1	Assessing the Impacts of Environmental and Ecological variables on the Performance of Fraser
2	Sockeye Salmon Forecast
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4	Yi Xu ¹ , Qi Liu ² , Caihong Fu ¹
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6	¹ Fisheries and Oceans Canada, Pacific Biological Station, 3190 Hammond Bay Road, Nanaimo,
7	BC, Canada
8	² Fisheries and Oceans Canada, Pacific Region Head Office, 401 Burrard Street, Vancouver, BC,
9	Canada
10	
11	
12	Corresponding author:
13	Yi Xu
14	Email: Yi.Xu2@dfo-mpo.gc.ca; xuyiouqd@gmail.com;
15	ORCIDs: https://orcid.org/0000-0002-9902-9588
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17 Abstract

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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 preseason 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

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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, it is imperative to improve forecasting ability for Fraser Sockeye, for which it has become necessary 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 based on Jack-knife cross validation (i.e., analysis being carried out by randomly leaving out 1 year's data at a time) conducted for the period of 1997 to 2004 (Grant et al. 2011).

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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 (SST) and Pacific Decadal Oscillation (PDO) that had been proven effective to reduce the degree of unexplained stock-recruitment variation in the past two decades are no longer applicable 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 nonstationarity 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 potentially 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.

2. 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. For all stocks, we chose female spawner from 1948 – 2018 brood year as an indicator of spawner abundance (also called effective female spawner). 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

instead of spawner was used for building the stock-recruitment relationship, because escapement data were in poor quality and had been heavily affected by the hatchery broodstock program (Ackerman et al. 2014). We assumed that age composition of Fraser Sockeye adults generally followed a similar pattern among brood years around historical average, which was typically dominated by age 4 class. 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).

2.2 Environmental and ecological covariates

Previous pre-season forecasts have incorporated a few local and large-scale environmental covariates in the Northeast Pacific Ocean, including (1) PDO in the winter preceding outmigration (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 (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 SST (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 SST database (https://psl.noaa.gov/data/gridded/data.cobe.html), matching with the Fraser Sockeye distribution areas identified based on tagging studies (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

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In this study, we re-evaluated the previously explored models, including eleven naïve and six 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. For model descriptions of

the 37 pre-season forecast models, please refer to Table 1 and Table S1. 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

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To evaluate the 37 forecast models for the 18 major stocks, we conducted the one-step-ahead retrospective analysis (i.e., iteratively stepping forward through time as each step added a new year to the estimation dataset) for the period between 2009 and 2020. For each stock, all the 37 forecast models were 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: $MAE = \frac{\sum_{i=1}^{T} |y_i - x_i|}{T}$ (Willmott and Matsuura 2009). RMSE provides a measure of forecast error variance reflecting both bias and uncertainty: $RMSE = \sqrt{\frac{\sum_{i=1}^{T}(y_i - x_i)^2}{T}}$ (Hyndman et al. 2006). MRE ($MRE = \frac{\sum_{i=1}^{T}y_i - x_i}{T}$) and MPE $(MPE = \frac{100\%}{T} \sum_{i=1}^{T} \frac{y_i - x_i}{x_i})$ 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 comparisons across stocks: Relative rank = $\frac{Overall\ rank}{Numbers\ of\ model\ evaluated}$. 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 observations is desired. A perfect model is located at the reference point with both correlation and standard deviation being 1 and RMSE being 0. All models, analyses and visualization were programmed using R 4.2.0 (R Core Team 2022).

3. Results

3.1 Forecast model comparisons

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

Relative rank based on overall rank of the 37 forecast models across the 18 stocks showed

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.

