The walleye pollock fishery in Alaska is the largest in the United States by volume and generated a wholesale gross value of $1.4 billion in 2008 (2). Chinook salmon are classified as a prohibited species catch in this fishery, meaning their incidental capture is strictly regulated (1). In response to record high bycatch in 2007, Amendment 91 established a hard cap of 60,000 Chinook salmon for the entire fishery, divided by sector and season (A and B), with the consequence that exceeding this limit results in a complete fishery closure. Additionally, a performance limit of 47,591 salmon is allocated across seasons and sectors, with a rule that if any sector exceeds its share in three out of seven consecutive years, it is permanently restricted to that limit (2). This approach balanced the need to incentivize bycatch reduction while accounting for natural variability in salmon encounters. However, while the bycatch in the fisheries was reduced, in response to low Chinook abundance Amendment 110 was introduced to add an adaptive mechanism where the performance limit is further reduced during periods of low salmon abundance based on an established index (1). To enforce these rules, 100% observer coverage is mandated on all vessels within the pollock fishery, ensuring compliance and accurate monitoring of bycatch levels (1).

Efforts to reduce Chinook salmon bycatch in the pollock fishery employ a variety of strategies, including fixed closure areas, short-term closures in high-bycatch zones, and salmon bycatch excluders in trawl nets (1). While these measures have contributed to bycatch reduction, they can also have unintended commercial and ecological consequences. For example, time-area closures designed to protect one species may concentrate fishing effort elsewhere, potentially impacting other species (4), and they often restrict fishing in areas where bycatch risk is low, as they are typically based on historical rather than real-time data (3). In contrast, dynamic ocean management leverages eco-informatics and near real-time data streams to support adaptive fishing practices, allowing for a more responsive and precise approach to bycatch mitigation (3). This strategy aligns with industry experience, which has shown that cooperative data-sharing is a highly effective method for reducing salmon bycatch (1). To this end, providing the industry with models that incorporate environmental covariates to predict species distribution across longitude, latitude, and depth would offer a valuable resource for further refining bycatch avoidance strategies.

Depth is of particular interest as Chinook salmon and walleye pollock occupy overlapping ranges. Pollock are found from the seafloor to midwater and near-surface depths, with most catches occurring between 50 and 300 meters using pelagic trawls (5). This aligns with the 0–500 meter range observed for Chinook salmon in tagging studies (6), highlighting a key factor driving bycatch. However, models of salmon occupancy patterns that can take into account real-time environmental conditions could help fishers refine their operations, allowing them to target specific depths where bycatch risk is lower.

While several studies have examined depth occupancy in Chinook salmon, they have primarily focused on understanding the factors influencing depth use rather than developing inferential tools for prediction (7). Machine learning has also been applied, but mainly to analyze how environmental covariates influence depth occupancy, rather than generating practical predictive models (7). Given that fish behavior in response to environmental factors is inherently stochastic, an effective model would not aim to pinpoint exact depths, but rather estimate the likelihood of salmon occupying different depth ranges within the water column. Framed in this way, the problem becomes an ideal application for a probabilistic deep learning classifier, capable of modeling uncertainty and providing flexible, data-driven depth distribution predictions.

The goal of this study is to develop a probabilistic deep learning classifier capable of predicting Chinook salmon depth occupancy in near-real time. To achieve this, we will first identify key environmental covariates from existing literature that can be measured or predicted and then use pop-up satellite archival tagging data from Chinook salmon in the Gulf of Alaska (7) to build and evaluate the model. This approach aims to provide a practical, data-driven tool for improving bycatch mitigation strategies in the pollock fishery.

1. Bering Sea Salmon Bycatch Update

2. Fisheries of the Exclusive Economic Zone Off Alaska; Chinook Salmon Bycatch Management in the Bering Sea Pollock Fishery

3. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries

4. What are we protecting? Fisher behavior and the unintended consequences of spatial closures as a fishery management tool

5. https://www.adfg.alaska.gov/index.cfm?adfg=walleyepollock.printerfriendly

6. Behavior and thermal environment of Chinook salmon Oncorhynchus tshawytscha in the North Pacific Ocean, elucidated from pop-up satellite archival tags

7. Chinook salmon depth distributions on the continental shelf are shaped by interactions between location, season, and individual condition