**An Effective Depth Model for Bycatch Risk Assessment of Chinook Salmon in the Gulf of Alaska**

**Introduction**

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.

**Methods**

**Data**

The data used is a series of tracks from 111 Chinook salmon (*Oncorhynchus tshawytscha*) caught and monitored between 2013 and 2022 (6)(8). These tracks were obtained from pop-up satellite archival tags which collect temperature, light level, and depth information at specified (sub day) intervals. Depth information was extracted from these tracks.

While depth is measured on the tag at intervals more frequent that 15 mins, upon upload to the satellite the data is aggregated to a per 15 minute granularity in order to reduce the amount of information going over the satellite. We had a few tags that had been recovered and had the full data streams and upon comparison with the aggregated data determined that the measurements uploaded give a sense of the central tendency of the fish within a range of values. Therefore in order to not over-represent the precision of the uploaded data we sampled drew 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 lower bound and does not include depths from the bins at shallower depths. In summary this gave us for each 15 minutes of tag deployment a sampled depth bin that the fish was likely in during that 15 minute interval. Before introduction to the model these depth bins were each given a float “id” 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 per Uber h3 resolution 4 cell and depth bin (as with the depth measurements) 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.

Before being included in the models all environmental features were rescaled to run between 0 and 1 with chlorophyll, net primary production, and mixed layer thickness being log scaled before doing so. This was intended to normalize the data for introduction into the neural network.

Temporal features were derived using the “suntimes” and “ephem” packages in Python with the former being 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, 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 diurnal cycle (cosines at 0 for sunrise and sunset) a time point was, 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 done.

**Building the Models**

We approached the model building by building a log-odds model (?).

The first step was to split into training and validation sets. Given the low number of individuals in the sample and the intention to demonstrate the technique's value as an EDA tool it was decided to not maintain a hold out test set.

72 individuals were randomly selected for training and 39 for validation.

The next step in building a log-odds model is to decide on the formulation of our choices. In our case we took each of the individual depth bins as a choice where depth bins below the elevation at the site in question were not considered. As such our model ends up predicting the probability, given the data, of occurrence in any one of those depth bins. Training data was derived by identifying the actual depth bin occupied.

Next, we needed to determine the specifics of the contrast sampling. For this example, after inspecting the distribution of number of choices per salmon and number of choices per decision, we decided on random sampling (with replacement) 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.

For each of the three models trained, the hyperparameters for the internal log-odds component of the model were parametrized in the following way:

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

We proceeded by grid search and used 6 separate seeds for each combination. Models were trained in Keras using an Adam optimizer for 75 epochs. Given this is a log-odds model we used categorical cross entropy as the loss function. Training was done on AWS Batch using Fargate instances of 2 vcpu's and 4 GB of memory.

Lowest loss (categorical cross entropy) at the end of the 75 epochs over the validation dataset was used to select the best set of parameters for each of the models trained.

**Visualizations**

Visualizations were either built using the training and validation data or by using a dataset built by rebuilding features but over every single H3 resolution 4 cell in a specified area (???) and over the course of a full year (2022). This second dataset allows us to see 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.

**Results**

**Modeling**

**Table 1: Model Selection**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 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 |

18 separate models were trained to explore the feature space with four (table 1) being the most salient. Judging off NLP-D Val we see a significant jump in going from a null model (random guessing) 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 2) and the model was able to capture this skew.

**Table 2: 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. However, 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:** Expected and actual proportion of fish in each depth bin by month over the validation dataset using model B.

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 meaningful trend in the depth occupancy over the course of a day (figure 2) this feature has a smaller effect because there is a large degree of variation in this pattern across fish with some in the data exhibiting no diel pattern or even the opposite of the pattern described here.

