Assessing the Impacts of Environmental and Ecological variables on the Performance of Fraser Sockeye Salmon Forecast

Yi Xu1, Qi Liu2, Caihong Fu1

1 Fisheries and Oceans Canada, Pacific Biological Station, 3190 Hammond Bay Road, Nanaimo, BC, Canada

2 Fisheries and Oceans Canada, Pacific Region Head Office, 401 Burrard Street, Vancouver, BC, Canada

Corresponding author:

Yi Xu

Email : [Yi.Xu2@dfo-mpo.gc.ca](mailto:Yi.Xu2@dfo-mpo.gc.ca); [xuyiouqd@gmail.com](mailto:xuyiouqd@gmail.com);

ORCIDs: <https://orcid.org/0000-0002-9902-9588>

**Abstract**

The Canadian Fraser River Sockeye salmon (*Oncorhynchus nerka*) is one of the largest stock complexes in North America, supporting major commercial, recreational, and First Nations fisheries. Sockeye fisheries management relies on annual pre-season forecast of adult return. In this study, we developed a framework of good visualization with Taylor diagram to evaluate pre-season forecast models on an annual basis and identify external drivers of importance for forecasting Sockeye return. Specifically, we incorporated five new covariates including sea surface temperature in the Gulf of Alaska and annual abundance of other salmon species into the existing forecast models. Results revealed good performances by either Ricker or Power models coupled with the newly included covariates. In addition, models selected a decade ago underperformed compared to those selected based on our retrospective analysis for the period of 2009 to 2020. We advocate that forecast models need to be continuously evaluated in the face of increasing environmental change, and that new models able to deal with non-stationary relationships between environment and Sockeye dynamics are to be developed and evaluated with environmental and ecological factors being explicitly incorporated and assessed for their impacts.

**Key words**: environmental covariates, *Oncorhynchus nerka*, pre-season forecast, salmon abundance, Taylor diagram

1. **Introduction**

Sockeye salmon (*Oncorhynchus nerka*) have significant economic, ecologic, and social contributions throughout the Northeast Pacific. The Canadian Fraser River Sockeye salmon is one of the largest stock complexes in North America, spawning in hundreds of distinct locations throughout the 220 000 km2 Fraser River basin (Figure 1; Burgner 1991; DFO 2018). These Fraser River Sockeye salmon stocks support major commercial, recreational, and First Nations fisheries (Ruggerone and Connors 2015), making the management of these Sockeye salmon fisheries imperative for sustaining these fisheries. This has been done through annual pre-season forecast of Sockeye run size (i.e., adult return including salmon to be caught by fisheries and those escaping to spawning ground), which has become mandatory for Fisheries and Oceans Canada (DFO) under a Pacific Salmon Treaty that initiated in 1985 (PSC 2022). Pre-season forecast of Fraser Sockeye return provides input to planning by fisheries managers and the fishing industry, and feeds to in-season assessment modeling (Haeseker et al. 2008; Michielsens and Cave 2019; DFO 2021). Additionally, pre-season forecast assists decision-making processes including international total catch allowance negotiation, escapement surveys, and hatchery enhancement experiments (Hawkshaw et al. 2020a, b).

Despite the tremendous importance of pre-season Fraser Sockeye forecast, rigorous evaluation of forecast performance has rarely been done both in terms of accuracy and uncertainty (Satterthwaite et al. 2020). The reliability of pre-season forecasts depends on good understanding and modelling of complex interactions between climate, ecosystems, and populations involving both climate regime shifts and ecosystem phase transitions (Wainwright 2021). Sockeye salmon return has been highly variable not only due to its cyclic nature for some large stocks (with a dominant year preceded and followed by three years of low return), but also unpredictable productivity at different life stages in both freshwater and marine environments (Ricker 1997; Akenhead et al. 2016a; Huang et al. 2021), which has made pre-season forecast of Sockeye return challenging.

In particular, confidence in pre-season forecast of Fraser Sockeye return has eroded among fisheries managers and harvesters in recent years since actual return has frequently fallen outside of the estimated distribution range (i.e., <10 percentile or >90 percentile of observations; DFO 2021). The inaccurate pre-season forecasts have led to potentially reduced economic opportunities, missed management targets and escapement goals, as well as increased conservation concerns. Therefore, there is a great need to improve forecasting ability for Fraser Sockeye and it is imperative to incorporate new information derived from recent scientific research into the forecast process particularly in the face of ever increasing challenge of climate change.

Sockeye return in any given year is influenced by the abundance of their parental spawners (Sockeye return that reach the spawning grounds), the proportions of age classes, and the survival rate of the adult recruits across the entire life cycle from egg to adult (Grant et al. 2010; Hawkshaw et al. 2020a, b). A wide variety of forecast models are typically available at a stock level for Fraser Sockeye from non-parametric ‘naïve’ models (i.e., models using recent and historical adult recruits only without considering spawners) to complex stock-recruitment models that incorporate environmental variables into the relationships between spawners and subsequent recruitment (Cass et al. 2006; Grant et al. 2011; DFO 2018; Hawkshaw et al. 2020a, b). Advanced forecast methods also incorporate Bayesian statistical approach into the stock-recruitment relationship to assess uncertainty associated with abundance estimates (Cass et al. 2006; Grant et al. 2011; Akenhead et al. 2016a). Model selection for Fraser Sockeye forecast has been an expert-driven process, primarily adopting forecast models identified on the basis of the study for the period of 1997 to 2004 (Grant et al. 2011).

Since the 1990s, Fraser Sockeye has generally declined with several populations being listed as endangered (COSEWIC 2017). Although the previously ranked good performing models of Grant et al. (2011) have been continuously used in pre-season forecast, their explanatory power has been low (Akenhead et al. 2016a; DFO 2021). Moreover, environmental covariates such as coastal sea surface temperature and Pacific Decadal Oscillation that have been proven effective to reduce the degree of unexplained stock-recruitment variation in the past two decades are no longer useful for most stocks (Cass et al. 2006; Litzow et al. 2020). These time-varying effects of environmental conditions on population and community processes, i.e., non-stationary relationships, have become more prevailing in the face of climate change and been increasingly recognized (e.g., Litzow et al. 2018, 2020; Ohlberger et al. 2022). Such non-stationarity requires that previously established Fraser Sockeye forecast models be continuously evaluated through annual retrospective analysis before carrying out pre-season forecasts. Furthermore, external drivers that are responsible for the interannual and long-term variability of Sockeye abundance and productivity continue to be explored and characterized in a changing environment (McKinnell 2008; Ruggerone et al. 2021).

