least biased and most precise recruitment forecasting method was then applied in the unfished spawning biomass simulation in the main report. This analysis was implemented in R programming language (R Core Team 2022) and is reproducible using code available at www.github.com/commfish/sitka-herring-unfished-biomass.

METHODS

Evaluation of Recruitment Forecasting Methods

Nine methods were evaluated by their ability to predict spawning biomass of Sitka Sound Pacific herring in an operating model using the performance metrics MPE and MAPE. The general idea was to use the 2023-forecast SCAA model to represent the true state of the stock (i.e., the "operating model"), truncate the final years of the operating model, produce recruitment forecasts (defined in this study as the number of immature and mature age-3 fish) using the nine methods under evaluation, and then use the forecasts to calculate spawning biomass (Figure 1D). The estimates of spawning biomass made by each recruitment forecast method were then compared to spawning biomass in the operating model using the performance metrics.

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This procedure (using recruitment forecasts to predict biomass for truncated years in the operating model) was repeated 12 times over varying degrees of truncation (i.e., truncating up to 12 years).[3] That is, spawning biomass estimates were made for the final δ years in the operating model, where δ represents the number of years truncated (and consequently projected by each recruitment forecasting method) and varied from $\delta = 1$ to $\delta = 12$. The full operating model, derived from the outputs of the 2023-forecast SCAA model, describes herring dynamics for the years 1980–2022. If $\delta = 3$, for example, then the operating model dynamics for the years 1980–2019 were used to forecast recruitment for the years 2020–2022 using each of the nine recruitment forecasting methods under evaluation.

After recruitment forecasts were made, projections for spawning biomass were calculated using weight-at-age and catch-at-age data from the Sitka Sound spring commercial purse seine herring catch, and survival and maturity from the operating model (Figure D1). As the 2023-forecast SCAA model estimates maturity as time-invariant, the same maturation schedule (34% maturity for age-3 herring, 95% maturity for age-4, and 100% maturity for age-5 and older) was used to calculate spawning biomass in each projection year. Survival, however, was estimated as time-varying in discrete time blocks. Thus, the annual survival fraction used to compute spawning biomass depended on which year was projected (77% survival for 2011–2014 and 69% survival for 2015–2022).

The performance metrics, MPE and MAPE, were used to evaluate the bias and precision, respectively, of each of the nine recruitment forecasting methods' estimates for spawning biomass in the operating model. The general form for these metrics is as follows:

$$\mathrm{MPE} = 100 \cdot \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{B}_i - B_i}{B_i}, \tag{1}$$

and

$$\mathrm{MAPE} = 100 \cdot \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{B}_i - B_i|}{B_i}, \tag{2}$$

where i indexes n estimates for spawning biomass ($\hat{B}_i$) in the operating model (B_i). The bias metric, MPE, may be positive (indicating overestimation) or negative (indicating underestimation) and values close to 0 indicate unbiasedness in estimating spawning biomass in the operating model. The precision metric, MAPE, is strictly nonnegative, and values closer to 0 indicate precise estimates of spawning biomass and large positive values indicate poor precision. For each recruitment forecasting method, the performance metrics were calculated over $n = 78$ percent errors since spawning biomass estimates were produced for each year, for each value of δ (i.e., one year of spawning biomass is predicted when $\delta = 1$, 2 years are predicted when $\delta = 2$, and so on until $\delta = 12$).

[3] When the operating model was truncated 13 years or more, the 3 Ricker-type models (basic Ricker model, environmentally conditioned Ricker models) produced combinations of parameters which yielded near-infinite estimates for spawning biomass in certain years. Therefore, only results from truncating 12 or less years are shown in this report.

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With one exception, the nine methods under evaluation can generally be classified as model-based or sampling-based. Recruitment forecasting methods were chosen based on their history of use in herring stock assessments (e.g., Beverton-Holt model), the hypothesized effect of environmental covariates on herring recruitment (e.g., sea surface temperature-conditioned Ricker model), or their prior application to unfished spawning biomass simulations (e.g., sampling algorithms). In addition, while not a model-based or sampling-based method, the simplex projection technique (Sugihara and May 1990) was shown to be skillful in forecasting the future biomass of multiple fish stocks in Van Beveren et al. (2021), so it was also considered as a candidate method.

