SEAK Pink Salmon 2022 Forecast Process

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1 Objective

To forecast the Southeast Alaska (SEAK) pink salmon commercial harvest in 2022.

2 Executive Summary

Forecasts were developed using an approach originally described in Wertheimer et al. (2006), and modified in Orsi et al. (2016) and Murphy et al. (2019). We used a similar approach to Murphy et al. (2019), but assumed a log-normal error. This approach is based on a multiple regression model with juvenile pink salmon catch-per-unit-effort (CPUE) and temperature data from the Southeast Alaska Coastal Monitoring Survey (SECM; Piston et al. 2021) or from satellite sea surface temperature data (SST and SST Anomaly, NOAA Global Coral Bleaching Monitoring, (https://coastwatch.pfeg.noaa.gov/erddap/griddap/NOAA_DHW_monthly.html; https://coastwatch.pfeg.noaa.gov/erddap/griddap/NOAA_DHW.html). See the document satellite_SST_process_5_Oct_2021 for details about the temperature variables. Based on prior discussions, the index of juvenile abundance (i.e., CPUE) was based on the pooled-species vessel calibration coefficient.

Leave-one-out cross validation (hindcast) and model performance metrics were used to evaluate the forecast accuracy of models. These metrics included Akaike Information Criterion corrected for small sample sizes (AICc values; Akaike 1973; Burnham and Anderson 2004), the mean absolute scaled error (*MASE* metric; Hyndman and Kohler 2006), the weighted mean absolute percentage error (*wMAPE*; based on the last 5 years), leave one out cross validation *MAPE* (*MAPE_LOOCV*), one step ahead forecasts (*MAPE_one_step_ahead*) for the last five years (years 2017 through 2021), and significant coefficients (i.e., covariates) in the model. The 2022 forecast was based on a model-averaged value using four methods.

Conclusions:

The four potential methods for model-averaged forecast predictions for 2022 are:

- equal weighting of all eighteen models;
- inverse *MAPE_one_step_ahead* weighting of all eighteen models;
- equal weighting for models with *MAPE_one_step_ahead* <0.14; and
- equal weighting for models with Δ_i AICc ≤ 4.

Table 1: Summary of model-averaged forecasts including the 80 percent prediction intervals (corrected for log transformation bias in a linear-model).

Method	fit	fit_LPI	fit_UPI
equal-weighting	14.37	6.75	30.59
inverse MAPE_one_step_ahead	14.35	6.80	30.31
equal-weighting (MAPE <0.14)	14.46	6.99	29.92
equal-weighting (change AICc < or equal to 4)	15.43	7.86	30.30

3 Analysis

3.1 Model data

The data used in the model are shown in table 2.

Table 2: Model data. This does not include the temperature data.

Year	Harvest	CPUE
1998	42.50	2.48
1999	77.80	5.62
2000	20.30	1.60
2001	67.00	3.73
2002	45.30	2.87
2003	52.50	2.78
2004	45.30	3.08
2005	59.10	3.90
2006	11.60	2.04
2007	44.80	2.58
2008	15.90	1.17
2009	38.00	2.32
2010	24.00	2.33

Year	Harvest	CPUE
2011	58.90	4.11
2012	21.30	1.51
2013	94.70	3.52
2014	37.20	2.14
2015	35.10	3.80
2016	18.40	2.45
2017	34.70	4.35
2018	8.10	0.35
2019	21.10	1.17
2020	8.07	1.14
2021	47.75	2.15
2022	NA	0.88

3.2 Hierarchical models

Eighteen hierarchical models were investigated. The full model was:

$$E(y) = \alpha + \beta_1 X_1 + \beta_2 X_2,$$

where X_1 is the average CPUE for catches in either the June or July survey, whichever month had the highest average catches in a given year, and was based on the pooled-species vessel calibration coefficient, and X_2 is a temperature index. The CPUE data were log-transformed in the model, but temperature data were not. The simplest model did not contain a temperature variable (model m1; see Appendix for parameter estimates).