In this study, we developed a framework that can be used by fisheries managers or other stakeholders easily with good visualization and on an annual basis to evaluate pre-season forecast models and to identify external drivers of importance for forecasting Sockeye return. Specially, we developed computer codes to conduct annual retrospective analysis of multiple Fraser Sockeye forecast models and for the first time employ Taylor diagram (Taylor 2001) to display simultaneously three statistics of predictive power, including Pearson’s correlation coefficient, normalized standard deviation and normalized root-mean-square error (RMSE). Taylor diagram is a useful visualization tool that has been employed to evaluate the performance of a variety of models such as those for ocean circulation (Lamine et al. 2022), satellite derived chlorophyll measurement (Lee et al. 2015), biogeochemical dynamics (Salihoglu et al. 2017), and stock assessment and population dynamics of tuna species (Kell et al. 2016; Inna et al. 2019). The framework developed through this study can be directly implemented in the process of Fraser Sockeye forecast so as to improve the performance of Sockeye forecast and assist fisheries management planning.

1. **Materials and methods**

**2.1 Fraser Sockeye spawner and recruit data**

In this study, we used the same spawner and recruitment data of Fraser Sockeye stocks within the Fraser watershed (Figure 1) that were approved for the 2022 pre-season forecast (DFO, in press). The spawner data have been collected by DFO since 1938 (Grant et al. 2011), and the recruitment data have been compiled by Pacific Salmon Commission (PSC) with details on data quality available in Ogden et al. (2015). Based on shared timing of returning to the Fraser River, the stocks were aggregated into four management units: Early Stuart, Early Summer, Summer, and Late Run. In this study, we focused on 18 ‘lake-type’ Sockeye stocks that typically spend two years in a nursery lake before migrating seawards and return to their natal rivers at age 4 or 5. We chose female spawners as an indicator for spawner abundance (also called effective female spawner) from 1948 – 2018 brood year for all stocks. Recruits included both sexes with the most recent recruitment data (4- and 5-year-old) available up to the 2017 brood year (i.e., the actual return year of 2021). For the Cultus Sockeye stock, juvenile abundance was used instead of spawner for building the stock-recruit relationship, because escapement data were in poor quality and had been heavily affected by the hatchery broodstock program (Ackerman et al. 2014). The overall age composition of Fraser Sockeye was typically dominated by age 4 class. We assumed that age composition of adults generally followed a similar pattern among brood years around historical average. Ten of the eighteen stocks had time series of paired spawner and recruit estimates from brood year going back to 1948, and the remaining eight stocks had shorter time series dating back to different years for different stocks (Nadina: 1973; Gates: 1968; Scotch: 1980; Fennell: 1967; Weaver: 1966; Portage: 1953), depending on the availability and quality of the data as well as consistency with previous pre-season forecasts (DFO 2018).

* 1. **Environmental and ecological covariates**

Previous pre-season forecasts have incorporated a few local and large-scale environmental conditions in the Northeast Pacific Ocean, including (1) Pacific Decadal Oscillation in the winter preceding outmigration (PDO, November-March, Mantua et al. 1997), (2) monthly average SST (April-June) from Entrance Island lighthouse (Ei.SST, Strait of Georgia, near Nanaimo, BC, Canada), (3) monthly average SST (April-July) from Pine Island (Pi.SST, Northeast corner of Vancouver Island) of the year of outmigration, (4) peak [Fraser River discharge (FRD.peak), and (5) average Fraser River discharge (FRD.mean) from April to June of the outmigration year, both measured at Hope, BC, Canada](https://wateroffice.ec.gc.ca/) (for data sources, please refer to DFO 2018; Hawkshaw et al. 2020a, b). All these time series of environmental indices were aligned with smolt outmigration year because that is when they influence marine survival of Sockeye and other Pacific salmon species the most (Cass et al. 2006).

Exploration of new biological and environmental covariates that may explain the interannual variability in Fraser Sockeye recruitment has long been suggested (Grant et al. 2010; MacDonald and Grant 2012; DFO 2015; Hawkshaw et al. 2020a, b). Recent analyses found that survival of Fraser Sockeye exhibited a similar temporal pattern among all stocks, indicating that Fraser Sockeye stocks might be related to oceanic environmental conditions and competition among Pacific salmon at a global scale (Akenhead et al. 2016a; Connors et al. 2020; DFO 2021; Ruggerone et al. 2021; Rosengard et al. 2021). Therefore, we further included Gulf of Alaska sea surface temperature (GOA.SST) and abundance of other Pacific salmon species in the stock-recruitment models, hypothesizing that inclusion of these covariates can help account for more of the environmental effects on interannual variability in the survival of all Fraser Sockeye stocks. The GOA.SST time series was extracted from the COBE model SST database (<https://psl.noaa.gov/data/gridded/data.cobe.html>), matching with the Fraser Sockeye distribution areas identified based on a tagging study (Myers et al. 1996; Ishii et al. 2005; Supplementary Figure S1). For the abundance of other Pacific salmon species, we specifically chose annual abundance (catch plus spawning escapement) of adult Pink, Chum, and other Sockeye stocks, and all three species combined (Salmon.Total) from 1950 – 2020 (brood year 1948 – 2018) (Ruggerone and Irvine 2018; Ruggerone et al. 2021). Altogether, ten covariates (six environmental and four ecological) were included in the pre-season forecast models (Figure 2).

**2.3 Forecast models**

In this study, we re-evaluated the previously explored models, including eleven naïve and seven biological models (Table 1 and Table S1). The biological models of Ricker, Power, and Larkin were also applied to data of dominant years only (i.e., RickerCyc, PowerCyc, and LarkinCyc) for the purpose of understanding if the dominant year class was driven by different biological and environmental processes. With the Ricker and Power models, we specifically coupled them respectively with each of the ten covariates to form ten new models. Table 1 and Table S1 list all equations and model descriptions for the 37 pre-season forecast models. Following previous forecasts (e.g., Cass et al. 2006; MacDonald and Grant 2012; Grant et al. 2011; DFO 2018; DFO in press), we used Bayesian statistical approach to estimate biological model parameters and MCMC (Markov Chain Monte Carlo) to assess estimation uncertainties.

**2.4 Retrospective analysis and model evaluation**

Previously, retrospective analysis using Jack-knife cross validation, i.e., analysis being carried out by leaving out 1 year’s data at a time, was conducted for the period from 1997 to 2004 to evaluate the performances of various models (Grant et al. 2011). In this study, we conducted the one-step-ahead retrospective analysis for the period between 2009 and 2020 for 18 major stocks to evaluate all 37 forecast models; it produced forecasts by iteratively stepping forward through time as each step added a new year to estimation dataset. All the models were then ranked using each of the following four performance measures related to forecast error: mean absolute error (MAE), root-mean-square error (RMSE), mean raw error (MRE), mean proportional error (MPE). MAE is the sum of absolute errors between forecast (*y*) and observation (*x*) divided by the time series length *T*:  (Willmott and Matsuura 2009). RMSE provides a measure of forecast error variance reflecting both bias and uncertainty: (Hyndman et al. 2006). MRE () and MPE ( ) reflect the long-term bias of forecasts. For each model, ranks across the four performance measures were averaged to generate an overall rank. We then calculated relative rank based on the overall rank to make comparison across stocks: . We also provided relative rank for RMSE only, as it has been commonly used by fisheries managers and other similar studies (Haeseker et al. 2008; Ovando et al. 2022).