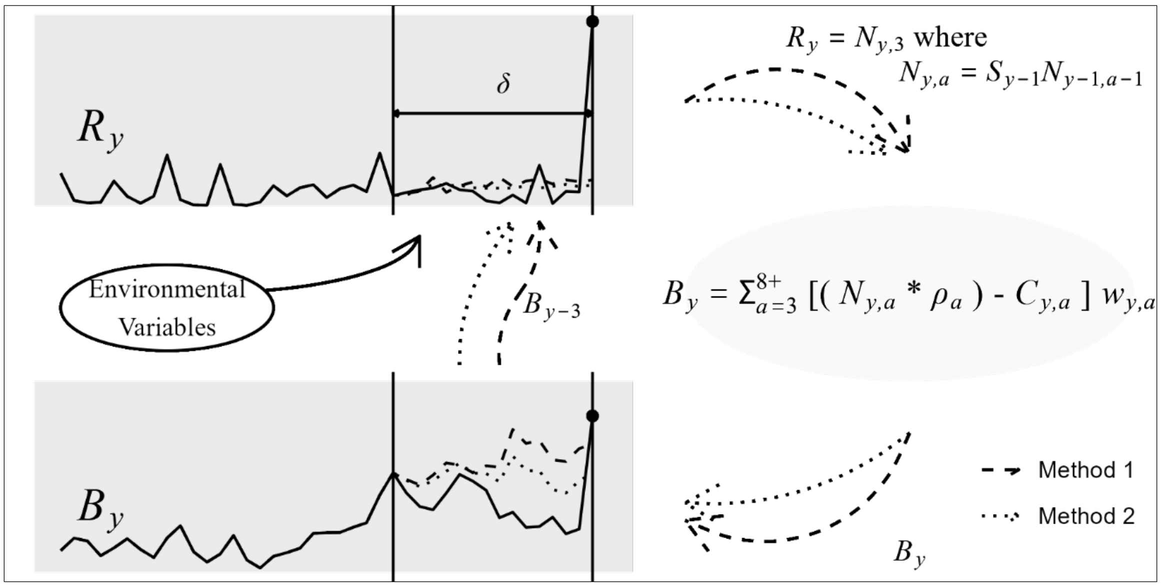

Figure D1.–Graphical representation of the approach used to compare recruitment forecasting methods. Two generic recruitment forecasting methods are shown as dotted and dashed lines (i.e., method one and method two). Recruitment was forecasted beginning δ years before the final year of the operating model. Recruitment forecasts, together with the statistical catch-at-age-estimated annual survival fraction (S_y), were used to estimate numbers-at-age ($N_{y,a}$), from which post-fishery spawning biomass (B_y) was calculated using age-specific maturity ($\rho_{y,a}$), mature catch-at-age ($C_{y,a}$), and time-varying weight-at-age ($W_{y,a}$). Then, new recruits were forecasted again using the post-fishery spawning biomass from 3 years prior (B_{y-3}). This process was repeated until the final year of the operating model.

Model-based methods

Five model-based methods were investigated. An intercept-only model was considered as it makes no assumptions on the spawner-recruit relationship, and provided a useful baseline for comparison to more complex models:

$$\log(R_y) = \log(\bar{R}) + \epsilon_y; \quad \epsilon_y \sim \mathcal{N}(\mu, \sigma^2), \tag{3}$$

where R_y is recruitment in year y, $\bar{R}$ is mean recruitment, and ϵ_y is normally distributed error with log-mean μ and log-variance σ^2. Due to their ubiquity in stock assessment science (Sharma et al.

2019), Ricker and Beverton-Holt models were also considered in this analysis. The basic Ricker model (Ricker 1954) was fit with the linearized formulation:

$$\log\left(\frac{R_y}{B_y}\right) = a + bB_y + \epsilon_y; \quad \epsilon_y \sim \mathcal{N}(\mu, \sigma^2), \tag{4}$$

where B_y denotes spawning biomass in year y; a and b are model parameters. The Beverton-Holt model (Beverton and Holt 1957) is given as:

$$R_y = \frac{B_y}{\alpha + \beta B_y} e^{\epsilon_y}; \quad \epsilon_y \sim \mathcal{N}(\mu, \sigma^2), \tag{5}$$