For each of the 18 Fraser Sockeye stocks, we presented the retrospective hindcast results (for the period 2009 – 2020) of the 37 forecast models on a Taylor diagram relative to the time series of observations (denoted as Observation and shown as a black solid circle; Figure 5a,b). The historical forecast based on previously selected models was also presented (denoted as Forecast and shown as a black solid square; Figure 5a, b) relative to the Observation. In general, the Forecast performed poorly compared to many other models. Correlations between the Forecast and the Observation were less than 0.5 for half of the stocks with some close to or even below zero. For all stocks, there were at least one model that outperformed the Forecast, 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). Power 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 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 the Observation, 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 Forecast (black solid square) and the Observation (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 was the dominant age class for most stocks. Power models coupled with new covariates consistently outperformed others for many stocks. The historical forecast of age 4 showed similarly poor performance for most stocks (Supplementary Figure S5). For age 5, Sibling models (yellow squares) were the best for many stocks compared to the naïve and biological models (Supplementary Figure S6).

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 $\frac{Observation-Forecast}{Forecast} \times 100\%$) of 192% (Supplementary Table S2). However, using the best model identified for each stock through the Taylor diagram 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).

To understand how the models that were ranked first based on either overall rank or one of the three statistics (correlation, standard deviation, and RMSE) performed compared to other models, we examined the top three stocks (Chilko, Late Shuswap, and Ouesnel) as examples (Figure 6). For Late Shuswap, where the 2022 forecast was done by the historically selected model (RickerEi.SST), the forecast resulted in a deviation of -57%, equivalent to a difference of 1.9 million Sockeye salmon relative to the actual returns. In contrast, the model ranked first based on overall rank (i.e., RickerGOA.SST) resulted in the most accurate forecast with the smallest uncertainty (Figure 6). The model RickerPi.SST also performed relatively well, being best according to either correlation, standard deviation, or RMSE. The model RS1, ranked third based on standard deviation following RickerPi.SST and RickerGOA.SST, also performed better than RickerEi.SST, which may indicate that standard deviation is an important factor to consider in the model selection process. The importance of standard deviation can also be seen with Chilko and Quesnel, where the top-rank models based on standard deviation (i.e., R1C and RickerSockeye, respectively) also performed the best with the highest accuracy and lowest uncertainty (Figure 6). By contrast, RickerCyc, although being best ranked according to correlation and RMSE, performed poorly for Chilko. Similarly, the model Larkin performed poorly for Quesnel despite being ranked best according to correlation.

4. Discussion

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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 forecast (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, fishery opening and licensing, allocation among commercial, recreational and indigenous fisheries, boat maintenance and gear purchasing, hatchery experiments, research and development, and international salmon treaty negotiation (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 used as good indicators for all Pacific Sockeye in river systems in North America and Asia and suggest that scientists consider including them in future forecast models.

4.1 Moving towards ecosystem-based fisheries management

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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,

2016; Satterthwaite et al. 2020; Connors et al. 2020; Wainwright 2021; Ohlberger et al. 2022; Kaeriyama 2022). Therefore, it is imperative to move 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 studies on 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-

ecosystem phase transitions, and competition of food and other resources (e.g., Patterson et al.

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2020, 2022) in the Gulf of Alaska showed that Fraser Sockeye shared marine habitat with

the spatial overlap with the latter two were less intensive

Sockeye from other river systems in cooler waters as well as Pink and Chum salmon, although

(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

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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 historically selected forecast models were not ideal compared to 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 covered 12 years, about 3 cycles; however, as the time series extends in future, it will be interesting to separate dominant years and plot cycle-specific Taylor diagrams to identify models specifically tailored to dominant years. It will also be interesting to examine how the relative positions of these forecast models evolve over time as time progresses in future. 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.

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.

4.3 Forecast models for non-stationary relationships

It has been commonly recognized that correlations established based on past observations can be easily broken down due to the non-stationary nature of environmental changes (e.g., Peterman & Dorner 2012; Malick 2020; Litzow et al. 2020). For the Chilko and Quesnel Sockeye stocks, the models RickerCyc and Larkin performed poorly although they were respectively ranked first based on correlation. This implies that the correlations established for the period 2009 to 2020 may be deteriorating as environmental conditions have been constantly changing. On the other hand, we found that the top-rank models based on standard deviations performed the best with the highest accuracy and lowest uncertainty for the two major stocks Chilko and Quesnel (Figure 6). With the Lake Shuswap Sockeye stock, all three models with the first three ranks based on standard deviation (i.e., RickerPi.SST, RickerGOA.SST, and R1C) performed better than the historical forecast (Figure 6). These phenomena may indicate that standard deviations established based on past observations are not as easily broken down as correlations and thus can be considered as an important factor in the model selection process.

