**A Depth Model for Context Specific Assessment of Chinook Salmon Bycatch Risk**

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**Introduction**

Bycatch—the unintentional capture of non-target organisms, including juvenile fish—is a persistent issue in many fisheries (Davies, 2009; Hall, 2000). While it first gained widespread public attention due to the incidental take of charismatic megafauna (Hall, 2000), subsequent research has illuminated a wide 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 such as sea turtles (Wallace, 2013) and cetaceans (D’Agrosa, 2000), trophic disruption through the removal of predators or prey (Estes., 2011), and broader destabilization of population dynamics (Hall, 2000). As a result, considerable attention has been directed toward reducing bycatch through both policy and innovation.

Mitigation strategies are highly context-dependent (Komoroske, 2015; Hall, 2000) and span a wide range of options (Squires, 2021). Regulatory approaches include time–area closures, limits on vessel size or trip length, and dynamic ocean management techniques that adjust spatial or temporal access in near real-time (Squires, 2021). These measures aim to reduce fishing effort in scenarios where bycatch is most likely or most harmful. At the other end of the spectrum are technological interventions that improve targeting without necessarily reducing effort such as the Nordmøre grids used in shrimp trawls (Graham, 2006) or salmon excluder devices used in the Alaska walleye pollock trawl fleet (NPFMC, 2022). Finally, there are process-based adaptations that seek to reduce bycatch through changes in fishing behavior. These can involve shifting the time of day that fishing occurs (Hall, 2000; Squires, 2021), using experience-based knowledge to avoid areas of high bycatch likelihood, or modifying gear deployment patterns to identify safer fishing zones before committing fully (Squires, 2021).

Several of these strategies are already at use in one of the most significant fisheries in Alaska – the walleye pollock (*Gadus chalcogrammus*) fishery (NPFMC, 2022). The walleye pollock fishery is the largest in the United States by volume (NPFMC, 2022) with the retained 2020 pollock catch in the GOA alone totaling 107,000 metric tons and valued at $70.6 million at first whole sale (Monnahan, 2021). Within this fishery, Chinook salmon (*Oncorhynchus tshawytscha)* are classified as a prohibited species catch (PSC), meaning their incidental capture is strictly regulated (NPFMC, 2022). Chinook 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). Once these limits are reached the fishery is shut down regardless of the remaining total allowable catch (NPFMC, 2024). To enforce these rules, 100% observer coverage is mandated on all vessels within the pollock fishery, ensuring compliance and accurate monitoring of bycatch levels (NPFMC, 2024).

Efforts to reduce Chinook salmon bycatch in the pollock fishery fall into several of the categories listed above, including fixed closure areas, short-term closures in high-bycatch zones, and salmon bycatch excluders in trawl nets (NPFMC, 2022). However, it has been shown that one of the more effective methods reducing salmon bycatch has been cooperative data-sharing amongst the fishers themselves (NPMFC, 2022). In line with this, providing the industry with models that incorporate the best scientific data on depth occupancy would offer another valuable resource for further refining bycatch avoidance strategies.

Depth here is selected as of particular interest as Chinook salmon and walleye pollock occupy overlapping ranges but do not necessarily use the water column in the same way. Pollock are found from the seafloor to midwater and near-surface depths, with most catches occurring between 50 and 300 meters using pelagic trawls (ADFG, 2025), a distribution which overlaps with the 0–500 meter range observed from Chinook salmon in tagging studies (Courtney, 2019). However, within these ranges both Pollock and Chinook show different and dynamic behaviors.