where α and β are model parameters. The intercept-only model and the basic Ricker model were fit with the least squares method and the Beverton-Holt model was fit with maximum likelihood. In addition to the intercept-only model, the basic Ricker model, and the Beverton-Holt model, 2 environmentally conditioned Ricker models were also investigated, each with a single environmental covariate. The chosen environmental variables were the oceanographic variable sea surface temperature within Sitka Sound, and the basin-wide oceanographic index of sea surface temperature variability, the Pacific Decadal Oscillation (PDO; Mantua et al. 1997; Newman et al. 2016). These 2 environmental covariates were based on data from the months of April and May (when larvae hatch in Sitka Sound; Haldorson and Collie 1990), lagged by 3 years (years 1977–2019). The three-year lag was chosen to correspond to the survival of the larval life stage of Pacific herring, ultimately affecting survival to age-3 recruitment. Sea surface temperature (averaged from April to May lagged by 3 years) and sea surface temperature variability (represented by the mean PDO averaged from April–May lagged by 3 years) were hypothesized to drive larval survival and subsequent age-3 recruitment magnitude based on the 'Match-Mismatch Theory' (Cushing 1975, 1990; e.g., Schweigert et al. 2013). These environmental variables were hypothesized to determine larval survival both directly (e.g., temperature-dependent larval survival; McGurk 1984; Chimura et al. 2009; Peck et al. 2012) and indirectly (e.g., temperature-dependent larval prey availability; Keister et al. 2011; Boldt et al. 2019). The 'Match-Mismatch Theory' (Cushing 1967, 1975, 1990), states that fish larvae survival during the early, first-feeding stage (critical period; Hjort 1914) through metamorphosis and just beyond, is enhanced by a match between suitable types of food production and larval emergence. Hence, the synchrony of temperature-dependent larval prey availability and larval emergence explains variability in fish recruitment. The sea surface temperature data used in this study were from the Extended Reconstructed Sea Surface Temperature (ERSST; Huang et al. 2017) dataset produced by the NOAA Physical Sciences Laboratory (PSL) and available at their website (https://psl.noaa.gov/). The ERSST dataset is available in a global 2° × 2° grid; the center of Sitka Sound is approximately at 57° N 135.5° W, hence the closest available coordinate was 56° N 136° W. The monthly PDO data were also obtained online at https://psl.noaa.gov/gcos_wgsp/Timeseries/PDO (Mantua and Hare 2002).

Sampling-based methods

Three different sampling-based methods were used to forecast recruitment. These methods are distinct from model fitting since they forecast recruitment by sampling past values instead of fitting a model to data. In each case, the sampling procedure (with replacement) was repeated 1,000 times and the median value was used for the recruitment forecast. The simplest algorithm, referred to as single-stratum sampling method, is based on sampling next year's recruitment from the varying

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number of previous years. In contrast, the three-strata sampling method divides the spawner-recruit data into 3 strata and samples next year's recruitment from the stratum corresponding to the value of spawning biomass in the current estimate. The strata were chosen using the *k*-means algorithm. Lastly, time-tapered sampling is single-stratum sampling but with the additional assumption that values from longer ago are less likely to occur than more recent values. In other words, the recruitment sizes of earlier year classes are sampled at a lower rate than more recent year classes.

Simplex projection method

The last recruitment forecasting method considered in this analysis was the simplex projection method. This method is neither a model-based method nor a sampling-based method; it is a deterministic, nonparametric time-series forecasting method that is commonly used to identify predictable patterns in chaotic time series (Sugihara and May 1990). The simplex projection method works by identifying the current dynamics of the series and all past dynamics of the series with the same length (referred to as "embedding dimension"). The past dynamics that most closely resemble the current state of the time series are used to provide a projection via a weighted mean.

RESULTS

The three-strata and single-stratum sampling methods generally produced fairly accurate estimates of spawning biomass across a range of conditions. On average, all recruitment forecasting methods were positively biased except for the intercept-only model (Table D1). That is, all methods overestimated spawning biomass in the operating model apart from the intercept-only model which underestimated spawning biomass. The three-strata sampling method had the lowest overall bias; on average, the three-strata sampling method overestimated spawning biomass in the operating model by 0.7%. The single-stratum sampling method also performed well (3.1% MPE). In contrast, the PDO-conditioned Ricker model had the highest overall bias of 67.7% and the basic Ricker model had a similar high bias of 61.3%. The three-strata sampling and single-stratum sampling methods were also the most precise according to this analysis, featuring 23.1% and 26.6% MAPEs, respectively. Similarly, the PDO-conditioned and basic Ricker models again performed most poorly in terms of MAPE at 82.2% and 78.7%, respectively.