A graph showing the value of a number of radians

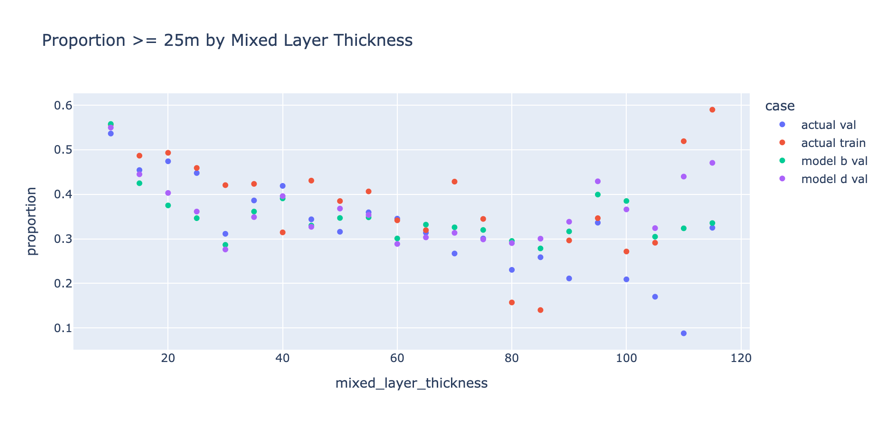
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**Figure 2: Diel Variation in August** x-axis is the passage of the day in radians (starting at night moving to day at 0 and then passing through the day). Note the variation between the training set and the validation set.

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 addition to the season and diel features. One interesting note is 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 for average proportion by mixed layer thickness in depth bin >= 25m (figure 3) we see no real difference between model b and model d indicating that seasonality is accounting for the broad 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 actually possess 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 as a feature to the model it had no effect on the NLP-C Val. It should be noted however 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 lower depths. Due to this and a great deal of variation in the actual proportions by depth while elevation could drop the NLP-C over the training data it could not do so over the validation data.

**Outcomes**

This modeling effort demonstrates the value of a depth model in reducing Chinook salmon bycatch, particularly in the walleye pollock fishery. At its core, the model provides a risk assessment for fishing in specific areas, times, and depths, quantified as the summed probability over depths. In theory, this could guide “optimized” fishing patterns with minimal bycatch risk. However, such an approach would be overly simplistic, as fishers and managers must consider additional factors like abundance levels, fuel costs, vessel speeds, localized closures, and weather. Our model assumes fish are present; an abundance model could indicate that a high-risk area poses little actual threat due to low expected numbers. Thus, this tool should complement, not replace, other decision-making inputs. We aim to explore how this model informs choices at multiple levels—from broad seasonal planning and spatial trends to real-time decisions on trawl depths and timing—demonstrating its value as an informational resource.

**Seasonal Choices**

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**Figure 4: Seasons with Minimal Risk** locations colored by the season that sees the minimal probability (at some point in the season) for depth range (25, 50].

In determining the months with minimal risk in the (25, 50] depth range and then mapping those months to their walleye pollock seasons (figure 4) we can see that season B is best for most near shore fishing in the Gulf of Alaska whereas in the EBS or far offshore season A captures the points in time with minimal risk.

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**Figure 5: Risk Sensitivity** locations are here colored by the difference in minimal risk between the best and worst months at that location. Risk differences are binned in increments of 5% absolute difference in probability.

We can also investigate with the model how sensitive timings are in each area over the months (figure 5). What we find is that in near shore regions in the GOA the difference in minimum probability in depth bin (25, 50] across months is around 5% whereas off coast it can range from 10-15%.

**Spatial Choices**

Rather than looking at what times are best at each location we can instead look across locations at a specific point in time (figure 6). Comparing two months from each of the seasons (August in season B and February from season A) we can see substantial differences in the patterning of risk across space for depth bin (25, 50]. Specifically in the August we see the risk increase as you move away from shore whereas in February we see the opposite and we also see a much steeper gradient in risk.

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**Figure 6: Fixed Month Spatial Variability in Minimum Risk** here we have per location in the months of August and February the minimum risk observed in that month for depth bin (25, 50]. Note that in the summer the risk falls off as you approach coastline in the GOA whereas in the winter the opposite is true.

**Local Temporal**

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**Figure 7: Depth Occupancy Over Time** the predicted probability of each depth bin at lat=52.3 and lon=-128.4 over the course of 2022. Note the large diel variance between July and September in the [0, 25] depth bin.

