Improving Preseason Forecasts with Artificial Intelligence Methods and Ecosystem Information

BBRSDA PROJECT SUMMARY REPORT
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Personnel:

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Project Introduction and Description

Modern computational tools such as *Machine Learning* have transformed predictive fields from advertising to weather forecasting. However, these methods are underutilized for managing ecological systems. Salmon are a natural, cultural, and economic keystone of Alaska, and accurate preseason forecasts of numbers of sockeye salmon, that will return to river systems of Bristol Bay play an important role in management and harvesting decisions. Errors in Bristol Bay preseason forecasts result in increased *risk* and *costs* for fishers, processors and managers, and increase the potential for *forgone yield*. Despite the importance of accurate forecasts, there has been little effort beyond what UW-FRI has invested in using emerging quantitative methods for improving forecasts. UW-FRI and ADF&G preseason forecasts have traditionally relied on relationships between age classes within a river system to predict future run size (e.g. the number of 2-ocean salmon are used to predict the number of 3-ocean salmon that will return the next year within a river system, based on long-term averages). This method has proven informative and surprisingly effective as the abundance of the younger salmon is a proxy for early marine survival for the older components of the return from a brood year, and thus provides information about unobserved year-to-year variation in survival.

However, these “traditional” forecast models have exhibited poorer performance in some recent years, suggesting they are becoming less useful under changing climate conditions or as a result of changes in sockeye life history (e.g. changing maturation schedule) or marine survival. This project evaluated the ability of different forms of modern statistical methods, including some machine learning methods from the field of artificial intelligence, to improve the accuracy of pre-season forecasts of Bristol Bay sockeye salmon using a range of ecosystem information.

The traditional methods used in the UW-FRI and ADF&G forecasts are based on "sibling" or cohort regression models. As part of this project, we used various machine-learning methods to explore how information on historic Bristol Bay sockeye return numbers across many different age classes and systems at once, together with data on environmental factors such as sea-surface temperature and abundance of other salmon species during a cohort's ocean phase, could improve pre-season forecast accuracy at the system, age-group, and Bay-wide level. Likewise, we explored the extent to which allowing changes in relationships among age classes over time could improve predictive performance.

Summary of Project Outcomes & Accomplishments

We tested eight different types of forecast models (*Table 1*) and simulated the forecast that each model would have produced for each year from 2000 to 2019, if the model was only provided with data from the years leading up to each forecast year.

Table 1. *Forecast models, including machine learning approaches, tested against traditional cohort regression models historically used for preseason Bristol Bay sockeye predictions.*

Model Name	Model ID	Description
1 - Boosted Regression Trees	boost_tree	Machine learning model that uses an ensemble of decision tree algorithms and utilizes resampling of the prediction data to create alternative regression trees and predictions, weighting each estimate proportional to predictive performance.
2 - Random Forest	rand_forest	Machine learning model that uses regression tree decision rules to generate predcitions for run size from average of ensemble regression trees.
3 - Recurrent Neural Network	rnn	Machine learning model that uses a memeory componenet implemented through recurrent layers that train neural networks to generate predictions based on trends and interactions between returns of different age classes.
4 - Dynamic Linear Model	dlm	State-space model that is similar to the traditional cohort (sibling) regression model, but allows both the intercept (average run size) and slope (number of older age class returning per individual of the younger age class) to change over time. The dynamic nature of this model allows both the average expected productivity and maturation schedule of a stock to change over time.
5 - Simplex	simplex	Empirical Dynamic Modelling simplex project algorithm, simplex projection builds forecast based on relationships between lagged sockeye returns.
6 - S-map	s-map	Sequentially locally weighted global linear maps that builds forecast based on relationships between lagged sockeye returns.
7 - Lag-1	lag	Forecast next year equal to observed returns prior year.
8 - Ensemble	esb	Machine learning approach that uses a boosted regression tree ensemble made of other candidate models.

In this way, we quantified model performance by replaying history and providing only what information would have been available during each fall forecast season to each model and comparing the accuracy of resulting predictions. For each river system we then selected the model that had the lowest pre-season forecast error from 2000 to 2019, and compared it to different benchmark forecasts, including the UW-FRI forecast released in each year.

Using combinations of models along with different kinds of ecosystem information provided meaningful improvements in forecast accuracy at the system, age group, and total return level. On average using the best-performing method in each river system reduced the error in pre-season run forecasts by 17%, with a minimum improvement of 6% (Nushagak) and a maximum of 28% (Kvichak), relative to the performance of the historic published pre-season forecasts (*Figure 1*).