Beginning with pollock, depth occupancy seems to largely be a function of their seasonal migrations and place in the trophic web. There is clear age based stratification in the EBS where juveniles tend to remain above the thermocline (in part due to their broader thermal tolerance (Duffy-Anderson, 2003)) and adults tend to stay below – a partitioning strategy that seems to help avoid cannibalism (Schwartzman, 1994). Within the GOA however there is less year class based stratification as cannibalism is less of an issue (Adams, 2007). Furthermore, while Juveniles show marked daily vertical migration (DVM) patterns (Schwartzman, 1994) adult depth occupancy is more variable and influenced by metabolism, body condition, temperature, and food availability. While some studies have found little evidence of diel migration in adults (Schwartzman, 1994), others observed vertical movement tied to prey like euphausiids, particularly in spring and summer (Adams, 2007) (Bailey, 2000). In these seasons, adult pollock may rise to within 20 meters of the surface at night in the GOA whereas at other times, such as November, they remain at greater depths and seem to be relying on different prey (Adams, 2007). In general, adult pollock are known to occupy shallower waters just prior to and after spawning (Kooka, 1998) after which the fish will move offshore and into deeper waters (Kooka, 1998) (ADF&G, 2005). Schwartzman (1994) also found that larger biomass schools were associated with shallower waters (<120m) and that average school depth increased with bottom depth, suggesting a dynamic link between aggregation size, depth, and oceanography.

In contrast Chinook show markedly different patterns. First is the fact that Chinook tend to spend the majority of their time in the portion of the water column between 0 and 50m but can be found all the way up to depths exceeding 500m (Courtney, 2019, 2021). The are also exceptionally active and have been observed to spend less than 25% of their time at any single 5-meter depth increment (Orsi, 1995). Diel activity has also generally been observed in one form or another but there is significant variability amongst individual fish (Freshwater, 2024) (Arostegui, 2017). Unlike species exhibiting a classic diel vertical migration (DVM) pattern—ascending at night and descending during the day—Chinook salmon display more flexible diel behaviors, sometimes reversing their movement patterns seasonally (Arostegui, 2017). Response to bottom depth is another key driver, with salmon distribution often correlating strongly with bathymetry, though fine-scale topographic influences remain less well understood (Freshwater, 2024). Similarly, size and maturity play a role, with larger fish tending to be found at deeper depths (Freshwater, 2024). Less consistent patterns have also been reported between depth occupancy and temperature, productivity indicators, and current velocity as well as other temporal drivers like the lunar cycle (Freshwater, 2024) (Orsi, 1995). Productivity-related features, such as zooplankton concentration and chlorophyll-a levels, have been weakly predictive, with some studies suggesting indirect links—such as higher chlorophyll-a near the surface in spring coinciding with shallower salmon distributions, potentially due to increased prey availability or reduced predation risk from decreased water clarity (Freshwater, 2024).

Despite these differences Walleye pollock and Chinook salmon do share the fact that seasonality is one of the strongest predictors for their depth occupancy with both species tending to occupy shallower depths in the spring and progressively deeper waters in summer, fall, and winter (Freshwater, 2024) (Orsi, 1995) (Walker, 2007). However, there are still clear differences in the drivers for this behavior as pollock are driven by their spawning cycle (ADF&G, 2005) whereas Chinook salmon, being semelparous and anadromous, are being driven by other factors.

Given these behavioral differences, a model that can take current scientific data and provide context specific predictions of Chinook salmon depth occupancy would likely be a step forward in refining bycatch mitigation strategies.

The several studies that have examined depth occupancy in Chinook salmon have primarily focused on understanding the factors influencing depth use rather than developing inferential tools for prediction (Freshwater, 2024). Machine learning has also been applied, but mainly to analyze how environmental covariates influence depth occupancy, rather than generating practical predictive models (Freshwater, 2024). 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 - like an approach taken by (Arostegui, 2017). However, like (Freshwater, 2024) we would like to apply machine learning to generate more fine scale predictions as machine learning methods are well known for being to elucidate complex, non-linear patterns from given datasets.

Our goal, therefore, is to explore whether a model, whose predictions of depth occupancy can be tailored to specific places and times, can offer meaningful guidance for avoiding Chinook salmon to reduce their incidental capture. We will do this by: (1) building a deep learning model to estimate the likelihood of depth-bin use (given presence at that latitude and longitude) based on environmental and temporal covariates, (2) evaluating the model predictions against observed depth occupancy as well as past research, and (3) generating a year's worth of depth occupancy predictions in the GOA so as to illustrate, with a few specific examples, how those predictions can guide the selection of places and times where the likelihood of Chinook occupancy, by depth bin, is minimized.

