Assessing the Impacts of Environmental and Ecological Factors on the Performance of Fraser Sockeye Salmon Forecasts

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Keywords: pre-season forecast, salmon abundance, *Oncorhynchus nerka*, Taylor diagram

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. The management of these sockeye salmon fisheries relies on annual pre-season forecast of sockeye adult return. In this study, we developed a novel framework of easy use and good visualization for fisheries managers or other stakeholders 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 (e.g., sea surface temperature in the Gulf of Alaska, annual abundance of adult Pink, Chum, and other Sockeye salmon stocks, and all three species combined) into the existing forecast models. Results revealed clear patterns of good performances by either Ricker or Power models coupled with the newly included covariates. Taylor diagrams showed that the models selected a decade ago based on data from an earlier period (1997-2004) underperformed compared to those selected based on our retrospective analysis for the period of 2009 to 2020. We advocate that all potential forecast models need to be continuously evaluated in the face of increasing environmental change, new models able to deal with non-stationary relationships between environment and sockeye dynamics are to be developed and consistently evaluated, and environmental and ecological factors that impact the performance of Fraser sockeye salmon forecasts should be assessed.

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; Grant et al., 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 (www.psc.org/publications/pacific-salmon-treaty/). Pof Fraser sockeye return 9DFO Additionally, pre-season forecast helps with international total catch allowance negotiation, escapement surveys, and hatchery enhancement experiments (Hawkshaw et al., 2020a, 2020b).

Despite the tremendous importance of pre-season Fraser sockeye forecast, or any fishery population forecast for that matter, rigorous evaluation of forecast performance both in terms of accuracy and precision has rarely been done (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 (with a dominant year preceded and followed by a few years of low return) among some large populations, but also unpredictable productivity at different life stages in both freshwater and marine environment (Ricker, 1997; Akenhead et al., 2016; Huang et al., 2021), which has made pre-season forecast of sockeye salmon return challenging.

In particular, confidence in pre-season forecasts of Fraser sockeye return has eroded among 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, or increased conservation concerns. Therefore, there is a great need to improve our forecasting ability for Fraser sockeye salmon 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 salmon 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, 2020b). Sockeye forecast models are primarily based on relationships between spawners and subsequent recruitment, i.e., stock-recruitment relationships. More advanced forecast methods incorporate Bayesian statistical approach into the stock-recruitment relationship to assess uncertainty associated with abundance estimates (Cass et al., 2006; Grant et al. 2012; Akenhead et al., 2016). A wide variety of forecast models are typically available at a stock level (management unit) for Fraser sockeye from non-parametric models using adult recruits only to complex stock-recruitment models that include environmental variables (Cass et al., 2006; Grant et al., 2011). Model selection 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 salmon has generally declined with several populations being listed as endangered (i.e., COSEWIC 2017). Although the previously identified top-ranked models of Grant et al. (2011) have been continuously used in pre-season forecasts, their explanatory power has been low (Akenhead et al. 2016; DFO, 2020). 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, wedframework that can be used by fisheries managers or other stakeholders easily with good visualization and on an annual basis whenevaluating pre-season forecast models and identifying 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 (*R*), normalized standard deviation (*SD*) 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 for ocean circulation ([Lamine et al, 2022](https://www.nature.com/articles/s41598-022-14151-8" \o "https://www.nature.com/articles/s41598-022-14151-8" \t "_blank)), satellite derived chlorophyll measurement ([Lee et al., 2015](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015JC011018" \o "https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015JC011018" \t "_blank)), biogeochemical models ([Salihoglu et al., 2017](https://www.frontiersin.org/articles/10.3389/fmars.2017.00339/full" \o "https://www.frontiersin.org/articles/10.3389/fmars.2017.00339/full" \t "_blank)), and stock assessment and population dynamics models on tuna species ([Kell et al., 2016](https://www.sciencedirect.com/science/article/pii/S0165783616301540" \o "https://www.sciencedirect.com/science/article/pii/S0165783616301540" \t "_blank); [Senina et al., 2019](https://cdnsciencepub.com/doi/full/10.1139/cjfas-2018-0470" \o "https://cdnsciencepub.com/doi/full/10.1139/cjfas-2018-0470" \t "_blank)). The framework developed through this study can then be directly implemented in the process of Fraser sockeye forecasts so as to improve the performance of sockeye forecast and assist fisheries management planning.