We used Taylor diagram as a visualization tool to guide the process of model selection both in terms of accuracy and uncertainty. The correlation between forecasts hindcasted by each model for the years 2009 – 2020 and the actual observed returns represents forecast accuracy. The standard deviation represents the magnitude of the variability of forecasts relative to variability of observations for the given years. The observed Sockeye returns from 2009 – 2020 (about 3 cycles for some major stocks; Supplementary Figure S2) were normalized as a reference point (i.e., Observation). The overall performance of a model was expressed as a relative position on the diagram, as it was also normalized by the standard deviation of observations from 2009 to 2020. Generally, a model that has relatively high correlation, small RMSE, and similar standard deviation as observation is desired. A perfect model is located at the reference point with both correlation andstandard deviation being 1 and RMSE being 0. All models, analyses and visualization were programmed using R 4.2.0 (R Core Team 2022).

1. **Results**

**3.1 Forecast model comparisons**

Relative rank based on overall rank of the 37 forecast models across the 18 stocks showed clear patterns of generally poor performances by the naïve models but relatively good performances by either Ricker or Power coupled with the newly included covariates (i.e., GOA.SST, Sockeye, Chum, Pink and Salmon.Total) (Figure 3). Relative rank based on RMSE showed similar patterns to those based on overall rank (Supplementary Figure S3).

Correlations between model forecasts and observations were generally lower for the naïve models than biological ones (Figure 4), reflective of lower forecast accuracy among the formers. Correlations were more homogeneous within each stock (across all models) than across the stocks (using a same model). This may indicate that model accuracy can be stock-dependent either related to data quality or specific stock dynamics. The small stocks of Gates and Raft had particularly low correlations across all models possibly associated with inaccurate survey methods applied (DFO, 2020). Similarly, standard deviation revealed disadvantage of the naïve models, tending to be farther away from one (Supplementary Figure S4). Standard deviation also showed high degree of consistency across all the models other than the naïve ones, particularly for the three stocks Nadina, Stellako, and Late Stuart, for which the model forecasts either didn’t capture uncertainty or had inflated variability compared to observations.

We presented the retrospective hindcast results of the 37 forecast models on Taylor diagrams for the 18 Fraser Sockeye stocks relative to the time series of observations from 2009 – 2020 (Figure 5a,b). The time series of historical forecasts for the years 2009 – 2020 based on previously selected models (Grant et al. 2011) were also presented relative to the observations. In general, the historical forecasts (i.e., the solid square; Figure 5a, b) performed poorly compared to the Observation (i.e., the solid circle; Figure 5a, b). Correlations between the historical forecasts and observations were less than 0.5 for half of the stocks with some close to or even below zero (i.e., forecasts had no correlation with observations or were negatively correlated with observations). For all stocks, there were at least one model that outperformed the historical forecasts, indicating that had we chosen a good performing model consistently throughout the years, we would have had more accurate forecasts compared to those obtained from the forecast models historically chosen.

Among biological models, Power coupled with new covariates (blue icons) generally outperformed other models with higher correlations, similar standard deviations to those in observations, and smaller RMSEs (Figure 5a, b). The Power models combined with previously adopted covariates (green icons) performed similarly well to the best models, yet they were rarely used in previous forecasts (Grant et al. 2011; DFO 2018; Hawkshaw et al. 2020a, b). Ricker models coupled with new covariates (red icons) also seemed to be better compared to those with old covariates (pink icons) with the latter having been frequently used in the previous forecasts. For most stocks, best model forecasts were in good agreement with observations, reaching correlations between 0.7-0.95. However, for a few stocks such as Gates and Raft, none of the existing models produced an accurate forecast, probably due to data quality issues as aforementioned. Naïve models (purple icons) tended to have larger standard deviations and performed worse compared to biological models.

Age-specific Taylor diagrams presented all 37 forecast models relative to the historical forecasts (black solid square) and observations (black solid circle) for age 4 and age 5 returns, respectively (Supplementary Figure S5 and S6). The age-4 Taylor diagrams showed similar results as the ones produced for total abundance (Figure 5a,b), since age 4 is the dominant age class for most stocks. Power models with new covariates consistently outperformed others for many stocks. The historical forecasts of age 4 showed similarly poor performance for most stocks. For age 5, the Sibling models (yellow squares) were the best for many stocks compared to the naïve and biological models.

**3.2 Model selection**

For Sockeye forecast in the year 2022, the forecast models selected by the Fraser River Panel resulted in an error (defined as ) of 192% (Supplementary Table S2). However, using the best model identified through the Taylor diagram for each stock has collectively and substantially improved the forecast for total return abundance, reducing the error to 30% (Supplementary Table S2), being the best over the past few years (Hawkshaw et al. 2020a, b). This forecast was also within a reasonable range compared to Sockeye forecasts in several other watersheds (Supplementary Table S2). We took the top three stocks (Chilko, Late Shuswap, and Quesnel) as examples to make comparisons among best performing models and observations (Figure 6). We found that for Chilko and Quesnel, where a top-ranking model was adopted in 2022, the forecasts were rather accurate with an error of +5% for Chilko and -7% for Quesnel and were less variable with smaller uncertainties (Figure 6). However, for Late Shuswap, where the 2022 forecast was done by the historically selected model, the forecast resulted in a deviation of -57%, equivalent to a difference of 1.9 million Sockeye salmon relative to the actual returns. Had any of the best models been chosen based either on the overall rank, correlation, standard deviation or RMSE, the forecast would have been more accurate for the Late Shuswap Sockeye stock (Figure 6).