In terms of stock-recruitment relationships, 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 relationships, 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 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-recruitment 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.

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446	reproduction in any medium, provided the original author(s) and source are credited.
447	Data availability
448	All data and code are available at Github repository. Access can be granted when contacting
449	corresponding author.
450	Competing interests
451	The authors declare there are no competing interests.
452	Supplementary material
453	Supplementary data are available with the article at https:
454	//doi.org/xxxx/cjfas-xxxxx.
455	

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Figure captions

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Figure 1. Locations of 18 major Fraser Sockeye salmon stocks where spawning data were 634 635 collected. Color indicates different run type: red for Early Stuart, green for Early Summer run 636 (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 637 638 (including Late Shuswap, Cultus, Portage, Weaver, and Birkenhead). Figure 2. Interannual variations of ten environmental and ecological variables from 1950-2020, 639 640 including sea surface temperature (SST, unit in °C) at Entrance Island and Pine Island, mean and peak Fraser River discharge at Hope (unit m³/s), Pacific Decadal Oscillation (PDO), SST in the 641 642 Gulf of Alaska, North Pacific Sockeye, Chum, Pink salmon abundance (catch plus escapement, number in million), and combined total of the three salmon species. 643 Figure 3. Relative rank among all 37 forecast models for all 18 stocks. The relative rank (scale of 644 0-1) for an individual stock was derived from the overall rank table by dividing the rank of a 645 model by the number of models evaluated for this specific stock. Blank indicates the model was 646 647 not applicable to the stock. Figure 4. Correlations between retrospective forecasts for the period of 2009 – 2020 based on all 648 37 forecast models and observations for all 18 Fraser Sockeye stocks. Correlation between 649 historical forecasts (denoted as Forecast) and observations was also shown. 650 Figure 5. (a) Taylor diagrams for Early Stuart Sockeye stock, seven Early Summer run (Bowron, 651 Fennel (Upper Barriere), Scotch, Nadina, Pitt, Seymour, Gates), and one Summer run (Chilko). 652 653 (b) Taylor diagrams for four Summer run (Quesnel, Late Stuart, Stellako, Raft) and five Late run (Late Shuswap, Cultus, Portage, Weaver and Birkenhead). Each Taylor diagram compares 37 654

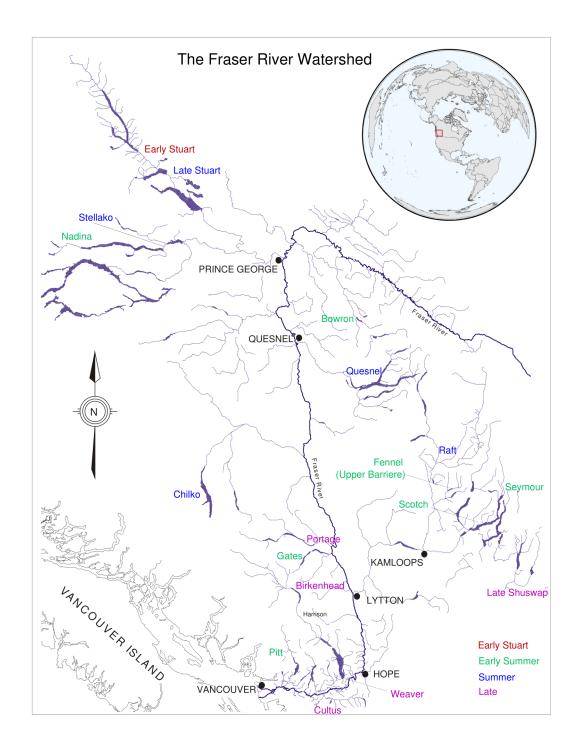
model forecasts and the historical Forecast (black solid square) against the Observation (black solid cycle on the x-axis). The distance from the origin is the normalized standard deviation with the normalized value for observations being 1. The angle describes the correlation (0 to 1) between model forecasts and observations. The dashed arcs 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 the forecast based on the historically selected model (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 of the Sockeye return in 2022 (PSC preliminary results). *The Chilko stock used age-specific forecast models with age 4 using RickerEi while age 5 Sibling; Descriptions for the model abbreviations are in Table 1.