Based on both performance metrics, the sampling-based methods outperformed the model-based methods. Every sampling-based method had an MPE closer to zero, and a lower MAPE, than every model-based method with one exception (i.e., time-tapered sampling method had a similar MPE to the Beverton-Holt model and the time-tapered sampling method had a higher MAPE than the intercept-only model). Furthermore, model-based methods tended to suffer from outliers with high positive percent errors; for example, the PDO-conditioned Ricker model had the greatest percent error of 329.5%. The simplex projection method was generally on par with the model-based methods, with a 42.5% MPE and a 56.9% MAPE.

Unsurprisingly, the magnitude of percent errors varied with how far into the future forecasts were made (Table D2). Spawning biomass forecasts made one or 2 years into the future were less than 5% away from the operating model spawning biomass for all recruitment forecasting methods other than the intercept-only model and simplex projection method. In contrast, forecasts made 5 or more years into the future were generally greater than 20% away from the operating model

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spawning biomass for all recruitment forecasting methods other than three-strata sampling. Note that all recruitment methods substantially underestimated the large 2019 recruitment, resulting in high underestimation of operating model spawning biomass in every 12-year forecast.

Table D1.–Table of summary statistics for percent errors in estimated spawning biomass for each recruitment forecasting method. The mean percent error (MPE) and the mean absolute percent error (MAPE) are used to indicate bias and precision, respectively, in the recruitment forecasting methods across all scenarios (truncating 12 years or less). There were 78 percent errors evaluated per method.

Method Type	Recruitment forecasting method	MPE (%)	MAPE (%)
Model-based	Intercept-only model	-29.1	32.0
Model-based	Beverton-Holt	12.8	36.4
Model-based	Ricker	61.3	78.7
Mode-based	Environmental-based Ricker (SST)	16.5	41.1
Model-based	Environmental-based Ricker (PDO)	67.7	82.2
Sampling-based	Single-stratum sampling	3.1	26.6
Sampling-based	Three-strata sampling	0.7	23.1
Sampling-based	Time-tapered sampling	12.4	32.7
Simplex	Simplex	42.5	56.9

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Table D2.–Mean percent error (MPE) in estimated spawning biomass for each recruitment forecasting method, averaged by the number of years being forecasted. For example, row one contains the percent error for the spawning biomass predicted for each method averaged over the following years forecasts.

Number of years forecasted	Intercept-only Model	Beverton-Holt	Ricker	Ricker (SST)	Ricker (PDO)	Single-stratum sampling	Three-strata sampling	Time-tapered sampling	Simplex
1	-7.02	-3.76	-3.35	-3.70	-2.98	-4.04	-2.90	-1.79	-0.28
2	-14.43	-1.20	0.18	-2.36	1.52	0.37	-0.22	3.51	11.10
3	-21.63	3.40	5.66	0.15	7.90	3.72	1.80	7.51	25.38
4	-27.06	11.29	14.17	5.87	16.76	9.78	3.90	13.75	45.04
5	-30.07	20.70	24.02	13.13	26.82	15.16	7.24	20.83	62.11
6	-33.12	29.14	33.04	19.17	35.68	19.94	8.19	25.77	72.35
7	-37.98	37.49	42.03	25.35	44.90	20.60	6.93	25.46	78.81
8	-42.13	41.63	46.40	26.99	50.48	15.23	3.03	22.22	77.71
9	-48.41	35.59	40.53	18.80	46.80	7.46	-4.09	15.01	74.16
10	-50.29	28.66	34.46	14.03	42.73	5.82	-3.46	14.48	78.86
11	-54.01	4.70	10.28	-2.86	16.75	-7.43	-17.56	-2.10	55.18
12	-75.39	-48.34	-45.19	-49.49	-43.49	-52.27	-57.72	-49.27	-18.91

CONCLUSION

Nine recruitment forecasting methods were compared by their ability to predict spawning biomass for Sitka Sound herring for use in the unfished biomass simulations. This analysis was conducted because the choice of which method was used to forecast recruitment within the Sitka Sound herring unfished biomass simulation was an influential methodological decisions to make in determining the output (i.e., the unfished biomass). According to this analysis, sampling methods (three-strata and single-stratum) were generally more accurate than model-based methods and the three-strata sampling method was the least biased and most precise recruitment forecasting method considered in terms of its ability to accurately forecast the spawning biomass in truncated years of the operating model. Almost all these techniques for forecasting recruitment generally overestimated the spawning biomass estimated by the 2023-forecast SCAA to varying degrees. However, three-strata sampling was nearly unbiased (made spawning biomass forecasts only 0.7% greater than SCAA model spawning biomass on average) over all projections. Therefore, the three-strata sampling method was applied to simulate new recruits in the simulation-based approach used to estimate unfished spawning biomass.

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