1. **Discussion**

Forecasting Sockeye return in the upcoming year is a challenging task given the complex life history and the dynamic freshwater and marine habitats they reside. In recent years, forecast accuracy has become worse, frequently going below 10% of observations or 90% above observations (DFO 2021). For example, in 2021, median forecast for the Fraser River sockeye was 1.33 million while the return was 2.549 million, 92% above the observation (Supplementary Table S2). Despite these uncertainties, the official forecast has been widely used by various groups for important decision making, such as escapement survey planning (stock assessors), fishery opening and licensing, allocation among commercial, recreational and indigenous fisheries (fisheries managers), boat maintenance and gear purchasing (fishing communities), hatchery experiments, research and development (hatchery managers), and international salmon treaty negotiation (bilateral governments) (Haeseker et al. 2008; Michielsens and Cave 2019; Hawkshaw et al. 2020a, b; DFO in press). Developing a framework to improve and streamline the existing forecast process is highly desired for a broad range of societies. In this paper, we developed a framework that allowed fisheries managers or other stakeholders to evaluate the performances of pre-season forecast models with good visualization and on an annual basis by using Taylor diagram, and to identify external drivers of importance for forecasting Sockeye return. Specifically, for the first time we incorporated new environmental and ecological covariates (i.e., GOA.SST, Pink, Chum, Sockeye, Salmon.Total) into the Ricker and Power forecast models, which has resulted in consistently robust forecasts across all 18 Fraser Sockeye stocks, regardless of data quality and survey method changes temporally over decades and spatially over the entire Fraser watershed. We concluded that these new covariates, particularly Pink and Salmon.Total, could be good indicators for all Pacific Sockeye in river systems in North America and Asia and suggest that scientists would consider including them in future forecast models.

**4.1 Moving towards ecosystem-based fisheries management**

Sockeye salmon have very complex life history, going through vastly different freshwater and marine environments at different life stages, resulting in very unpredictable productivity (e.g., Ricker 1997; Akenhead et al. 2016b; Huang et al. 2021). Generating reliable pre-season forecasts of Sockeye return is dependent on reliable modelling of their complex life history and particularly of impacts from their physical and biological environments through climate change, ecosystem phase transitions, and competition of food and other resources (e.g., Patterson et al. 2016; Satterthwaite et al. 2020; Connors et al. 2020; Wainwright 2021; Ohlberger et al. 2022; Kaeriyama 2022). Therefore, it is imperative to move the pre-season Sockeye forecast and management towards ecosystem-based approaches that account for ecosystem processes, including fishing and/or climate variability in conjunction with species interactions (Sissenwine and Murawski 2004; Link 2011). Multiple studies have found that Sockeye salmon in BC have been negatively affected by the significant increase of Pink salmon abundance in the north Pacific in recent decades through competition for limited resources on both broad and localized scales (Ruggerone and Connors 2015; Connors et al. 2020; Ruggerone et al. 2021; Litz et al. 2021). Even though the existing Fraser Sockeye stock assessment and fisheries management are still heavily single-species based, this study helps move a step forward towards ecosystem-based fisheries management by incorporating the covariates of Pink, Chum, other Sockeye abundance, and their combined abundance, implicitly accounting for inter-specific (other salmon species) and intra-specific (other Sockeye salmon) interactions of competition. Indeed, our forecast framework revealed that models combined with the salmon covariates were generally highly ranked retrospectively from 2009-2020, highlighting that Fraser Sockeye dynamics were closely related to the abundances of other Pacific salmon stocks.

In addition, tagging study of Sockeye salmon (Myers et al. 1996; Ishii et al. 2005; Supplementary Figure S1) indicated that Fraser Sockeye distributed widely in North Pacific, with one Sockeye caught in the eastern hemisphere (176.2˚E). Recent high seas survey (2019-2020, 2022) in the Gulf of Alaska showed that Fraser Sockeye shared marine habitat with Sockeye from other river systems in cooler waters as well as Pink and Chum salmon, although the spatial overlap with the latter two were less intensive (Weikamp et al. [unpublished](https://www.youtube.com/watch?v=thCmnoPEw6s)). Salmon’s extended period of residence in the GOA, their high degree of spatial overlap in this region, and evident co-variability among salmon species made the GOA an area of significance for salmon abundance. The GOA is influenced by decadal thermal variability and has experienced three marine heatwave events since 2013, resulting in unprecedented reductions in fishery recruitment and shifts in the biological community of this region (Blaisdell et al. 2021). The inclusion of GOA.SST into the pre-season Sockeye forecast was another step of moving forward towards ecosystem-based fisheries management. The forecast model RickerGOA.SST (Ricker coupled with GOA.SST) performed extremely well for the Late Shuswap stock (one of the three major stocks) compared to all other models with the exception of RickerPi.SST (Figure 3). Had the RickerGOA.SST model been adopted in 2022 for the Late Shuswap stock, the median forecast for this stock would have been reduced from 3.42 million to 1.48 million (equal to the observation), and the error for Fraser River Sockeye would have been reduced from -30 to -10% (Supplementary Table S2). It is also worth noting that the current GOA.SST map only represents part of northeastern Pacific (Supplementary Figure S1), which can be expanded when more SST measurements become available in new locations. Nevertheless, this paper sheds some light on how forecast can be improved by incorporating biotic and abiotic metrics from ecosystem perspectives. Overall, this paper showed that the models coupled with newly added covariates not only produced more accurate forecasts but also reduced uncertainties, which would be a great help to fisheries managers who tend to face high pressure from political parties when forecast is inaccurate or has high uncertainty.

**4.2 Taylor diagram and future implications**

Taylor diagram has allowed us to visually compare time series of forecasts from 37 forecast models along with the historical forecasts against the observations in one graph both in terms of forecast accuracy and uncertainty. Therefore, it can help simplify the model selection process by illustrating the performance quantitatively among all forecast models. Based on the Taylor diagrams for all 18 Fraser Sockeye stocks, we concluded that the forecasts based on the historically selected forecast model were not ideal compared to those from many other forecast models. The framework developed through this study can be adopted for future model selection and forecast.

Many Fraser Sockeye stocks showed strong cyclic patterns with a dominant year every four years (Supplementary Figure S2). Forecasting for the dominant years was more challenging with usually less accuracy compared to other years (DFO, 2021). Nevertheless, our forecast for the dominant year 2022 was promising. Our retrospective analysis only goes back to 2009, about 3 cycles; as the time series extends, it will be interesting to separate dominant years and plot cycle-specific Taylor diagrams to identify models specifically tailored to dominant years.

Currently, our framework allows us to select a model by visually looking at the models’ relative positions in Taylor diagrams, which could be subjective. For example, a best RMSE model may not have best standard deviation or best correlation or vice versa. To be more objective, a single distance metric, similar to Mohn’s rho value (Mohn, 1999), can be calculated and integrated to automate the model selection process to come up with best machine-suggested models.We currently only used 12 years’ retrospective results to draw the Taylor diagrams. As time progresses, it will be interesting to examine how the relative positions of these forecast models evolve over time. Theoretically, informative models will move closer to the Observation as more years of data becoming available. Models with false alarms will either wander around or move further away from the Observation. Monitoring the directions of each model for multiple years may give us hints on which models are better or have the tendency to become better.