**Methods**

**Data**

The data used was a series of tracks from 111 Chinook salmon (*Oncorhynchus tshawytscha*) caught and monitored between 2013 and 2022 (Seitz, 2023). Fish were caught and near Dutch Harbor, AK and Chignik, AK (n=31), Homer, AK (n=19), Kodiak, AK (n=14), Yakutat, AK (n=16), Sitka, AK (n=22), and the Eastern Bering Sea (n=9). In the EBS they were caught via midwater trawl or by hook and line with all other catches happening by hook and line (Seitz, 2023). Fork length varied from 62-100cm. The tracks were obtained using pop-up satellite archival tags which collect temperature, light level, and depth information at specified (sub day) intervals. While the data is sampled at a sub-minute interval the uploaded data is aggregated to a 15 minute period before being sent over the satellite link in order to conserve battery power. This data is then passed through a proprietary algorithm from Wildlife Computers to determine likely longitude and latitude during each day of monitoring (Wildlife Computers, 2025).

A few tags were recovered, giving access to the full frequency data streams and upon comparison with the aggregated data it was determined that the measurements uploaded only provide a sense of the central tendency of the fish during that time period. Therefore, so as to prevent over-representing the precision of the uploaded data we sampled depth measurements from a normal distribution centered at the uploaded depth and with a standard deviation of 10% of that uploaded depth. From there we assigned each measurement to a depth bin in increments of 25, 50, 75, 100, 150, 200, 250, 300, 400, and 500 meters where each bin indicates its upper bound and does not include depths from the bins at shallower depths. This left us with an assigned depth bin for every 15-minute interval during tag deployment for each of the 111 fish used in the study. Before inclusion in the model, these depth bins were normalized to a decimal between 0 and 1 with bin 25 corresponding to 0.1, 50 to 0.2, and so on.

Environmental data was derived from the Global Ocean Biogeochemistry Hindcast dataset (10.48670/moi-00019) and the Global Ocean Physics Reanalysis (10.48670/moi-00021) from the E.U. Copernicus Marine Service Information. Statistics were aggregated by taking the mean per Uber h3 resolution 4 cell, depth bin, and day in the Northern Pacific. Features pulled were chlorophyll, net primary production, nitrate, oxygen, phosphate, silicate, elevation, mixed layer thickness, salinity, temperature, and north and easterly current velocity. In the case of model training these were then joined to the fish tracks on location and time.

Before being used in the modeling, all environmental features were normalized by rescaling to be between 0 and 1 with chlorophyll, net primary production, and mixed layer thickness also being log scaled before rescaling to the [0, 1] interval.

Finally, we derived a series of temporal features representing seasonality, lunar cycle, and day/night cycle using the “ephem” and “suntimes” packages in Python. The former was used to compute day/night features and the latter to compute lunar cycle features. Time in all cases was represented by taking the cycle in question, decomposing it to radians (0 at the beginning of the cycle and at the end of the cycle), and then providing the sine and cosine of that feature to the models. As such we built a seasonal feature indicating the number of days through the year, a day night feature indicating how far through the diel cycle a sample was (cosines at 0 for sunrise and sunset, sines positive during the day and negative at night), and a final set of sines and cosines indicating progress through the lunar cycle. Given the range of sines and cosines are -1 to 1 no further normalization was needed.

**Models**

Given our desire to predict the likelihood of occupancy per depth bin at each time step given the features in our dataset, we decided to train a probabilistic deep learning model. Specifically, we decided to adopt a log-odds modeling approach (Gietzmann-Sanders, --) as the number of depth bins is not constant and the overall dimensionality of our space can get quite large.

Data was first divided into training and validation sets. Given the low number of individuals in the sample it was decided not to maintain a holdout test set. 72 individuals were randomly selected for training and 39 for validation.