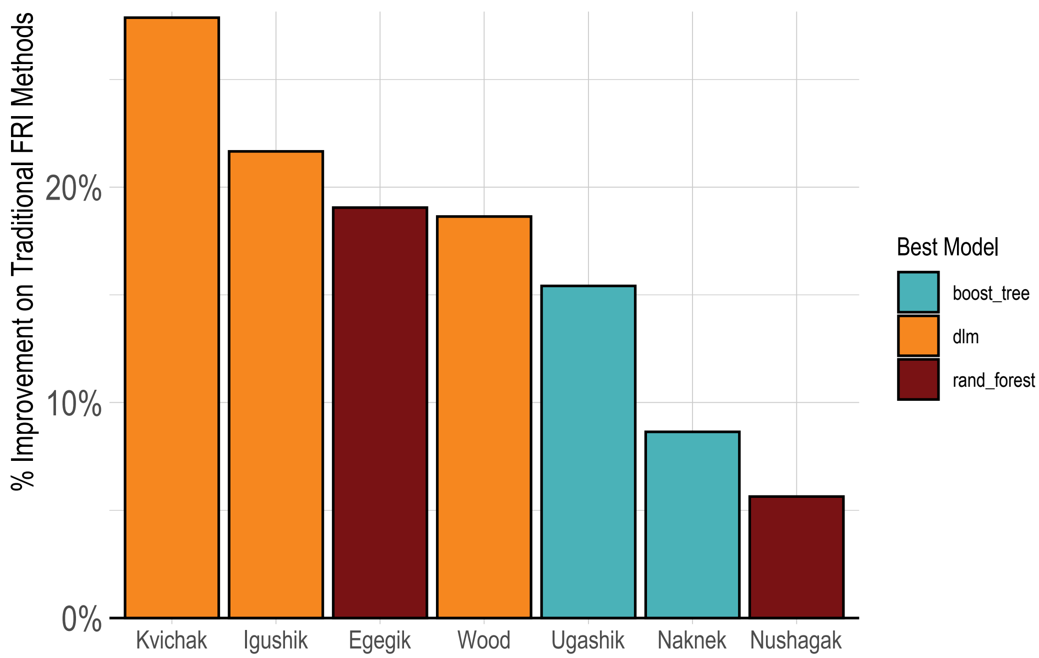

Figure 1. *Percent improvement in pre-season forecast accuracy of best-performing model (color) at the river system level, relative to the traditional UW-FRI pre-season forecast. Model abbreviations are as follows: "dlm" for Dynamic Linear Model, "boost_tree" for a Boosted Regression Tree model, and "rand_forest" for a Random Forest model.*

The extremely large Bristol Bay sockeye runs of the last few years are partly due to a large increase in the numbers of 1.2 fish in five systems including the Wood, Naknek, Egegik, and Ugashik rivers. Traditional sibling-based methods can struggle with predicting returns of younger fish such as the 1.2 age group, since the model has little data on the return abundance of younger age classes from that cohort (i.e. only 1.1's) on which to base a forecast. However, partly through inclusion of ecosystem data one of our machine learning methods was able to improve the forecast accuracy of the 1.2 age group by over 25%. However, none of our evaluated methods was able to improve on the traditional UW-FRI forecast for the 1.3 age group annually (*Figure 2*). Due in part to improved forecast of the 1.2 age group our best-performing machine-learning model for total returns was able to predict the persistently high returns from 2017 to 2019 reasonably well (*Figure 3*), and forecasted another year of more than 50 million returning sockeye salmon for 2020 (*Table 2*).