**4.3 Forecast models for non-stationary relationships**

In terms of stock-recruit relationship, parametric models, such as Ricker, Power, and Larkin, have been primarily employed in the past (Ricker 1997; Cass et al. 2006; Grant et al. 2010, 2011; Akenhead, et al., 2016a; DFO 2018; Hawkshaw et al. 2020a, b). However, these parametric models have limited forms to encompass the inherently large uncertainties associated with large annual variability in multiple environmental factors that affect salmon dynamics throughout their complex life history stages (e.g., Healey, 2011; Martins et al., 2012; Padilla et al., 2015). They are thus inadequate to incorporate anthropogenic changes (Akenhead et al., 2016b), which can result in unexplained residual patterns in the stock-recruit relationship, resulting in less accurate pre-season forecasts. In addition, these parametric models are also unable to deal with non-stationary Sockeye dynamics (Peterman & Dorner 2012; Malick 2020), which may have caused the Chilko Sockeye return to have been persistently over-estimated in the last decade (DFO 2021). Climate-induced non-stationarity in relationships between marine environments and fish communities has been increasingly recognized (e.g., Litzow et al. 2018, 2020; Ohlberger et al. 2022). It has been advocated that new approaches capable of dealing with non-stationarity in the Sockeye dynamics should be explored (Peterman & Dorner 2012; Malick 2020).

Machine learning models, such as generalized additive models (Wood 2017), boosted regression trees (Elith et al. 2008), random forest (Breiman 2001), empirical dynamic models(Ye et al. 2015), and artificial neural network (Ripley, 1996), use algorithms to learn the relationships between responses and predictors, not confined to certain functional forms. Therefore, these more flexible machine learning models can be developed to represent non-stationary stock-recruit relationships in the dynamics of Sockeye stocks. Taylor diagram can then be used to show how these machine learning models perform compared to the traditional parametric models. Additionally, we can also incorporate multiple covariates at the same time to evaluate their relative importance in forecasting Sockeye return. In summary, we advocate that all potential forecast models need to be continuously evaluated in the face of increasing environmental change and new models able to deal with non-stationary relationships between environment and Sockeye dynamics should be developed and consistently evaluated in order to identify good performing forecast models and to understand the impacts of environmental and ecological factors on the performance of Fraser Sockeye forecast.

**Acknowledgements**

The authors would like to thank all the staff from Fisheries and Oceans Canada and Pacific Salmon Commission who have collected the Fraser Sockeye data and contributed in previous forecast model development and evaluation processes. Special thanks are given to recent contributors, including Mickey Agha, Taren Bell, Brendan Connors, Mary Beth Fagan, Emily Breiteneder, Kelsey Campbell, Peter Chandler, Tracy Cone, Catharina De Monye, Scott Decker, Travis Desy, Kaitlyn Dionne, Maxine Forest, Nicole Frederickson, Jin Gao, Sue Grant, Merran Hague, Mike Hawkshaw, Stacey Hobson, Roy Hourston, Jim Irvine, Les Jantz, Dennis Klassen, Stu LaPage, Steve Latham, Brian Leaf, Doug Lofthouse, Nancy Louie, Jennifer Lynne, Bronwyn MacDonald, Michael Malick, Nate Mantua, Fiona Martens, Catherine McClean, Catherine Michielsens, Matt Mortimer, Judy Munsell, Chuck Parken, Matthew Parslow, David Patterson, Gottfried Pestal, Lucas Pon, Nicole Porteous, Tony Rathbone, Karen Richards, Rice Robert, Loraine Roper, Gordon Rose, Sarah Rosengard, Gregory Ruggerone, Jamie Scroggie, Amy Seiders, Michael Staley, Angus Straight, Madeline Thomson, Matthew Townsend, Strahan Tucker, Maxime Veilleux, Tanya Vivian, Paul Welch, Timber Whitehouse, and Serena Wong (in alphabetic order by last name). This project was initially supported by Sockeye and Pink Analytical Program, Fraser and Interior Area, DFO when the lead author was leading the 2022 Fraser Sockeye pre-season forecast process. The remaining work was done while the lead author was supported by the Salmon Data Unit, Fishery & Assessment Data Section, DFO. The lead author would like to thank Shelee Hamilton for her support.

**Copyright**

© 2022 The Crown. This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and source are credited.

**Data availability**

All data and code are available at Github repository. Access can be granted when contacting corresponding author.

**Competing interests**

The authors declare there are no competing interests.

**Supplementary material**

Supplementary data are available with the article at https:

//doi.org/xxxx/cjfas-xxxxx.

**References**

Ackerman, P.A., Barnetson, S., Lofthouse, D., McClean, C., Stobbart, A., and Withler, R.E. 2014. Back from the Brink: The Cultus Lake Sockeye Salmon Enhancement Program from 2000 - 2014. Can. Manuscr. Rep. Fish. Aquat. Sci. 3032: vii + 63p.

Akenhead, S.A., Irvine, J.R., Hyatt, K.D., Johnson, S.C. and Grant, S.C.H. 2016a. Stock-recruit analyses of Fraser River sockeye salmon. N. Pac. Anadr. Fish Comm. Bull 6: 363-390.

Akenhead, S.A., Irvine, J.R., Hyatt, K.D., Johnson, S.C., Michielsens, C.G.J. and Grant, S.C.H. 2016b. Habitat manipulations confound the interpretation of sockeye salmon recruitment patterns at Chilko Lake, British Columbia. N. Pac. Anadr. Fish Comm. Bull. 6: 391-414.

Blaisdell, J., Thalmann, H.L., Klajbor, W,, Zhang, Y., Miller, J.A., Laurel, B.J. and Kavanaugh, M.T. 2021. A Dynamic Stress-Scape Framework to Evaluate Potential Effects of Multiple Environmental Stressors on Gulf of Alaska Juvenile Pacific Cod. Front. Mar. Sci. 8:656088. doi: 10.3389/fmars.2021.656088

Breiman, L. 2001. Random Forests. Machine Learning 45, 5–32.

Burgner, R. L. 1991. Life history of sockeye salmon (*Oncorhynchus nerka*). In Pacific Salmon Life Histories. Groot, C. and Margolis, L. (eds.). University of British Columbia Press, Vancouver, Canada. 1: pp 1-118.

Cass, A., Folkes, M., Parken, C., and Wood, C. 2006. Pre-season run size forecasts for Fraser River sockeye in 2006. Can. Sci. Advis. Sec. Res. Doc. 2006/060: pp. iii + 72.