As we have a relatively large number of decisions (up to ten) we applied contrast sampling to remove class imbalance from the output (Gietzmann-Sanders, --). In contrast sampling, instead of presenting the model with full decisions containing all 10 choices, we create training pairs, or contrasts, where each pair consists of one selected choice and one unselected choice. This reframing of the problem only works given the internal architecture of a log-odds model (Gietzmann-Sanders, --). In this example, after inspecting the distribution of number of choices per salmon and number of choices per decision, we decided on a random sample (with replacement) of 5,000 decisions per individual and 10 choices per decision. Over a validation/training split of 39, 72 this resulted in 5,550,000 contrasts of which 3,600,000 were used in training and the rest in validation.

We explored a wide variety of different hyperparameters including layer sizes, number of layers, batch size, and learning rate but for the models presented in this paper the hyperparameters of the internal log-odds component of the model were parametrized as described in Table 1.

|  |  |
| --- | --- |
| Component | Options |
| Layers | 2, 3 |
| Units per Layer | 24, 32 |
| Batch Size | 200,000 |
| Learning Rate | 0.001 |

**Table 1: Hyperparameters**

The hyperparameter grid searched during model tuning.

We searched the hyperparmeters space with a grid search used 6 separate seeds for each combination of hyperparameters. Models were trained in Keras using an Adam optimizer for 75 epochs. Categorical cross entropy was used as the loss function. Training was done on AWS Batch using Fargate instances of 2 vcpu's and 4 GB of memory.

After training the models were compared using the average negative log likelihood over the contrasts (NLP-C) as well as the average log likelihood, per individual fish, over the original decisions (NLP-D). Overall, 18 separate sets of features were explored. Models were selected on the basis of having the lowest NLP-C with models within 0.1% of one another being considered equivalent. Of these the model with the fewest features was selected. We also report on the series of models whose subset of features lead up to the selected model so as to illustrate the incremental value of each of these sets of features.

**Model Evaluation**

Beyond reporting the NLP-C and NLP-D, we also computed a series of statistics over the model’s predictions and the actual occupancy data in order to explore the overall quality of fit.

To evaluate seasonal effects, we aggregated the proportion of fish in each depth bin over each month of the year and compared this to the predicted proportion of fish in each depth bin given the model (Figure 1). Similarly, we converted our sin\_sun and cos\_sun features back into radians and then computed actual and predicted proportions of the fish at depths lower than 25m (Figure 2). Finally, for each of our selected environmental features (mixed layer thickness, salinity, and nitrate) we binned our environmental feature and then computed observed proportion over the testing and training data as well as predicted proportions given a model with the environmental features and a model without (Figure 3). The latter comparison is intended to show the degree of co-variation between the environmental features and seasonal patterns.

**Visualizations of Model Predictions**

To illustrate how the model predictions can guide the selection of places and times where the likelihood of Chinook occupancy, by depth bin, is minimized, we first built a dataset of model features that included each depth bin, over every single H3 resolution 4 cell, in each hour, over the full year of 2022 in the Gulf of Alaska and Eastern Bering Sea. This resulted in over 96 million entries. Using AWS Batch, we then ran model inference over these points to determine the likelihood associated with each of the entries. This second dataset allows us to understand how the model behaves over the full course of the year in a full space as opposed to just over the training and testing data.

From this inferential dataset we then built three visualizations. First, we looked at fine scale temporal patterns over the course of the entire year for four locations – near-shore and off-shore around Yakutat and Chignik. Offshore sites were the closest h3 cell to the respective location that was on the edge of the continental shelf and nearshore sites were simply the closest h3 cell to the location in question. Yakutat and Chignik were chosen as they represent to very different locations (Southeast Alaska and the Aleutian Islands) and were areas in which fish were caught during tagging. For each of these we plotted, by hour, the model’s likelihood of depth bin occupancy for each of the depth bins at the location in question (Figure 4).