Plotting the timeline of probability per depth bin across a full year for one h3 cell (84129c1ffffffff) shows us a great deal of interesting detail (figure 7). We see a gradual rise in the depth occupancy from September through July, and then a quite significant diel pattern beginning in mid-July that tapers off in September.

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**Figure 8: Depth Occupancy Over a Day** same as figure 7 but over a single day (times are in UTC).

We can zoom in on a specific set of days in July and August to look at the diel pattern more closely (figure 8). We see that the diel pattern peaks at 9a.m. UTC (midnight AKST) in both cases but that in July fish are rising to the full [0, 50] set of bins as opposed to August where they rise only to the [0, 25] bin and drop out of the (25, 50] like the rest of the deeper bins.

**Discussion**

Our goal in this paper was to develop a model that could be used to assess and help mitigate bycatch risk. The model built seeks to predict the probability that an individual fish will occupy a specific depth bin given some set of environmental and seasonal covariates. This clearly is not a direct prediction of risk. However if enough fish are present in the water column the expected distribution of fish should approach the probabilities predicted for individuals. Therefore we posit that our model 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 only 72 distinct individuals. While we are confident that the model does generalize to the other 39 fish held out in the validation set there still remains the risk that the overall sample of 111 fish is not representative. Indeed, we know that the fish caught were larger fish caught in specific locations at specific times. The observations that follow must be considered in this light.

**Comparison to Known Drivers**

Previous studies examining Chinook salmon depth distribution have identified several major and consistent patterns. First is the fact that Chinook tend to occupy a specific portion of the water column between 0 and 50m although they can be found in depths exceeding 500m. Beyond this seasonality is one of the strongest predictors, with Chinook salmon generally occupying shallower depths in the spring and progressively deeper waters in summer, fall, and winter. Additionally, diel variability has been observed, although with substantial individual differences. 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. 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. Similarly, size and maturity play a role, with larger fish tending to be found at deeper depths. However, these patterns only emerge in the aggregate as individual variation is extreme, with salmon spending less than 25% of their time at any single 5-meter depth increment, highlighting the importance of large datasets for characterizing their depth distribution.

Less consistent patterns have been reported for temperature, productivity indicators, and current velocity and other temporal drivers like the lunar cycle. 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. Similarly, current velocity and thermocline depth have shown only weak relationships with depth selection.

Several plausible explanations exist for the stronger patterns observed in Chinook salmon depth distributions. Light availability has been hypothesized as a key driver, influencing both foraging efficiency and predator avoidance. Many pelagic fish adjust their vertical position to balance the trade-off between feeding opportunities and the risk of predation, particularly from visually oriented predators like harbor seals. Seasonal shifts in prey behavior are another critical factor, as key forage fish such as Pacific herring exhibit predictable depth changes throughout the year, which salmon may track. Lastly, bathymetric and environmental structuring—such as bottom depth and potentially seafloor slope—may shape salmon depth use. However, most of these explanations remain hypotheses.

Our model successfully captured many of these established patterns. The strongest predictor was depth itself, consistent with previous findings that Chinook salmon tend to occupy specific depth ranges. Specifically, the highest-priority depth bins were 0–25 meters and 25–50 meters, aligning well with expectations from the literature. 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. Additionally, our model identified a diel pattern, with a general tendency toward shallower depths at night and deeper depths during the day, mirroring observations from previous studies. This was in spite of the fact that extreme variation in diel patterning was observed in individual fish. Maturity was not included as that information was not available and size was left out as the fish, by nature of the tagging process, 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 however 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 our 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. Temperature and lunar cycle especially are likely 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.

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 secondary roles.

**Providing Additional Detail**

The purpose of this model in providing a next step in depth modeling for bycatch avoidance was to provide predictions that both provide an assessment of bycatch risk and allow for the determination of this risk at a fine spatial and temporal scale. This finer scale would then allow stakeholders to developing targeting strategy specific to an area or time in question.