Connors, B., Malick, M.J., Ruggerone, G.T., Rand,P., Adkison, M., Irvine, J.R., Campbell, R., and Gorman, K., 2020. Climate and competition influence Sockeye salmon population dynamics across the Northeast Pacific Ocean. Can. J. Fish. Aquat. Sci. 77(6): 943–949.

COSEWIC, 2017. COSEWIC assessment and status report on the Sockeye Salmon Oncorhynchus nerka, 24 Designatable Units in the Fraser River Drainage Basin, in Canada. Committee on the Status of Endangered Wildlife in Canada. Ottawa. xli + 179 pp.

DFO, 2015. Pre-Season Run Size Forecasts for Fraser River Sockeye (*Oncorhynchus nerka*) and Pink (*O. gorbuscha*) Salmon in 2015. Can. Sci. Adv. Sec. Sci. Response 2015/014: pp. 55.

DFO, 2018. Pre-season run size forecasts for Fraser River Sockeye (*Oncorhynchus nerka*) salmon in 2018. Can. Sci. Advis. Sec. Sci. Resp. 2018/034: pp. 70.

DFO, 2021. Pre-Season run size forecasts for Fraser River Sockeye (*Oncorhynchus nerka*) and Pink (*O. gorbuscha*) Salmon in 2021. Can. Sci. Advis. Sec. Sci. Resp. 2021/038: pp. 105.

DFO, in press. Pre-season run size forecasts for Fraser River Sockeye (*Oncorhynchus nerka*) in 2022. Can. Sci. Advis. Sec. Sci. Advis. Rep. 2023/xxx: pp. 342.

Elith, J., Leathwick, J.R. and Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol., 77: 802-813. <https://doi.org/10.1111/j.1365-2656.2008.01390.x>

Grant, S.C.H., MacDonald, B.L., Cone, T.E., Holt, C.A., Cass, A., Porszt, E.J., Hume, J.M.B., and Pon, L.B., 2011. Evaluation of uncertainty in Fraser sockeye (*Oncorhynchus nerka*) wild salmon policy status using abundance and trends in abundance metrics. DFO. Can. Sci. Advis. Sec. Res. Doc. 2011/087. pp.183.

Grant, S.C.H., Michielsens, C.G.J., Porszt, E.J., and Cass, A.J. 2010. Pre-season run size forecasts for Fraser River sockeye salmon (*Oncohrynchus nerka*) in 2010. Can. Sci. Advis. Sec. Res. Doc. 2010/042: pp.125.

Haeseker, S.L., Peterman, R.M., Su, Z., and Wood, C.C., 2008. Retrospective evaluation of preseason forecasting models for sockeye and chum salmon. N. Am. J. Fish. Manag. 28(1): 12–29.

Hawkshaw, M., Xu, Y., and Davis, B. 2020a. Pre-season Run Size Forecasts for Fraser River Sockeye (*Oncorhynchus nerka*) and Pink (*Oncorhynchus gorbuscha*) Salmon in 2019. Can. Tech. Rep. Fish. Aquat. Sci. 3391: vi + 52 p.

Hawkshaw, M., Xu, Y., and Davis, B. 2020b. Pre-season Run Size Forecasts for Fraser River Sockeye (*Oncorhynchus nerka*) Salmon in 2020. Can. Tech. Rep. Fish. Aquat. Sci. 3392: iv + 56 p.

Healey, M. 2011. The cumulative impacts of climate change on Fraser River sockeye salmon (*Oncorhynchus nerka*) and implications for management. Can. J. Fish. Aquat. Sci. 68: 718-737.

Huang, A-M., Pestal, G., and Guthrie, I. 2021. Recovery Potential Assessment for Fraser River Sockeye Salmon (*Oncorhynchus nerka*) – Nine Designatable Units: Probability of Achieving Recovery Targets - Elements 12, 13, 15, 19-22. DFO Can. Sci. Advis. Sec. Res. Doc. 2021/043. x + 96.

Hyndman, Rob J.; Koehler, and Anne B., 2006. Another look at measures of forecast accuracy. Int. J. Forecast.. 22 (4): 679–688. doi:10.1016/j.ijforecast.2006.03.001.

Inna S., Lehodey, P., Sibert, J., and Hampton, J., 2019. Integrating tagging and fisheries data into a spatial population dynamics model to improve its predictive skills. Can. J. Fish. Aquat. Sci. 77(3): 576-593. <https://doi.org/10.1139/cjfas-2018-0470>

Ishii, M., Shouji, A., Sugimoto, S., and Matsumoto, T., 2005. Objective Analyses of Sea-Surface Temperature and Marine Meteorological Variables for the 20th Century using ICOADS and the Kobe Collection. Int. J. Climatol., 25, 865-879.

Kaeriyama, M., 2022. Warming climate impacts on production dynamics of southern populations of Pacific salmon in the North Pacific Ocean. Fish. Oceanogr. doi:10.1111/fog.12598

Kell, L. T., Kimoto, A., and Kitakado T., 2016. Evaluation of the prediction skill of stock assessment using hindcasting. Fish. Res., 183: 119–127.

Lamine, B.E., Schickele, A., Goberville, E. Beaugrand, G., Allemand, D., and Raybaud, V. 2022. Expected contraction in the distribution ranges of demersal fish of high economic value in the Mediterranean and European Seas. Sci Rep 12, 10150. https://doi.org/10.1038/s41598-022-14151-8

Lee, Y. J., Matrai, P.A. Friedrichs M.A.M., Saba, V.S., Antoine, D., Ardyna, M., Asanuma, I., Babin, M., Belanger, S., Benoit-Gagne, M., Devred, E., Fernandez-Mendez, M., Gentill, B., Hirawake, T., Kang, S.-H., Kameda, T., Katlein, C., Lee, S.H., Lee, Z., Melin, F., Scardi, M., Smyth, T.J., Tang, S., Turpie, K.R., Waters, K.J., and Westberry, T.K., 2015. An assessment of phytoplankton primary productivity in the Arctic Ocean from satellite ocean color/in situ chlorophyll-a based models, J. Geophys. Res. Oceans, 120, 6508– 6541, doi:[10.1002/2015JC011018](https://doi.org/10.1002/2015JC011018).

Link, J., 2011. Ecosystem-based Fisheries Management: Confronting Tradeoffs. Cambridge University Press, Cambridge.

Litz, M.N.C., Agha, M., Dufault, A.M., Claiborne, A.M., Losee, J.P., and Anderson, A.J. 2021. Competition with odd-year pink salmon in the ocean affects natural populations of chum salmon from Washington. Mar. Ecol. Prog. Ser. 663:179-195.