Next for the months of February (winter) and August (summer) we identified, per h3 cell, the minimum predicted probability of depth occupancy in depth bins (50, 300]m across all times in that month. We then plotted these minimums spatially in order to see how minimum depth occupancy in that bin is spatially distributed (Figure 5). The choice of (50, 300]m is to correspond with the depths at which walleye pollock are most often captured.

Finally, to show how the time of day that minimizes depth occupancy for the (50, 300] m depth bin varies spatially we took the days of February 15 and August 15 and computed for each h3 cell the 5th percentile likelihood of depth occupancy for that bin. Then we averaged our sin\_sun feature (negative values indicating night and positive values indicating day) over all the samples below the 5th percentile per h3 cell and plotted that average spatially for each of the two days (Figure 6).

**Results**

**Modeling**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Features | NLP-C Train | NLP-C Val | NLP-D Train | NLP-D Val |
| Null |  |  |  | 1.835 | 1.740 |
| A | depth\_bin | 0.470 | 0.526 | 1.412 | 1.457 |
| B | A + season | 0.438 | 0.487 | 1.330 | 1.368 |
| C | B + diel | 0.429 | 0.480 | 1.313 | 1.352 |
| D | C + nitrate, salinity, mlt | 0.426 | 0.474 | 1.308 | 1.339 |

**Table 2: Model Selection**

NLP stands for the averaged negative log likelihood over either the contrasts (C) or original decisions (D). Lower values indicate better-fitting models. Notice that as we add features the NLP-D Val decreases (the model performance improves) but with diminishing returns.

The selected model (model D) used depth\_bin, season, our diel feature, nitrate, salinity, and mixed layer thickness as features. Table 2 illustrates how each of these features add information to the predictions starting with a null model (no features) and moving up to our selected model. Judging off NLP-D Val we see a significant jump in performance going from a null model (equal probability to each depth bin) to a model aware of the depth bin (1.740 to 1.457). This is expected as the distribution of fish across depth bins was highly skewed toward the shallower depths (table 3) and the model was able to capture this skew.

**Table 3: Depth Skew**

|  |  |
| --- | --- |
| Depth Bin | Proportion of Samples |
| [0, 25] | 46.4% |
| (25, 50] | 16.6% |
| (50, 75] | 13.4% |
| (75, 100] | 10.7% |
| (100, 150] | 13.0% |
| (150, 200] | 4.9% |
| (200, 250] | 1.3% |
| (250, 300] | 0.6% |
| (300, 400] | 0.2% |
| (400, 500] | <0.1% |

Next, we see another substantial improvement in NLP-D Val by adding our season features (1.457 to 1.368). This is also expected as there are strong changes in depth occupancy of fish through the seasons (figure 1). We did observe a difference between the observed and predicted proportions of fish per depth bin in the validation data, however this is due to differences in those proportions between the validation and training data sets. In general, across both sets the pattern is the same – fish tend to move deeper in the winter months with a peak in the depth <=25 bin in the months of May and June.

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**Figure 1:** Actual and predicted proportion of fish in each depth bin by month over the validation dataset using model B (table 2).

Next, model C sees a small improvement over B (1.368 to 1.352) with the inclusion of our diel features. While we clearly see a trend in the depth occupancy over the course of a day (figure 2) with occupancy in the [0, 25]m bin rising at night, these diel features have a smaller effect because there is a large degree of variation in this pattern across fish with some fish in the dataset exhibiting no diel pattern or even a pattern opposite to the average tendency seen here.