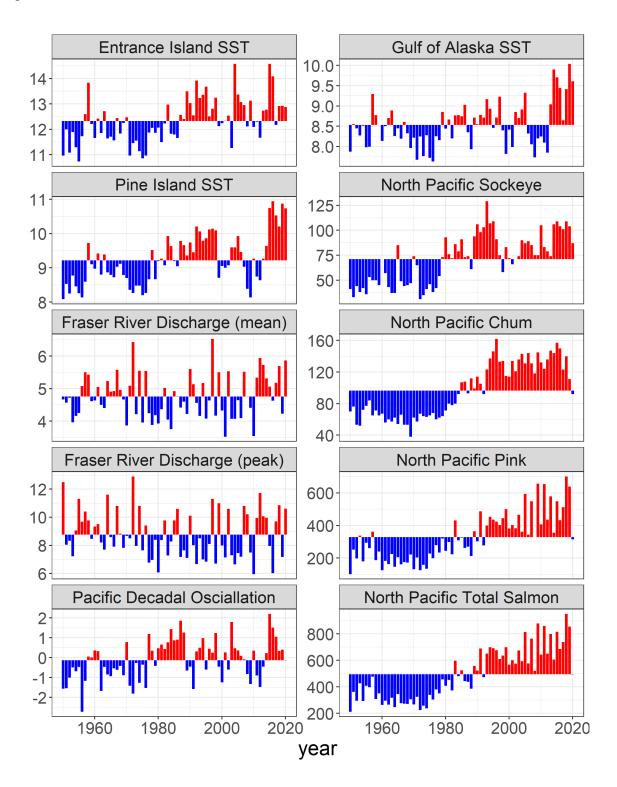
Table 1. Descriptions of 37 models under three categories (A: non-parametric/na $\ddot{}$ ve, B: biological, and C: biological models coupled with covariates) along with Sibling model that was used as an additional option for forecasting age 5 specifically, where R is recruitment, S is spawner, a for the intercept measuring density-independent per capita R, and b for the slope measuring density-dependent R.

MODEL	DESCRIPTION			
CATEGORY				
A. Non-Parametric (Naïve) Models				
LLY, R1C,	Models only used returns from selected years, not considering spawners. Detailed model			
R2C, RAC,	descriptions are listed in Supplementary Table S2.			
TSA, RS1,				
RS2, RS4yr,				
RS8yr, MRS,				
RSC				
B. Biological Models				
Ricker	Bayesian Ricker model, $\log_e(R_t/S_t) = a - b S_t + \mathcal{E}_t$			
RickerCyc	Same as above, using cycle line data only			
Power	Bayesian power model, $\log_e(R_t) = a + b \log_e(S_t) + \mathcal{E}_t$			
PowerCyc	Same as above, using dominant year data only			
Larkin	Bayesian Larkin model, $\log_e(R_t) = a + b_1 \log_e(S_t) + b_2 \log_e(S_t) + b_3 \log_e(S_t) + \mathcal{E}_t$			
LarkinCyc	Same as above, using cycle line data only			
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			
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			
Additional model for age 5				
Sibling	Bayesian sibling model, $\log_e(R_5, t) = a + b \log_e(R_4, t - l) + \mathcal{E}_t$			

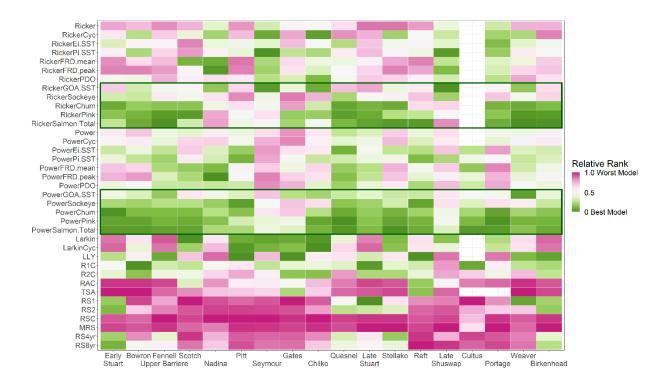
677 Figure 1.