Litzow, M. A., Ciannelli, L., Puerta, P., Wettstein, J. J., Rykaczewski, R. R., and Opiekun, M., 2018. Non-stationary climate–salmon relationships in the Gulf of Alaska. Proc. Royal Soc. B., 285 (1890), 20181855. https://doi.org/10.1098/rspb.2018.1855

Litzow, M. A., Hunsicker, M. E., Bond, N. A., Burke, B. J., Cunningham, C. J., Gosselin, J. L., Norton, E. L., Ward, E. J., & Zador, S. G.,2020. The changing physical and ecological meanings of North Pacific Ocean climate indices. PNAS, 117(14), 7665–7671. https://doi.org/10.1073/pnas.19212 66117

MacDonald, B.L., and Grant, S.C.H. 2012. Pre-season run size forecasts for Fraser River sockeye salmon (*Oncorhynchus nerka*) in 2012. Can. Sci. Advis. Sec. Res. Doc. 2012/011(April): pp. v + 64 p.

Malick, M.J. 2020. Time-varying relationships between ocean conditions and sockeye salmon productivity. Fish Oceanogr. 29: 265– 275.

Mantua, N.J., Hare, S.R., Zhang, Y., Wallace, J.M., and Francis, R.C. 1997. A Pacific Interdecadal Climate Oscillation with Impacts on Salmon, Bull. Am. Meteorol. Soc., 78(6):1069–1079.

Martins, E.G., Hinch, S.G., Cooke, S.J., Patterson, D.A., 2012. Climate effects on growth, phenology, and survival of sockeye salmon (*Oncorhynchus nerka*): a synthesis of the current state of knowledge and future research directions. Rev.Fish Biol. Fish. 22: 887–914.

McKinnell, 2008 Fraser River sockeye salmon and climate; a re-analysis that avoids an undesirable property of Ricker’s curve Prog. Oceanogr., 77, pp. 146-154

Michielsens, C.G.J., and Cave, J.D., 2019. In-season assessment and management of salmon stocks using a Bayesian time-density model. Can. J. Fish. Aquat. Sci. 76: 1073–1085. dx.doi.org/10.1139/cjfas-2018-0213

Mohn, 1999. The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. ICES J. Mar. Sci., 56, pp. 473-488

Myers, K.W., Aydin, K.Y., Walker, R.V., Fowler, S., and Dahlberg, M.L. 1996. Known Ocean ranges of stocks of Pacific salmon and steelhead as shown by tagging experiments, 1956-1995. N. Pac. Anadr. Fish Comm. Doc. 192(4).

Ogden, A.D., Irvine, J.R., English, K.K., Grant, S., Hyatt, K.D., Godbout, L., and Holt, C.A. 2015. Productivity (recruits-per-spawner) data for sockeye, pink and chum salmon from British Columbia. Can. Tech. Rep. Fish. Aquat. Sci. 3130: vi + 57 p.

Ohlberger, J., Ward, E. J., Brenner, R. E., Hunsicker, M. E., Haught, S. B.,Finnoff, D., Litzow, M. A., Schwoere, T., Ruggerone, G. T., and Hauri, C., 2022. Non-stationary and interactive effects of climate and competition on pink salmon productivity. Glob. Chang. Biol., 28(6), 2026–2040. https://doi.org/10.1111/gcb.16049

Ovando D.,  Cunningham, C., Kuriyama, P., Boatright, C., and Hilborn, R., 2022. Improving forecasts of sockeye salmon (*Oncorhynchus nerka*) with parametric and nonparametric models. Can. J. Fish. Aquat. Sci. 79(8): 1198-1210. <https://doi.org/10.1139/cjfas-2021-0287>

Padilla, A., Rasouli, K., and Déry, S.J., 2015. Impacts of variability and trends in runoff and water temperature on salmon migration in the Fraser River Basin, Canada, Hydrol. Sci. J., 60:3, 523-533, doi: 10.1080/02626667.2014.892602

Patterson DA, Cooke SJ, Hinch SG, Robinson KA, Young N, Farrell AP, Miller KM (2016) A perspective on physiological studies supporting the provision of scientific advice for the management of Fraser River sockeye salmon (*Oncorhynchus nerka*). Conserv. Physiol. 4(1): cow026.

Peterman, R.M. and Dorner, B. 2012. A widespread decrease in productivity of sockeye salmon (*Oncorhynchus nerka*) populations in western North America. Can. J. Fish. Aquat. Sci. 69(8): 1255–1260.

PSC, 2022. Treaty between the Government of Canada and the Government of the United States of America concerning Pacific Salmon. 2022. Prepared by Pacific Salmon Commission. <http://www.psc.org/publications/pacific-salmon-treaty/>

R Core Team, 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/>.

Ricker, W.E. 1997. Cycles of abundance among Fraser River sockeye salmon (*Oncorhynchus nerka*). Can. J. Fish. Aquat. Sci. 54: 950–968. doi:10.1139/cjfas-54-4-950.

Ripley, B. D., 1996. Pattern Recognition and Neural Networks. Cambridge.

Rosengard, S.Z., Freshwater, C., McKinnell, S., Xu, Y., and Tortell, P.D., 2021. Covariability of Fraser River sockeye salmon productivity and phytoplankton biomass in the Gulf of Alaska. Fish. Oceanogr. 30: 666-678.

Ruggerone, G.T., and Connors, B.M., 2015. Productivity and life history of sockeye salmon in relation to competition with pink and sockeye salmon in the North Pacific Ocean. Can. J. Fish. Aquat. Sci. 72(6): 818–833. doi:10.1139/cjfas-2014-0134.

Ruggerone, G.T. and Irvine, J.R., 2018. Numbers and biomass of natural- and hatchery-origin pink, chum, and sockeye salmon in the North Pacific Ocean, 1925-2015. Mar. Coast. Fish. Dyn. Manage. Ecosyst. Sci. 10: 152-168.

Ruggerone, G.T., Irvine, J.R., and Connors, B., 2021. Did recent marine heatwaves and record high Pink salmon abundance lead to a tipping point that caused record declines in North Pacific salmon abundance and harvest in 2020? NPAFC Tech. Rep. 17: 78-82.

Salihoglu B., Arkin, S.S., Akoglu, E., and Fach, B.A., 2017. Evolution of Future Black Sea Fish Stocks under Changing Environmental and Climatic Conditions. Front. Mar. Sci. 4:339. doi:10.3389/fmars.2017.00339

Satterthwaite, W.H., Andrews, K.S., Burke, B.J., Gosselin, J.L., Greene, C.M., Harvey, C.J., Munsch, S.H., O’Farrell, M.R., Samhouri, J.F., and Sobocinski, K.L., 2020. Ecological thresholds in forecast performance for key United States West Coast Chinook salmon stocks. – ICES J. Mar. Sci., 77: 1503–1515. doi:10.1093/icesjms/fsz189

Sissenwine, M., and Murawski, S., 2004. Moving beyond ‘intelligent thinking’: advancing an ecosystem approach to fisheries. In: Perspectives on Ecosystem-based Approaches to the Management of Marine Resources. Mar. Ecol. Prog. Ser., vol. 274, pp. 269–303.

