Bycatch — the capture of non-target organisms — is a persistent issue in many fisheries (Davies, 2009; Hall, 2000). While it first gained public attention through incidental take of charismatic megafauna (Hall, 2000), subsequent research has illuminated a range of concerns. These include the waste of edible protein (Hall, 2000; Zeller., 2018), conflicts between fisheries targeting different species (Lomeli, 2021; NPFMC, 2022), increased extinction risk for vulnerable species (Wallace, 2013) (D’Agrosa, 2000), trophic disruption (Estes., 2011), and destabilization of population dynamics (Hall, 2000). As a result, considerable attention has been directed toward reducing bycatch.

Of particular concern in the state of Alaska is the incidental capture of Chinook salmon (*Oncorhynchus tshawytscha*) in the walleye pollock (*Gadus chalcogrammus*) fishery (NPFMC, 2022). The pollock fishery is the largest in the United States by volume (NPFMC, 2022). The retained 2020 pollock catch in just the Gulf of Alaska (GOA) totaled 107,000 metric tons and had a first wholesale value of $70.6 (Monnahan, 2021). Yet, regardless of the remaining allowable catch, the fishery is shut down if Chinook salmon bycatch allowances are exceeded (NPFMC, 2024). For the Gulf of Alaska these limits are set at 18,316 fish for the Central GOA and 6,684 for the Western GOA, (Amendment 93) with limited provisions for reallocation of unused PSC between sectors (Amendment 103) (NPFMC, 2024). With such limited allowances, bycatch avoidance has been an area of active development.

Of those developments, one of the most promising has been cooperative data-sharing amongst fishers (NPMFC, 2022). Through such programs fishers can dynamically adjust their response to bycatch risk based on up-to-date information shared through the whole fleet. This information is also used to setup short-term closures in high-bycatch zones (NPFMC, 2022) – yet another tool in the dynamic ocean management toolbox that draws its power from near real-time, local information on bycatch risk (Squires, 2021).

Adding information on depth occupancy to this toolbox could prove fruitful. Adult pollock are largely demersal (Adams, 2009) (Duffy-Anderson, 2003) whereas Chinook salmon are very active in the water column (Courtney, 2019, 2021) (Orsi, 1995). While Chinook salmon spend most of their time between 0 and 50 m their overall observed range extends beyond 500 m (Courtney, 2019, 2021). They also display flexible diel behaviors, sometimes reverse their movement patterns seasonally (Arostegui, 2017) (Courtney, 2019, 2021), and seem to vary their depth occupancy in relation to temperature, productivity indicators, and current velocity (Freshwater, 2024) (Orsi, 1995) (Hinke, 2005). In contrast, while pollock are known to exhibit diel patterns, (Adams, 2009) (Miyashita, 2004) the majority of adult pollock are primarily demersal – a pattern reinforced by the fact that the fishery targets them at or near the sea floor (Stratton, 2023). These differences suggest that bycatch risk could be further mitigated if localized and dynamic information on Chinook salmon depth occupancy was available.

A model capable of producing such information for Chinook salmon has not yet been built. Most studies on depth occupancy in Chinook salmon have focused on understanding the factors influencing depth (Cite this studies) as opposed to developing inferential tools for localized prediction (Freshwater, 2024). One exception was Freshwater et al., (2024) who trained a model that leveraged localized environmental and temporal covariates to predict expected depth. However, to assess risk in a specific depth range, a model needs to estimate the distribution of fish within the water column. Arostegui et al. (2017) did produce such a distributional model, but without features amenable to localized and dynamic predictions. Combining these two approaches remains an open opportunity for Chinook salmon.

Therefore, our goal is to build a Chinook salmon depth model capable of local prediction and show it can inform bycatch mitigation strategies. We will do this in three steps. First, we will build a model that leverages environmental and temporal context to predict the relative likelihood of depth-bin occupation throughout the water column. Second, we will evaluate the model’s predictions against observed depth occupancy and compare it to past research. Finally, we will generate a year's worth of predictions over the Gulf of Alaska and illustrate how those predictions can inform the selection of places and times where there is lower risk of Chinook occupancy near the sea floor.