**2 Data and Methods**

**2.1 Fraser sockeye salmon spawner and recruit data**

**data**

In this study, we used the same Fraser sockeye salmon spawner and recruitment data that were approved for the 2022 pre-season forecast (DFO in press). The spawner data were collected by DFO since 1938 (Grant et al., 2011), and the recruitment data were collected by Pacific Salmon Commission with details on data quality being available in Ogden et al. (2015). We compiled data of spawners and recruits for 18 major sockeye salmon stocks within the Fraser watershed (Figure 1). Based on shared timing of returning to Fraser River, the stocks were aggregated into four management aggregates: Early Stuart, Early Summer, Summer, and Late Run. In this study, we focused on ‘lake-type’ sockeye, which typically spend two years in a nursery lake before migrating seaward, and return to their natal rivers at age 4 or 5. Harrison River sockeye stock, typically contributing a small proportion to the total Fraser sockeye returns (average of 3% during 1948-2022), was excluded from our analysis because of its different life-history, rearing in freshwater for one year prior to moving downstream to the estuary (without lacustrine parr). Spawners were limited to females (also called effective female spawner) extending up to the 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 (the actual return year of 2021). For Cultus, 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. The overall age composition of Fraser sockeye was typically dominated by age 4. We assumed that age composition of adults generally followed a similar pattern among brood years around historical average. Ten of the 18 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 2019; DFO 2020; DFO 2021).

**2. 2 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, Zhang et al. 1997; 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 Hawkshaw et al., 2020a, 2020b). 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 (Mueter et al. 2002; Cass et al. 2006).

Exploration of new biological and environmental covariates that may explain the inter-annual variability in Fraser Sockeye recruitment has long been suggested (Grant et al. 2010; MacDonald and Grant 2012; DFO 2015; Hawkshaw et al. 2021). Recent analyses found that survival of Fraser sockeye salmon exhibits a similar temporal pattern among all stocks, indicating that Fraser sockeye stocks may be related to oceanic environmental conditions and competition among Pacific salmon at a global scale (Akenhead et al. 2016; Connors et al. 2020; DFO 2021; Ruggerone et al. 2021; Rosengard et al. 2022). 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 Fraser sockeye survival among all 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 ; 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 salmon stocks, and all three species combined(Salmon.Total) from 1950-2020 (brood year 1948-2018) (Ruggerone and Irvine 2018; Ruggerone et al. 2021). Altogether, 10 covariates (six environmental and four ecological data) were included in the pre-season forecast models (Figure 2).

**2.3 Forecast models**

In previous pre-season forecasts of Fraser sockeye salmon abundance, both non-parametric ‘naïve’ models (i.e., models using recent and historical adult recruits only without considering spawners) and biological models with the stock-recruitment relationships of Ricker, Power, Larkin, and Sibling have been commonly adopted (e.g., Cass et al. 2006; Grant and MacDonald 2010; Grant et al., 2011; Hawkshaw et al., 2020a, 2020b). In addition to the previously adopted models, in this study, we specifically explored a set of models composed of either Ricker or Power model and each of the 10 covariates. Equations and model descriptions of all 11 naïve, 7 biological, and 20 coupled models (Ricker or Power coupled with each of the 10 covariate) are listed in Table S1. The biological models of Ricker, Power, and Larkin have also been applied to data of dominant years only, forming a unique set of models (i.e., RickerCyc, PowerCyc, and LarkinCyc) (Table S1), in order to understand if the dominant year class was driven by different biological and environmental processes. Following previous forecasts (e.g., Cass et al., 2006; MacDonald and Grant, 2010; Grant et al., 2011; 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 evaluation of forecast error**

Previously, one-step-ahead retrospective analyses, i.e., carried out by leaving out 1 year’s data at a time, have been conducted for the period from 1997 to 2004 to evaluate the performances of various models (Grant et al., 2011). In this study, we conducted retrospective analyses for the period between 2009 and 2020 for 18 major stocks to evaluate all 37 pre-season forecast models. All the models were then ranked using each of these four performance measures related to forecast error: mean absolute error (*MAE*), root-mean-square error (*RMSE*), mean proportional error (*MPE*), and mean raw error (*MRE*). *MAE* is calculated as 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 precision: (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 ranking based on the overall rank to make comparison across stocks: Relative ranking = overall rank/number of models evaluated. We also provided relative ranking for *RMSE* only, as it has been commonly used by fisheries managers and other similar studies (Haeseker et al. 2008; [Ovando et al. 2022](https://cdnsciencepub.com/doi/full/10.1139/cjfas-2021-0287)).