3.3 Performance metrics

The model summary results using the performance metrics AICc, *MASE*, *wMAPE*, *MAPE_LOOCV*, and *MAPE_one_step_ahead* (Table 3) are shown in table 4. For all of these metrics, the smallest value is the preferred model. Models with Δ_iAICc ≤ 2 have substantial support, those in which $4 \leq \Delta_i$AICc ≤ 7 have considerably less support, and models with Δ_iAICc > 10 have essentially no support (Burnham and Anderson 2004). The performance metric *MAPE* was calculated as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|\frac{A_t - F_t}{A_t}|$$

where A_t is the observed value and F_t is the predicted value. The performance metric *wMAPE* was calculated as:

$$wMAPE = \sum_{t=1}^{n}\frac{1}{w_t}\sum_{t=1}^{n}|\frac{A_t - F_t}{A_t}|w_t.$$

where w_t is the weight for each year. For the *wMAPE* metric, the last 5 years (juvenile years 2016-2020) were given a weight of 1 and all other years, a weight of 0.001. Therefore, compared to the performance metric *MAPE_LOOCV*, the performance of the model in the last 5 years was given more weight in the *wMAPE* metric.

The performance metric *MAPE_LOOCV* uses five steps.

1. The dataset is split into a training set. The training set uses all but one observation of the full dataset.

2. Run the regression model based on the training set.
3. Use the regression model based on the training set to predict F_t for the one observation left out of the model.
4. Repeat the process n times based on the number of observations in the dataset, leaving out a different observation from the training set each time.
5. Calculate *MAPE*, based on the average of all the training datasets (i.e., one *MAPE* is calculated for each training set and then these are averaged).

The performance metric *MAPE_one_step_ahead* involves three steps:

1. Estimate the regression parameters at time t from data up to time $t-1$.
2. Make a prediction of F_t at time t based on the predictor variables at time t and the estimate of the regression parameters at time t.
3. Calculate the *MAPE* based on the prediction of F_t at time t and the observed value of A_t at time t.
4. Repeat this for data up through year 2016 (e.g., data up through year 2016 is $t-1$ and the forecast is for year 2017; t), data up through year 2017 (e.g., data up through year 2017 is $t-1$ and the forecast is for year 2018; t), data up through year 2018 to forecast 2019, data up through year 2019 to forecast 2020, and data up through year 2020 to forecast 2021.
5. The *MAPE_one_step_ahead* will then be an average of the *MAPE* calculated from these five forecasts.

The AICc in Table 3 is the AICc value and not the Δ_iAICc.

Table 3: Summary of model outputs and forecast error measures. These metrics included Akaike Information Criterion corrected for small sample sizes (AICc values), the mean absolute scaled error (MASE metric), the weighted mean absolute percentage error (wMAPE; based on the last 5 years), leave one out cross validation MAPE (MAPE_LOOCV), and one step ahead forecasts (MAPE_one_step_ahead).

model	AdjR2	AICc	MASE	wMAPE	MAPE_LOOCV	MAPE_one_step_ahead
m1	0.596	32.46	0.389	0.190	0.117	0.214
m2	0.810	16.09	0.255	0.117	0.079	0.133
m3	0.792	18.31	0.257	0.122	0.079	0.122
m4	0.743	23.33	0.312	0.137	0.096	0.150
m5	0.795	18.01	0.269	0.105	0.082	0.112
m6	0.774	20.29	0.288	0.113	0.087	0.122
m7	0.775	20.14	0.245	0.124	0.076	0.123
m8	0.731	24.51	0.320	0.137	0.099	0.148
m9	0.765	21.26	0.270	0.119	0.083	0.130
m10	0.751	22.64	0.303	0.119	0.092	0.129
m11	0.780	19.62	0.252	0.125	0.078	0.117
m12	0.749	22.78	0.305	0.131	0.094	0.135
m13	0.784	19.16	0.261	0.106	0.080	0.108
m14	0.768	20.96	0.286	0.112	0.087	0.112
m15	0.762	21.56	0.273	0.136	0.085	0.130
m16	0.736	24.06	0.314	0.139	0.097	0.145
m17	0.770	20.66	0.276	0.116	0.084	0.114
m18	0.752	22.51	0.300	0.123	0.091	0.123