To demonstrate this we began by comparing predictions in four different regions – two locations and two different positions along the continental shelf – across an entire year (2022). Across all cases, we observe lower and less variable depths in winter and late fall, a rise to shallower depths in spring, and increased variability during summer months. One immediate point of interest here is that the historically observed shallowest depths in the spring are due to a combination of a rise in the depth occupancy and a lack of overall variability. Technically speaking the shallowest occupancy occurs during the summer months, but due to the extraordinary degree of variability in this season the average across the day is lower than in the spring. In the summer then a large degree of risk mitigation can be achieved simply by selecting the timing of fish well a point we will return to shortly. Beyond these shared characteristics there are differences both between Yakutat and Chignik and between in-shore and off-shore patterns. The pattern from in-shore to off-shore is somewhat predictable in the sense that greater depths are available and the fish take advantage of these but it is worth noting that while coastal Yakutat tends to be shallower for the same reason (fewer depth bins) it also shows much higher variability in the summer. Overall, predictions in Yakutat exhibit greater variability in early winter compared to Chignik, a faster rise to shallower depths at the continental shelf edge, and a higher summer tendency for depths in the 0–25m bin.

Noting the relative lack of variation in the winter months a natural question is whether there are steep spatial gradients in depth sensitivity. Looking at the 25-50m depth bin in February we see exactly this – the minimum risk across all hours in the month follows a reasonably steep in-shore to off-shore gradient suggesting that where fishing happens can have a significant effect on bycatch risk from a depth occupancy perspective alone. This strong gradient shifts in summer, with minimal spatial variability along the coastal Gulf of Alaska but a persistent gradient in the Eastern Bering Sea. These shifts suggest that optimal fishing locations may vary by season, with certain areas at the edge of steep winter gradients being better suited for summer fishing and indeed this is what we see. What is interesting to note is that these trends not strictly an inshore versus offshore distinction, as some inshore locations prove more favorable in winter.

As was noted early there is considerable variation by hour in the predictions during the summer. One question is where do the minimums occur? Note that we have been looking at the 25-50m depth bin which is the second nearest to the surface but does not actually include the surface itself. This seems to lead to some interesting interactions with the diurnal activity of the fish (at least in prediction). In summer (August), risk in the 25–50m depth bin is consistently minimized at night likely indicating that the fish largely occupy the 0-25m bin at night and then shift to lower waters (including the 25-50 bin) during the day. However in winter this is not necessarily the case and we see plenty of areas who’s risk for the 25-50m depth bin is minimized during the day. This is likely due to the fact that in winter the fish occupy a larger portion of the water column at night during the winter as indicated by our comparisons between Yakutat and Chignik.

These findings highlight the value of considering seasonal, spatial, and diel factors when developing bycatch avoidance strategies. The model’s ability to resolve fine-scale patterns makes it a valuable tool for optimizing fishing timing and location, allowing stakeholders to navigate risk with increased precision.

**Future Directions**

Despite its advantages, the model presents significant usability and digestibility challenges due to the large data volume it generates. 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. Without a structured means of distilling insights, the model’s practical utility will be limited. 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, starting from high-level summaries and progressively refining insights to fine-scale details.
* 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 fishermen had access to fine-scale depth occupancy assessments that 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.

Importantly, these improvements do not require changes to the model’s methodology. Instead, they involve the inclusion of additional data and features. Because this model leverages machine learning, incorporating new information would enhance predictive accuracy automatically without requiring fundamental structural modifications.

Finally, 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 abundance. Avoiding Chinook hotspots is a primary strategy for bycatch reduction, and integrating abundance data would allow fishermen to identify low-risk alternatives with greater confidence. Even in high-risk depth zones, if overall Chinook abundance is predicted to be low, the practical risk of bycatch remains manageable.

Likewise, this model is only half of the picture. If the predictions of high likelihood salmon abundance by depth happens to always coincide with pollock depth occupancy, the usefulness of this as a targeting strategy is going to be quite limited. Therefore, it would make sense to build a pollock depth occupancy model in much the same way so that differences between occupancy can be searched for, discovered, and taken advantage of.

**Conclusion**

This study demonstrates the effectiveness of a probabilistic deep learning classifier in predicting Chinook salmon depth occupancy, offering a valuable tool for helping reduce bycatch in the walleye pollock fishery. By leveraging environmental covariates, 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, incorporating additional environmental parameters, 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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