**2.5 Visualization of model performance measures**

We used Taylor diagram as a visualization tool to guide the process of model selection both in terms of accuracy and precision. The Taylor diagram displays the degree of correspondence between the time series of forecast and observation via three statistics: the Pearson’s correlation coefficient (*R*), the *RMSE*, and the normalized standard deviation (*SD*). The for the years 2009 – 2020 ; the higher *R*, the greater accuracyThe The observed sockeye returns from 2009 2020 (about 3 cycles; Figure S2) were normalized as a reference point (i.e., observation). The overall performance of a model was expressed as a relative value 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 coefficient, small *RMSE*, and *SD* is desired. A perfect model is located at the reference point with both *R* and *SD* being 1 and RMSE being 0.

**3. Results**

**3.1 Forecast model comparisons**

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

Correlations between model forecasts and observations also tended to be lower for the naïve models; in particular, the LLY model resulted in generally low correlations across most stocks (Figure 4). However, there appears to have higher consistent correlations within the stocks (across all models) than across the stocks (using a same model) (Figure 4). This may indicate that model accuracy can be stock-dependent either related to data quality or specific stock dynamics. The stocks of Gates and Raft typically had low returns and observations tended to be less reliable due to the inaccurate survey methods applied (DFO, 2020). Therefore, the particularly low correlations for these two stocks across all models could be due to low data quality. Similarly, standard deviations also revealed disadvantage of the naïve models, tending to be farther away from one (Figure S4). Standard deviations 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 models on Taylor diagrams for the 18 Fraser sockeye stocks relative to the time series of observations from 2009 – 2020 (Figure 5a,b). As well, the time series of historically selected model forecasts for the years 2009 – 2020 were also presented relative to the observations (the solid square vs solid circle on the x-axis). In general, historical forecasts for the period from 2009 – 2020 performed poorly compared to observations. The 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 if we chose a good performing model consistently through the years, we would have more accurate forecasts compared to what had obtained using the forecast models historically chosen (Grant et al., 2011).

The Taylor diagram also revealed Power models coupled with new covariates (blue icons) generally outperformed other models in all three statistics with higher correlations, similar standard deviations to those in observations, and smaller RMSEs. The Power models with old covariates (green icons) were rarely used in the previous forecasts but they were as good as best models. Generally, Ricker models 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 none of the existing models seemed to have an accurate forecast (e.g., Gates and Raft), 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 forecasts were also conducted retrospectively from 2009 to 2020 for age-4 and age-5 sockeye salmon abundance. Age-specific Taylor diagrams presented all 37 forecast models relative to the historical forecasts (shown as the solid square) and observations (solid circle) for age 4 (Figure S5) and age 5 returns (Figure S6), respectively. The age-4 Taylor diagram showed similar results as total abundance (Figure 5a,b), which was due to the fact that age 4 was the dominant age class for most stocks. Power models with new covariates consistently outperformed 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 historically selected forecast model resulted in an error (defined as (observation-forecast)/forecast) of 192% (Table S2). However, using a best model identified through the Taylor diagram has substantially improved the forecast, reducing the error to 30% (Table S2), being the best over the past few years. This forecast was also within a reasonable range compared to other sockeye forecasts in nearby Rivers (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 close to observations (+5% Chilko, -7% Quesnel), and the forecast returns had less uncertainties (Figure 6). However, for Late Shuswap, where forecast was done by the historically selected model, observed return was -57% of the forecast with a difference of 1.9 million sockeye salmon. Had any of the best models been chosen based either on the overall ranking, correlation, *SD* or *RMSE*, the forecast would be more accurate for the Late Shuswap sockeye stock (Figure 6).