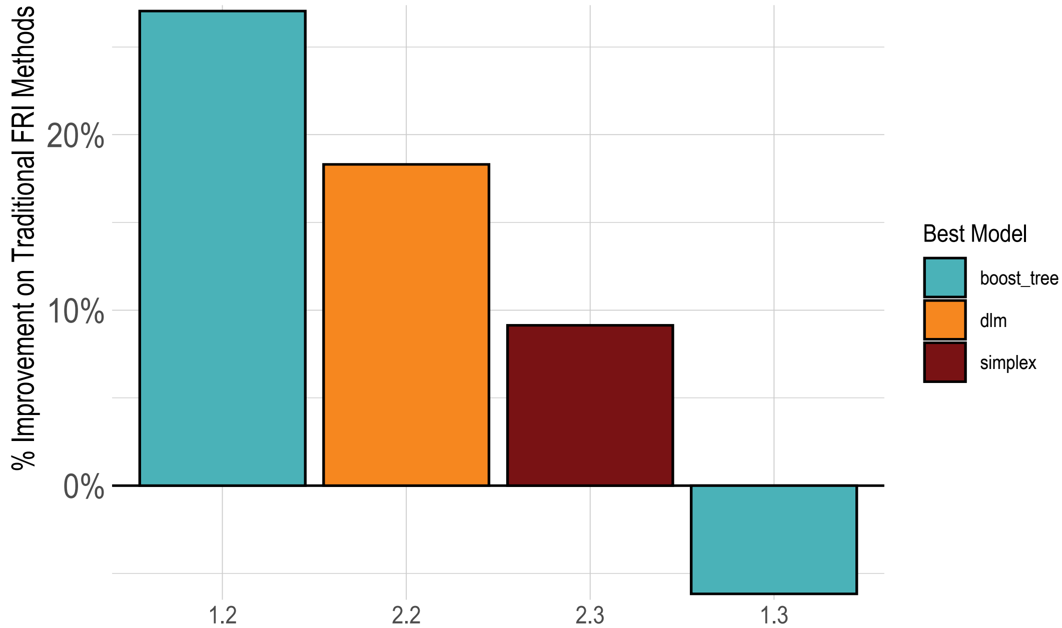

Figure 2. *Percent improvement in pre-season forecast accuracy of best-performing model (color) at the age group level, relative to the traditional UW-FRI pre-season forecast. Model abbreviations are as follows: "boost_tree" for a Boosted Regression Tree model, "dlm" for Dynamic Linear Model, and "simplex" for the Empirical Dynamic Modelling simplex project algorithm.*

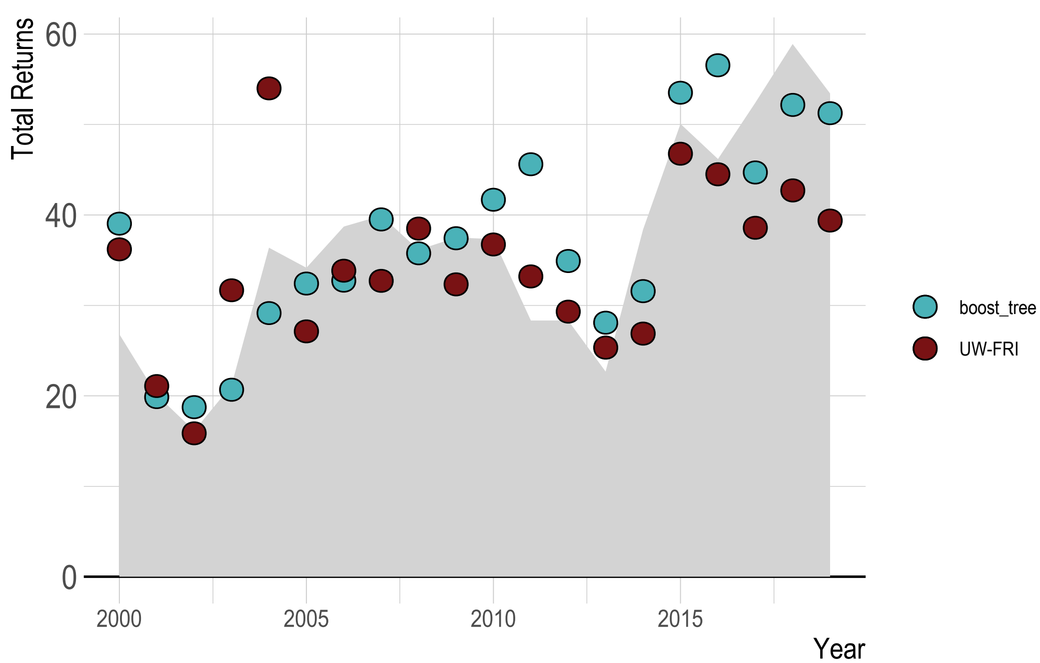

Figure 3. *Total returns (catch + escapement) of sockeye salmon across Bristol Bay (grey shaded area) and forecast by machine learning method (boost_tree) and the UW-FRI forecast from 2000 to 2019.*

Table 2. *Forecasted returns (millions of sockeye) by age group and river system for 2020 by best performing (at the river system and age group level) machine learning model.*

	Age Group				
	1.2	1.3	2.2	2.3	Totals
2020					
Egegik	6.05	2.10	2.67	1.23	**12.05**
Igushik	0.52	0.96	0.02	0.01	**1.51**
Kvichak	4.57	2.46	0.97	0.27	**8.27**
Naknek	3.48	2.80	0.38	0.50	**7.17**
Nushagak	1.03	3.91	0.10	0.06	**5.11**
Ugashik	2.47	1.73	0.37	0.14	**4.72**
Wood	10.04	3.07	0.18	0.03	**13.33**
Totals	**28.17**	**17.04**	**4.69**	**2.25**	**52.15**

Lessons Learned

- Machine learning methods, a type of artificial intelligence, can improve pre-season forecasts of Bristol Bay sockeye salmon.
  - This was partly due to inclusion of ecosystem information and allowing for changes in sibling relationship over time (Dynamic Linear Models) likely resulting from changing maturation schedules and marine mortality.
- No one model was able to perform well across all systems and age classes.
  - Instead, just as the UW-FRI forecast has always done, we need to consider what model is best to use in specific situations. But, adding the models we have developed to the list stands to make meaningful improvements (*Figure 4 on following page*).