A graph showing the value of a number of radians

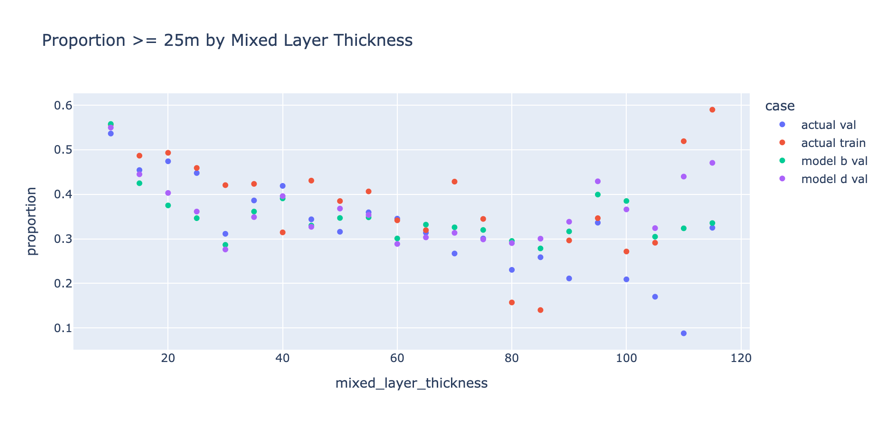
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**Figure 2: Diel Variation in August** x-axis is the passage of the day in radians (starting at night (negative radians), sunrise at 0 radians, and then moving through the day (positive radians). y-axis is the actual and then expected probability (from model C) of occupancy in the [0-25]m depth bin. Note the variation between the training set and the validation set in the actual proportions.

Our final model (1.352 to 1.339 NLP-D Val) includes three environmental covariates, nitrate, salinity, and mixed layer thickness. These features were chosen from the slew of options as they were the only ones with an appreciable pattern in the data that also individually added value to the model in the validation set when combined with the features in model C. It is interesting to note that the “value” of these features is somewhat hidden by the fact that they are all captured to some extent by the seasonality feature itself. For example, the average proportion by mixed layer thickness in depth bin >= 25m (figure 3) sees no real difference between model B and model D indicating that seasonality is accounting for the broader patterns that mixed layer thickness can identify.

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**Figure 3: Environmental Features** proportion by each feature for depth >= 25m for actuals in validation and training and two models. Note that models b and d are largely the same even though b does not include a mixed layer thickness feature.

Finally, it should be noted that while elevation did not, in fact, end up as a feature this was because when elevation was added it had no effect on the NLP-C Val. This is likely due to the fact that there is an implicit addition of elevation in the model at low depths because while the log-odds will remain the same, the number of options will shrink thereby boosting all the probabilities in shallower depths.

**Inference over a Full Year**

To illustrate the value of this model as data driven tool for informing bycatch avoidance strategies, we selected a few different views over an inference run over an entire year – 2022.

In the comparison of predictions over four sample regions in 2022 (Figure 4) it is clear that local context is important. First it should be observed that while average depth occupancy is shallowest in the spring, this seems to be due to an overall lack of variability during that time period. Technically speaking the shallowest instantaneous occupancy occurs during the summer months, but due to the extraordinary degree of variability in depth occupancy in this season the average across the day is lower than that in the spring. When fishing occurs, both seasonally and within each day, matters a great deal to minimizing the likelihood of incidental capture within a specific depth bin. Second there are clear, and expected, differences between the inshore and offshore locations – fish are driven to shallower depths by the corresponding shallower bathymetry. However, while depth occupancy in coastal Yakutat tends to be shallower than that in Chignik for the same reason (fewer depth bins) Yakutat shows higher variability in the occupancy per depth bin. This means that proper selection of timing can lead to similar levels of risk between Chignik and Yakutat, even given their differences in overall depth.

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**Figure 4: Fine Scale Temporal Patterns** Likelihoods per depth bin per hour over the course of 2022 for four locations.

Looking at the intra-day variation we see that while timing can have a large impact during the summer months there is much less power in timing during the winter. Spatial choice takes precedence in winter. Specifically, looking at the gradient in minimum depth occupancy in the 50-300m depth bins we see a steep spatial gradient in depth sensitivity during February (Figure 5). As one moves from in-shore to offshore the likelihood of depth occupancy in these bins climbs dramatically. This strong gradient lessens in extent during the summer in the GOA and in fact inverts in southeast Alaska. But once again, summer risk mitigation is largely a matter of choosing when to fish.