**4. Discussion**

Forecasting sockeye salmon 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, the forecast accuracy has become worse, frequently going below 10% of observations or 90% above observations (DFO, 2021). For example, in 2021, median forecast was 1.33 million while the return was 2.549 million, 92% above the observation (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, 2020b; DFO, 2022). 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, we for the first time 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 conclude 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 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., 2016; 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 (Connors et al. 2020; Ruggerone et al. 2021; Litz et al. 2021; Ruggerone and Connors, 2015). 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 salmon 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; Figure S1) indicated that Fraser sockeye distributed widely in North Pacific, with one sockeye caught in the eastern hemisphere (176.2E). 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 top 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 (exactly equal to the observation), and the error for Fraser sockeye would have been reduced from -30 to -10% (Table S1). It is worth noting that the current GOA.SST map only represents part of northeastern Pacific (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 produced not only 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, Taylor diagram 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 forecast based on the historically selected forecast model was 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 (Figure S2). Forecasting for the dominant years was more challenging with usually less accurate forecasts 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 cycle years and plot cycle-specific Taylor diagrams to identify models specifically tailored to cycle years.

Currently, our framework allows us to select a model by visually looking at the models’ relative positions in Taylor diagram, which could be subjective. For example, a best RMSE model may not have best SD or best R or vice versa. In the future, we intend to automate this process by automatically calculating a single distance metric, similar to Mohn’s rho value (Mohn, 1999) and integrating this metric into the model selection process for coming up with the best machine-suggested models.

We currently only used 12 years’ retrospective results to draw the Taylor diagram. As time progresses, it will be interesting to examine how the relative positions of these models evolve over time. Theoretically, informative models will move closer to observations as more years of data becoming available. Models with false alarms will either wander around or move further away from observations. 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, Beverton-Holt, and Larkin, have been primarily employed in the past (Ricker, 1997; Beverton and Holt, 1957; Bradford et al., 2000; Maxwell et al., 2006; Grant et al., 2010; Akenhead, et al., 2016b). 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. Mueter et al., 2002; 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, 2019, 2020; Ma et al., 2021; Ohlberger et al., 2022). It has been advocated that new approaches capable of dealing with non-stationarity in the sockeye salmon dynamics should be explored (Peterman & Dorner 2012; Malick, 2020).

Machine learning models (Breiman, 2001), such as generalized additive models, boosted regression trees, random forest, and empirical dynamic models, 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 understanding the impacts of environmental and ecological factors on the performance of Fraser sockeye salmon forecasts.

Acknowledgements

The authors would like to thank all the staff from Fisheries and Oceans Canada who have collected Fraser salmon data in the past seven decades. Added more people here, will reword: from Data Contributors • Fisheries Data: Steve Latham, Tracy Cone, Scott Decker, Tanya Vivian, Paul Welch, Stu LaPage, Brian Leaf, Lucas Pon, Jennifer Lynne, Doug Lofthouse, Angus Straight, Catharina De Monye, Mary Beth Fagan, Catherine McClean, Maxine Forest • Env Data: David Patterson, Peter Chandler, Nate Mantua, Roy Hourston, Jackie King, Michael Malick, Sarah Rosengard, Gregory Ruggerone, Jim Irvine, Strahan Tucker • Model Contributors • Catherine Michielsens, Gottfried Pestal, Jin Gao, Mike Hawkshaw, Brooke Davis, Bronwyn MacDonald Sue Grant • HR, admin, financial & others support • Timber Whitehouse, Jamie Scroggie, Karen Richards, Judy Munsell, Matthew Townsend, Matthew Parslow, Serena Wong, Taren Bell, Loraine Roper, Emily Breiteneder, Nicole Porteous, Les Jantz, Fiona Martens, Stacey Hobson, Dennis Klassen, Nancy Louie, Merran Hague, Mickey Agha • Les Jantz, Jamie Scroggie, Gordon Rose, Mike Hawkshaw, Catherine Michielsens, Merran Hague, Mickey Agha, Michael Staley, Kelsey Campbell, Nicole Frederickson, Matt Mortimer, Scott Decker, Rice Robert, Amy Seiders, Madeline Thomson, Maxime Veilleux, Serena Wong, Jin Gao

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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/##.####/cjfas-2023-####.

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