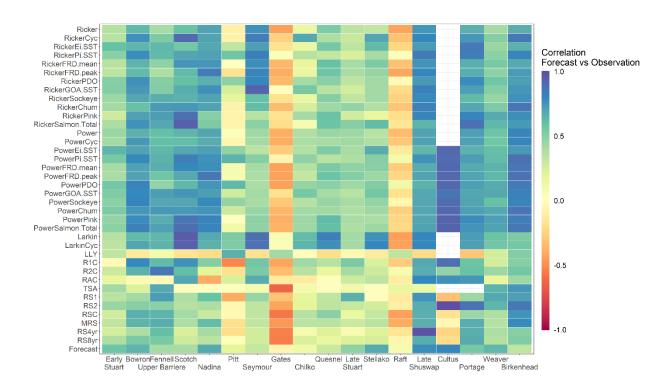
679 Figure 2.



681 Figure 3.



683 Figure 4.



685 Figure 5a

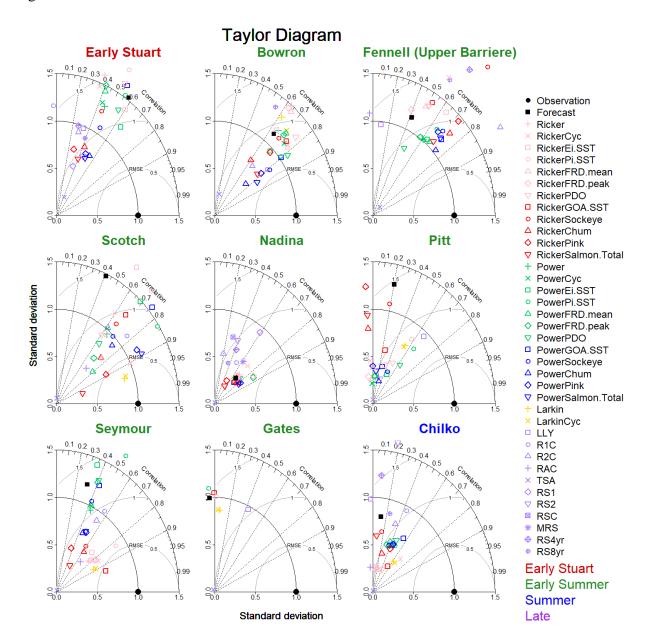
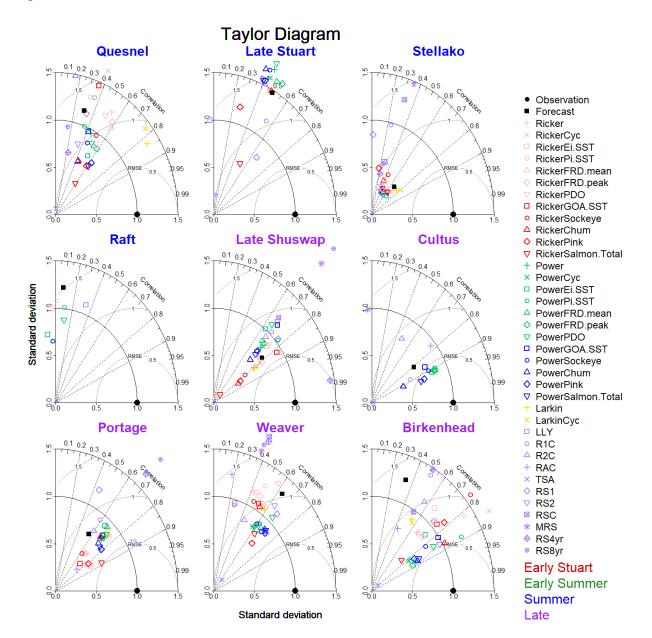


Figure 5b.



689 Figure 6.