Finally, while intra-day timing is an important aspect of minimizing risk of incident capture, we posit that simple rule of thumb heuristics do not always work as there are complex interactions between season, diel patterns, and the depth bin to be fished. As an example, when looking at the depth bin (50, 300] in February and August we see some interesting interactions with the diurnal activity of the fish in prediction (Figure 7). In summer (August), risk in the 50–300m depth bins is consistently minimized at night likely indicating that the fish largely occupy the 0-50m bins at night and then shift to lower waters (including the 50-300 bins) during the day. However, in winter this is not necessarily the case with most in-shore minimums occurring during the day and some, but not all, off-shore minimums happening at night. These examples highlight the model’s usefulness as a tool to aid in determining how fishing timing and location affects the likelihood of incidental capture, allowing stakeholders to navigate risk with increased precision.

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**Figure 5: Minimum Risk Gradients** For February and August, the minimum risk in the month for depth bin (50, 300]m. Note the steep gradient in the winter months.

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**Figure 6: Time of Day Minimization** Average of the sine of our diurnal radians feature over the hours in which the risk for depth bin (50, 300]m was in the lower 5th percentile for the month in question. Negative values indicate minimization at night whereas positive values indicate minimization during the day.

**Discussion**

Our goal in this paper was to explore whether a model, whose predictions of depth occupancy can be tailored to specific places and times, can offer meaningful guidance for avoiding Chinook salmon to reduce their incidental capture. The model developed predicts the likelihood (assuming presence at the given longitude and latitude) of occupancy by depth bin for individual fish given a series of temporal and environmental covariates. Therefore, a high likelihood from the model is in indicative of a high likelihood of finding fish at a specific depth. This indicates that our model theoretically allows for a practical assessment of risk.

However, before proceeding to describe the outcomes it is important to acknowledge the limitations of this model. For one thing, the model’s predictions are inherently constrained by the covariates included, meaning that unaccounted-for local variations may lead to discrepancies between predicted and actual distributions. Sampling bias is another potential concern. The model is learning the likelihood of occupying specific bins by observing the patterns in 72 distinct individuals. While we are confident that the model does generalize to the other 39 fish held out in the validation set there remains the risk that the overall sample of 111 fish is not representative. Indeed, we know that the fish caught were generally larger in size (due to the need to be able to carry a large tag) and that the distribution amongst regions sampled was not even. The observations that follow must be considered in this light.

**Evaluation of the Model**

Overall, our findings reinforce the major patterns documented in the literature while providing some additional suggestions that interactions with water chemistry may have generalizable predictive power. However, while nitrate and salinity appear to exert slight influences on depth distribution, their effects are largely embedded within seasonal variation. Therefore, our results suggest that seasonality, diel patterns, and bottom depth remain the dominant known drivers of Chinook salmon vertical distribution, with environmental features playing derived roles.

The strongest predictor was depth itself, consistent with previous findings that Chinook salmon tend to occupy specific depth ranges. Specifically, the highest-likelihood depth bins were 0–25 meters and 25–50 meters, aligning well with expectations from the literature (Courtney, 2019, 2021). Seasonality emerged as the next most important factor, reinforcing prior observations that salmon occupy shallower depths in the spring and successively deeper waters in summer, fall, and especially winter (Freshwater, 2024) (Orsi, 1995) (Walker, 2007). Additionally, our model identified a diel pattern, with a general tendency toward shallower depths at night and deeper depths during the day during the summer and early winter months and a reversal of this pattern in late winter and spring, mirroring observations from previous studies (Freshwater, 2024) (Arostegui, 2017). It is interesting to note that this pattern emerged despite the fact there was extensive variation in diel patterning observed across individual fish. Maturity was not included as that information was not available and size was left out as the fish, by nature of the size of the tags they need to carry to collect the data, all have very similar sizes.