Table 4: Summary of model forecasts including the 80 percent prediction intervals (corrected for log transformation bias in a linear-model).

model	terms	fit	fit_LPI	fit_UPI
m1	CPUE	16.491	9.040	30.083
m2	CPUE + ISTI20_MJJ	15.561	10.302	23.503
m3	CPUE + Chatham_SST_May	16.377	10.632	25.228
m4	CPUE + Chatham_SST_MJJ	13.286	8.188	21.558
m5	CPUE + Chatham_SST_AMJ	14.820	9.645	22.772
m6	CPUE + Chatham_SST_AMJJ	13.324	8.468	20.966
m7	CPUE + Icy_Strait_SST_May	15.861	10.126	24.844
m8	CPUE + Icy_Strait_SST_MJJ	13.705	8.354	22.483
m9	CPUE + Icy_Strait_SST_AMJ	14.325	9.039	22.703
m10	CPUE + Icy_Strait_SST_AMJJ	13.579	8.437	21.854
m11	CPUE + NSEAK_SST_May	16.214	10.401	25.277
m12	CPUE + NSEAK_SST_MJJ	13.120	8.128	21.177
m13	CPUE + NSEAK_SST_AMJ	14.303	9.205	22.222
m14	CPUE + NSEAK_SST_AMJJ	13.137	8.290	20.818
m15	CPUE + SEAK_SST_May	15.671	9.871	24.880
m16	CPUE + SEAK_SST_MJJ	13.035	7.963	21.337
m17	CPUE + SEAK_SST_AMJ	13.853	8.784	21.848
m18	CPUE + SEAK_SST_AMJJ	12.978	8.058	20.901

3.4 Log transformation bias in a linear-model

To correct for log transformation bias in a linear-model, a bias correction (Miller 1984) was applied to the predicted 2022 SEAK harvest and its prediction interval (output from the car package (Fox and Weisberg 2019) in program R (R Core Team 2020)) from each of the eighteen models. The bias correction, applied to each value, is:

$$\hat{E}(Y_m) = \exp(\hat{\mu_{\rm m}} + \frac{\hat{\sigma_{\rm m}}^2}{2})$$

where $\hat{\mu}$ is the predicted value (or 80% upper or lower prediction interval value) from the individual model m.

3.5 Model averaging (multi-model inference)

The model-averaged forecast prediction for 2022 was based on four methods:

- equal weighting of all eighteen models;
- inverse *MAPE_one_step_ahead* weighting of all eighteen models;
- equal weighting for models with *MAPE_one_step_ahead* <0.14 (i.e., only 14 models included; models m1, m4, m8, m16 were excluded); and
- equal weighting for models with Δ_i AICc ≤ 4. (i.e., only 5 models included; models m2, m3, m5, m11, m13 were included).

The calculation of the standard error of the model-averaged prediction (i.e., the square root of the unconditional variance estimator; equation 9 in Buckland et al. 1997; derivation in Burnham and Anderson 2002:159-162) is:

$$\widehat{\text{var}}(\tilde{Y}) = \left(\sum_{m=1}^{M} w_m \sqrt{\widehat{\text{var}}(\hat{Y_m}) + \gamma_m^2} \right)^2$$

where $\tilde{Y}$ is the model-averaged estimate (or prediction), $\hat{Y_m}$ is the individual model m output, and γ_m (i.e., the misspecification bias of model m) is computed as $\gamma_m = \hat{Y_m} - \tilde{Y}$. The prediction interval is then calculated as:

$$\tilde{Y} \pm z_{1-\alpha/2} \widehat{\text{se}}(\tilde{Y})$$

where $\widehat{\text{se}}(\tilde{Y}) = \sqrt{\widehat{\text{var}}(\tilde{Y})}$, and $z_{1-\alpha/2} = 1.28$.