Taylor, K.E. 2001. Summarizing multiple aspects of model performance in a single diagram. J. Geophys. Res. 106: 7183–7192. doi:10.1029/2000JD900719.

Wainwright, T.C. 2021. Ephemeral relationships in salmon forecasting: A cautionary tale. Prog. Oceanogr., 193, 102522

Willmott, C. J. and Matsuura, K., 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Clim. Res. 30: 79–82. doi:10.3354/cr030079.

Wood S., 2017. Generalized Additive Models: An Introduction with R, 2 edition. Chapman and Hall/CRC.

Ye H., Beamish, R.J., Glaser, S.M., Grant, S.C., Hsieh, C.H., Richards, L.J., Schnute, J.T., and Sugihara, G., 2015. Equation-free mechanistic ecosystem forecasting using empirical dynamic modeling. Proc. Natl. Acad. Sci. 112(13): E1569–E1576.

**Figure captions**

Figure 1. Locations of 18 major Fraser Sockeye salmon stocks where spawning data were collected. Color indicates different run type: red for Early Stuart, green for Early Summer run (including Bowron, Fennel (Upper Barriere), Scotch, Nadina, Pitt, Seymour, and Gates), blue for Summer run (including Chilko, Quesnel, Late Stuart, Stellako, and Raft), and purple for Late run (including Late Shuswap, Cultus, Portage, Weaver, and Birkenhead).

Figure 2. Interannual variations of ten environmental and ecological variables from 1950-2020, including sea surface temperature (SST, unit in oC) at Entrance Island and Pine Island, mean and peak Fraser River discharge at Hope (unit m3/s), Pacific Decadal Oscillation (PDO), SST in the Gulf of Alaska, North Pacific sockeye, chum, pink salmon abundance (catch plus escapement, number in million), and combined total of the three salmon species.

Figure 3. Relative rank among all 37 forecast models for all 18 stocks. The relative rank (scale of 0-1) for an individual stock was derived from the overall rank table by dividing the rank of a model by the number of models evaluated for this specific stock. Blank indicates the model was not applicable to the stock.

Figure 4. Correlations (*R*) between retrospective forecasts for the period of 2009 – 2020 based on all 37 forecast models and observations for all 18 Fraser sockeye stocks. Correlation between historical forecasts (denoted as Forecast) and observations was also shown.

Figure 5. (a) Taylor diagrams for Early Stuart, seven Early Summer run (Bowron, Fennel (Upper Barriere), Scotch, Nadina, Pitt, Seymour, Gates), and one Summer run (Chilko). (b) Taylor diagrams for four Summer run (Quesnel, Late Stuart, Stellako, Raft) and five Late run (Late Shuswap, Cultus, Portage, Weaver and Birkenhead). Taylor diagram was employed to compare 37 model forecasts against the observation (solid black cycle on the x-axis). The distance from the origin is the normalized standard deviation with the normalized value for observation being 1. The angle describes the correlation (0 to 1) between model and observation. The dashed semi-circles around the observation illustrate the root-mean-square error (RMSE). Models with negative correlations are not shown for each stock. The closer the model is to the observation, the better predictive power the model has.

Figure 6. Comparisons among observation (forecast for the year 2022) and the forecasts by three top-ranked models using either best overall rank (Rank), standard deviation (SD), correlation (R), or root-mean-square error (RMSE) for three most abundant Fraser sockeye stocks: Chilko, Late Shuswap and Quesnel. The 50 percentile (P50: solid black line) and forecast distribution (box: P25-P75, range: P10-P90) were compared with the observation (PSC preliminary results). \*The Chilko stock used age-specific forecast models with age 4 using RickerEi while age 5 Sibling; detailed descriptions for the models are in Table 1.

Table 1. List of 37 models under three categories (A: non-parametric/naïve, B: biological, and C: biological models coupled with covariates). Where applicable, models use effective female spawner data (EFS) as a predictor.

| **MODEL CATEGORY** | **DESCRIPTION** |
| --- | --- |
| **A. Non-Parametric (Naïve) Models** | |
| LLY, R1C, R2C, RAC, TSA, RS1, RS2, RS4yr, RS8yr, MRS, RSC | Models only used returns from selected years and not considered spawners. Details of model description are listed in Supplementary materials Table S2. |
| **B. Biological Models** | |
| Ricker | Bayesian Ricker model, loge(*Rt*/ *St*) = *a* – *b* *St* + *Ɛt* |
| RickerCyc | Same as above, using cycle line data only |
| Power | Bayesian power model, loge(*Rt*) = *a* + *b* loge (*St*) + *Ɛt* |
| PowerCyc | Same as above, using dominant year data only |
| Larkin | Bayesian Larkin model, loge(*Rt*) = *a* + *b*1 loge (*St*) + *b*2 loge (*St*) + *b*3 loge (*St*) + *Ɛt* |
| LarkinCyc | Same as above, using cycle line data only |
| Sibling | Bayesian sibling model, loge(*R4, t*) = *a* + *b* loge (*R3, t-1*) + *Ɛt* |
| **C. Biological Models** (B for Ricker or Power) **coupled with Environmental and Ecological Covariates** | |
| B\_FRD.mean | B coupled with Mean Fraser discharge flow from April to June |
| B\_FRD.peak | B coupled with Peak Fraser Discharge at a given year |
| B\_Ei.SST | B coupled with Mean Entrance Island sea-surface temperature (SST) from April to July |
| B\_Pi.SST | B coupled with Mean Pine Island SST from May to July |
| B\_PDO | B coupled with Pacific Decadal Oscillation in winter preceding outmigration from November to March |
| B\_GOA.SST | B coupled with Mean Gulf of Alaska annual SST |
| B\_Pink | B coupled with Abundance of pink salmon in the North Pacific Ocean |
| B\_Chum | B coupled with Abundance of chum salmon in the North Pacific Ocean |
| B\_Sockeye | B coupled with Abundance of sockeye salmon in the North Pacific Ocean |
| B\_Salmon.Total | B coupled with Abundance of pink, chum, sockeye salmon altogether in the North Pacific Ocean |

Map

Description automatically generated

Figure 1

A picture containing timeline

Description automatically generated

Figure 2

A picture containing background pattern

Description automatically generated

Figure 3

Background pattern

Description automatically generated

Figure 4

Chart, map

Description automatically generated

Figure 5a

Map

Description automatically generated

Figure 5b

Chart, box and whisker chart

Description automatically generated

Figure 6