

**FISHERIES** 

Modeling the effect of climate on recruitment within single-species assessment models, with implications for management for eastern Bering Sea walleye pollock

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# Introduction

### **Results and Discussion**

The CE-SSM and the status quo model each produced similar estimates of recruitment and spawning stock biomass, and recruitment curves. This is due to large amount of age composition data that dominate the recruitment estimates relative to the predictions from the fitted recruitment model.

Higher temperatures results in reduced recruitment and productivity (i.e., *R/SSB*) (**Figure 1**). For example, increases of 1 °C and 2 °C would lower recruitment for any given stock biomass by 12.6% and 30.9%, respectively, and average to low recruitment occurred in years with high SSTs (**Figure 2**).

Incorporation of environmental variables into existing population models used for resource management (i.e., climateenhanced single-species fishery stock assessment models, CE-SSMs) is an important component of the Alaska Climate Integrated Modeling Project (ACLIM), and CE-SSMs are a direct pathway for adapting existing fishery management tools for projected climate change. However, formal model selection techniques are often not applied when considering whether to accept CE-SSMs or the simpler status quo model. Although Bayesian methods are often used in stock assessments, there is no clear preferred Bayesian model selection procedure among the many alternatives. The purpose of this study to evaluate a CE-SSM for eastern Bering Sea (EBS) walleye pollock (*Gadus chalcogrammus*) using posterior distributions and two common Bayesian model selection techniques, and consider the implications for management.

# Methods

### **Climate-enhanced spawner-recruit function**

The time series of recruitment was estimated within the assessment model as a vector of parameters. An estimated recruitment curve was fit within the model to these recruitment estimates, and in the CE-SSM this curve was a modified Ricker model incorporating summer sea surface temperature (*SST*):

 $R_t = f(SSB_{t-a})e^{\alpha + x_1SST_{t-a} + x_2SST_{t-a}^2}e^{\varepsilon_{t-a}} \quad \text{Eq. 1}$ 

where *R* is recruitment, *a* is age of recruitment, *f(SSB)* is the Ricker stock recruitment curve as a function of spawning stock biomass (*SSB*),  $\varepsilon$  is random error, and  $x_1$  and  $x_2$  are linear and quadratic coefficients for the temperature-recruitment relationship. The constant term  $\alpha$  is a function of  $x_1$  and  $x_2$  and ensures that the expected value of the temperature relationship (i.e., the term in red in Eq. 1) is 1 over the observed data. Summer sea surface temperatures were obtained from highresolution Regional Ocean Modelling System (ROMS) model (Kearney et al 2020). Warmer summer temperatures are thought to decrease the availability of zooplankton prey and overwinter survival. Markov Chain Monte-Carlo (MCMC) integration was used to generate posterior distributions of parameters, and posterior predictions of data and their probability densities.

### **Bayesian model selection methods**

Two Bayesian model selection techniques were applied, each of which considers the ability of the model to predict new data:

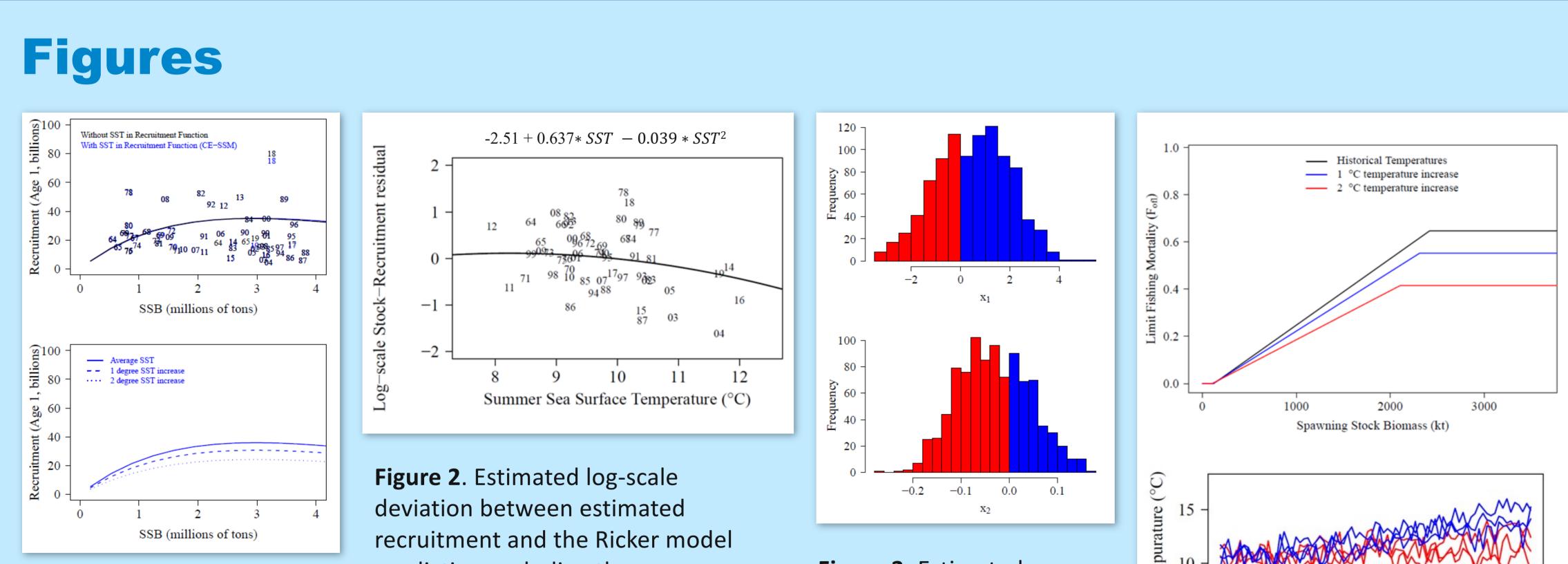
The estimates of PPL and WAIC were very similar between the models:

	Model	
	Status quo	Climate-Enhanced
PPL	120.2	120.2
WAIC	2826.6	2827.2

This illustrates a complication with applying these Bayesian model selection procedures to complex models in which estimated quantities (i,e. recruitment) are modeled with multiple processes (i.e., the stockrecruitment curve, and time series of estimated recruitments). However, posterior distributions of the estimated parameters  $x_1$  and  $x_2$  can be used for model evaluation. Values of  $x_1$  and  $x_2$  of zero suggest no temperature effect, and lower negative values of  $x_2$  result in stronger reductions in recruitment at higher temperatures. Posterior distributions indicate that 61% of the distribution of  $x_1$  is above zero, and 65% of the distribution of  $x_2$  is below zero (Figure 3). Increased temperatures and reduced (*R/SSB*) result in reduced fishing rates and more conservative harvest control rules (Figure 4, top). Projections from climate models indicate that the summer SST in the eastern Bering Sea is expected to increase (Figure 4, bottom).

Watanabe Akaike Information Criterion (WAIC): Uses observed data to estimate predictive ability, and asymptotically approximates leave-one-out cross validation.

*Posterior Predictive Loss* (PPL): A decision-theoretic method in which a loss is a function of the ability to fit hypothetical replicates of the data (i.e., posterior predictive distributions).



## **Conclusions and Future Research**

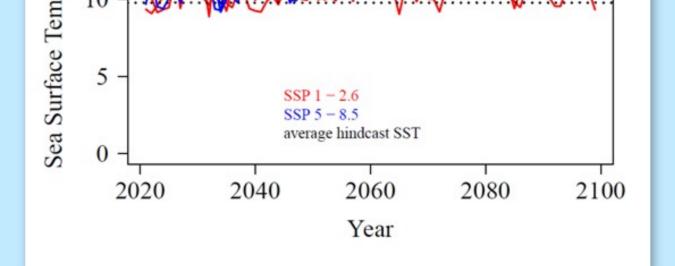
The complexity of modeling recruitment in data-rich single-species models complicates application of Bayesian model selection procedures. However, other information such as posterior distributions of key parameters can inform model selection.

Figure 1. Estimated SSB and recruitment with fitted spawner recruit curves (top panel, labeled by year class), and estimated spawnerrecruit curves with increases in SST (bottom panel). The CE-SSM in the top panel has the quadratic temperature multiplier in Eq. 1 set to its

expected value of 1.

prediction excluding the temperature effect (labeled by year and scaled to mean of zero), and fitted curve from the temperaturerecruitment relationship.

**Figure 3.** Estimated posterior distributions of parameters  $x_1$  and  $x_2$  of the temperature-recruitment relationship.



**Figure 4**. Estimated harvest control rules, which specify limit fishing mortality rates and are a function of the estimated spawner-recruit relationship (top panel).Projected sea surface temperatures under two Shared Socioeconomic Pathways (SSP) representing low (SSP 5 – 8.5) and high (SSP 1 – 2.6) carbon mitigation scenarios (bottom panel). With each SSP, projections from three climate models are shown. The reductions in productivity implied by warming temperatures would result in reductions in recommended fishing rates. Future work will included projections of future stock dynamics and yield under various static and dynamic harvest control rules and incorporating the estimated temperature-recruitment relationship and its estimated uncertainty.

#### References

Kearney, K., A. Hermann, W. Cheng, I. Ortiz, and K. Aydin. 2020. A coupled pelagicbenthicsympagic biogeochemical model for the Bering Sea: documentation and validation of the BESTNPZ model (v2019.08.23) within a high-resolution regional ocean model. Geoscientific Model Development 13:597–650. doi:10.5194/gmd-13-597-2020

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