Beyond these well-established predictors, our model detected slight but consistent improvements in performance when incorporating nitrate levels, salinity, and mixed layer thickness. These features added only marginal predictive value beyond seasonality, suggesting that their effects are largely confounded with seasonal variation. Deep learning models, given their flexibility, can learn unknown features from given features if relationships between the unknown and known features are strong. Given that environmental conditions such as salinity and nutrient availability fluctuate in predictable seasonal cycles, it is likely that most of their predictive power is learnable from the seasonality features. We consider this same explanation to be behind the fact that we found that features such as temperature, lunar cycle, and chlorophyll-a did not provide generalizable performance improvements unlike in prior studies (Freshwater, 2024). Temperature and lunar cycle especially are more or less directly derivable from seasonality.

Finally, our model did not end up including features detailing either bathymetry or bottom slope or topography. The latter features were not included as we lack the spatial resolution to include meaningful “bottom roughness” features. In terms of bathymetry, we did attempt to build a model with mean elevation in the h3 cell but found that it was not helpful over the validation data. This is likely because elevation is implicitly included in the log-odds modeling approach as depths below the given bathymetry would not be included in the choices presented to the model thereby lifting the likelihood of all physically possible depth bins.

**Risk Mitigation**

**Future Directions**

Despite its advantages, the model presents significant usability and digestibility challenges due to the large volume of predictions it enables. Predictions cover every depth bin, at every hour, across all days within a specific year, for the entire Gulf of Alaska and Eastern Bering Sea—resulting in an overwhelming dataset. While the above examples were illustrative, they were but a drop in the bucket of predictions available. Processing such extensive data requires sophisticated computational resources and data analysis tooling and training. Therefore, a clear next step for this research would be providing an application layer that allows stakeholders to easily navigate and explore the data. This layer must:

* Provide hierarchical data navigation, allowing stakeholders to start with the level of summarization that makes most sense to them and progressively uncover more detail.
* Offer multiple views and filters, allowing decision-makers to incorporate specific constraints and easily interpret how different variables affect risk.
* Enable interactive visualization tools, so fishermen can dynamically adjust filters and quickly extract relevant risk assessments based on operational constraints.

Additionally, enhancing the model with expanded data sources could improve predictive capabilities. Environmental covariates, such as mixed-layer thickness, showed minimal effect in validation, likely due to their correlation with seasonality. More targeted data collection across environmental gradients—ensuring coverage across different seasons and times of day—could allow for better differentiation of these effects.

Another critical area for improvement is stock-specific risk assessment. Chinook salmon exist in multiple substocks, some more vulnerable than others. If stakeholders had access to fine-scale depth occupancy assessments that could differentiate between high-risk and low-risk substocks, they could refine their avoidance strategies further. Expanding data collection efforts to include genetic or tag-based identification of these substocks would be a valuable step forward.

Furthermore, this kind of risk assessment will be most effective when paired with other kinds of models. One example would be an abundance forecast of Chinook. The current model estimates the likelihood of fish occurring at different depths, given their presence, but it does not predict overall local abundance. Even in high-risk depth zones, if the habitat is not suitable for Chinook, the practical risk of bycatch would remain manageable.

Finally, as was stated in the introduction, this model is only half of the picture when it comes to bycatch avoidance in the walleye pollock fishery specifically. Pairing this with a similar model built over pollock depth occupancy data would allow for much more targeted identification of areas and times where Chinook and pollock depth occupancy are out of sync.

**Conclusion**

This study demonstrates the effectiveness of a probabilistic deep learning classifier in predicting Chinook salmon depth occupancy, offering a valuable tool for informing context specific by-catch avoidance strategies. By leveraging local context, our model provides fine-scale predictions that expand upon known seasonal, diel, and spatial patterns in salmon distribution. This approach allows fishers and managers to make more informed decisions by identifying optimal fishing times and locations that minimize bycatch risk.

Future work should focus on expanding data collection to improve model accuracy and reduce bias and developing user-friendly tools that allow stakeholders to efficiently interpret and apply model outputs. By integrating these refinements, the predictive power of this approach can be further enhanced, supporting more dynamic and responsive bycatch mitigation strategies.

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