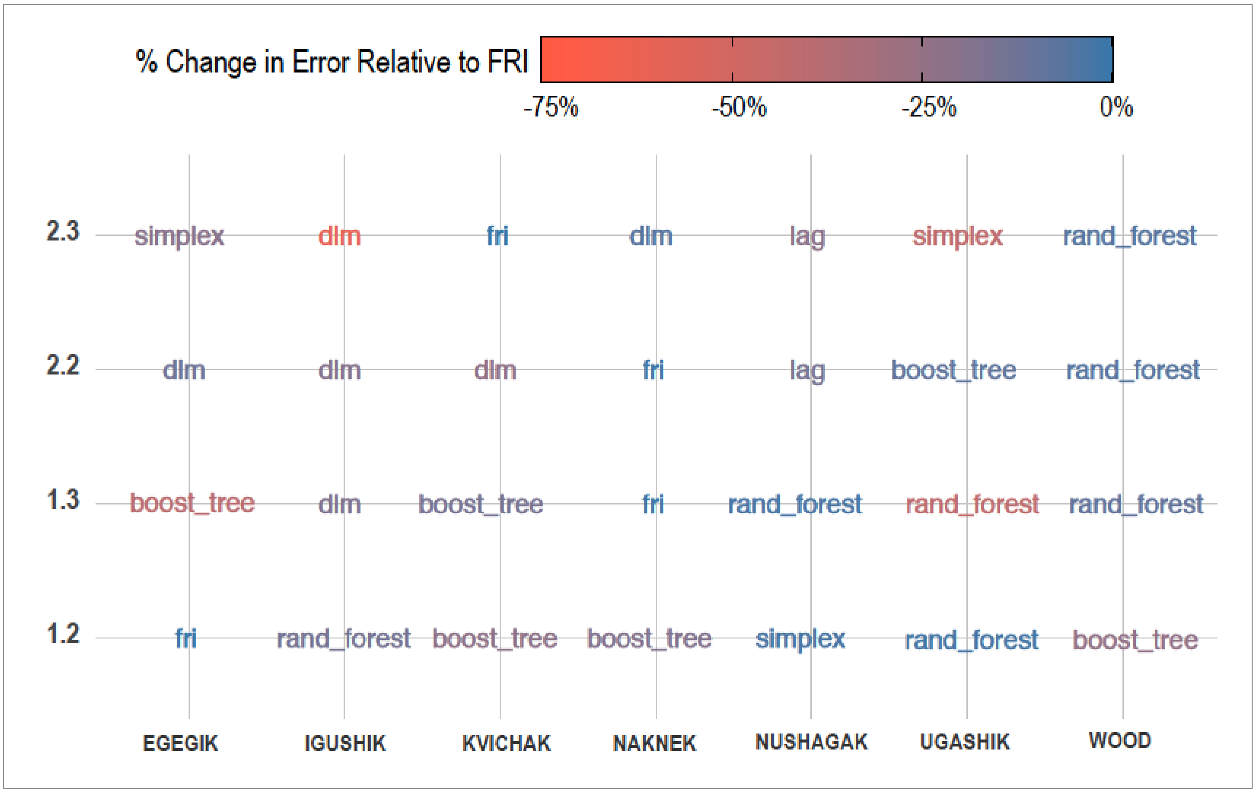

Figure 4. *Text within body of the table indicate best performing model 2000-2019 by age class (vertical axis) and river system (horizontal axis). Color is proportional to how much the best performing model generated a more accurate prediction than the traditional FRI model, with blue meaning the tested model performed as well as traditional FRI model. Cases where* **fri** *is listed as the best model means that the traditional FRI model outperformed all the new models tested. Model abbreviations are as follows: "rand_forest" for a Random Forest model, "boost_tree" for a Boosted Regression Tree model, "simplex" for the Empirical Dynamic Modelling simplex project algorithm, "lag" for Lag-1 model, and "dlm" for Dynamic Linear Model.*

Challenges

- While we are able to improve pre-season forecasts in many cases, none of our models were able to successfully predict returns in some systems and age groups in particular years, such as the Wood river system in 2018.
    - The fact that all of our models struggled in the same year suggests there was some common difference in the ecosystem, data, or run reconstruction process that caused a similar bias in all models explored.
    - This also tells us that we simply need to collect additional data if we want to try and understand what drivers contribute to sudden spikes in returns such as those observed in the Wood river system in recent years.

List of Deliverables

- Development and implementation of several classes of Dynamic and Machine Learning models for Bristol Bay preseason forecasting.

- Housing of all analysis code and project results in a publicly-available Github repository (https://github.com/DanOvando/salmon-forecast-paper).
- Direct comparison of model performance and improvement relative to traditional preseason forecast methods.