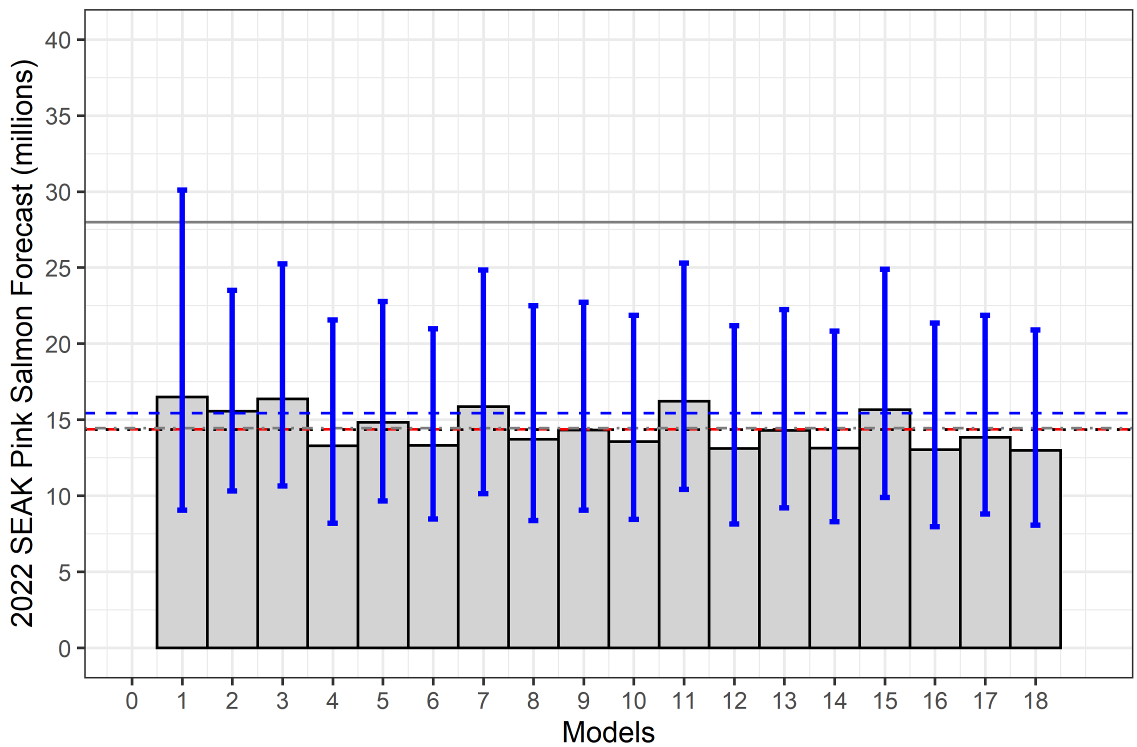

Figure 1: The 2022 SEAK pink salmon harvest (millions) forecast by model with 80% prediction intervals (corrected for log transformation bias in a linear-model) around each forecast. The dotted horizontal lines are the model-averaged forecast across all models based on the four methods. The SEAK pink salmon harvest in 2021 (based on the November 18, 2020 advisory announcement) was a point estimate of 28 million fish (80% prediction interval: 19–42 million fish; grey horizontal line).

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5 Appendix

Table 5: Parameter estimates for the 18 models.

model	term	estimate	std.error	statistic	p.value
m1	(Intercept)	2.3342051	0.211	11.069	0.000
m1	CPUE	0.4306816	0.073	5.907	0.000
m2	(Intercept)	7.2631893	0.979	7.415	0.000
m2	CPUE	0.4934177	0.051	9.591	0.000
m2	ISTI20_MJJ	-0.5619633	0.110	-5.088	0.000
m3	(Intercept)	5.5756634	0.712	7.836	0.000
m3	CPUE	0.4889562	0.054	9.091	0.000
m3	Chatham_SST_May	-0.4489598	0.096	-4.662	0.000
m4	(Intercept)	6.7117487	1.196	5.612	0.000
m4	CPUE	0.4655961	0.059	7.912	0.000
m4	Chatham_SST_MJJ	-0.4563397	0.123	-3.697	0.001
m5	(Intercept)	6.3128293	0.856	7.373	0.000
m5	CPUE	0.4796665	0.053	9.049	0.000
m5	Chatham_SST_AMJ	-0.5351621	0.113	-4.720	0.000
m6	(Intercept)	6.7967192	1.054	6.450	0.000
m6	CPUE	0.4735312	0.055	8.543	0.000
m6	Chatham_SST_AMJJ	-0.5250449	0.123	-4.283	0.000
m7	(Intercept)	5.1866381	0.680	7.629	0.000
m7	CPUE	0.5025704	0.057	8.841	0.000
m7	Icy_Strait_SST_May	-0.4216535	0.098	-4.313	0.000
m8	(Intercept)	6.2102662	1.132	5.488	0.000
m8	CPUE	0.4690316	0.061	7.747	0.000
m8	Icy_Strait_SST_MJJ	-0.3961020	0.114	-3.466	0.002
m9	(Intercept)	5.8758516	0.879	6.685	0.000
m9	CPUE	0.4902258	0.057	8.527	0.000
m9	Icy_Strait_SST_AMJ	-0.4947989	0.121	-4.098	0.001
m10	(Intercept)	6.2524467	1.036	6.037	0.000
m10	CPUE	0.4795924	0.059	8.177	0.000
m10	Icy_Strait_SST_AMJJ	-0.4624278	0.121	-3.832	0.001
m11	(Intercept)	5.2522639	0.680	7.729	0.000
m11	CPUE	0.4662654	0.054	8.576	0.000
m11	NSEAK_SST_May	-0.4011202	0.091	-4.411	0.000
m12	(Intercept)	6.4966134	1.106	5.872	0.000
m12	CPUE	0.4487189	0.058	7.789	0.000
m12	NSEAK_SST_MJJ	-0.4273826	0.112	-3.805	0.001
m13	(Intercept)	6.0279603	0.835	7.217	0.000
m13	CPUE	0.4620667	0.054	8.604	0.000
m13	NSEAK_SST_AMJ	-0.4994394	0.111	-4.499	0.000
m14	(Intercept)	6.5058949	1.016	6.401	0.000
m14	CPUE	0.4582373	0.056	8.231	0.000
m14	NSEAK_SST_AMJJ	-0.4892964	0.118	-4.156	0.000
m15	(Intercept)	5.2464912	0.739	7.101	0.000
m15	CPUE	0.4659144	0.057	8.224	0.000
m15	SEAK_SST_May	-0.3709363	0.092	-4.040	0.001
m16	(Intercept)	6.2674076	1.120	5.596	0.000
m16	CPUE	0.4417794	0.059	7.481	0.000
m16	SEAK_SST_MJJ	-0.3832128	0.108	-3.553	0.002
m17	(Intercept)	5.9944080	0.883	6.787	0.000

model	term	estimate	std.error	statistic	p.value
m17	CPUE	0.4610340	0.055	8.320	0.000
m17	SEAK_SST_AMJ	-0.4598502	0.109	-4.213	0.000
m18	(Intercept)	6.3194518	1.046	6.040	0.000
m18	CPUE	0.4520626	0.057	7.881	0.000
m18	SEAK_SST_AMJJ	-0.4392579	0.114	-3.857	0.001