**A Depth Model for Informing Chinook Salmon Bycatch Risk in the Gulf of Alaska**

* **Marcel Gietzmann-Sanders** (Corresponding Author), University of Alaska Fairbanks College of Fisheries and Ocean Sciences, 2150 Koyukuk Drive, 245 O’Neill Building, PO Box 757220, Fairbanks, Alaska 99775-7220
* **Michael Courtney**, University of Alaska Fairbanks College of Fisheries and Ocean Sciences, 17101 Point Lena Loop Rd., Juneau, AK 99801
* **Andrew Seitz**, University of Alaska Fairbanks College of Fisheries and Ocean Sciences, 2150 Koyukuk Drive, 245 O’Neill Building, PO Box 757220, Fairbanks, Alaska 99775-7220
* **Curry J. Cunningham**, University of Alaska Fairbanks College of Fisheries and Ocean Sciences, 17101 Point Lena Loop Rd., Juneau, AK 99801

**Abstract**

**Background**

Bycatch of Chinook salmon (*Oncorhynchus tshawytscha*) in the Gulf of Alaska walleye pollock (*Gadus chalcogrammus*) fishery poses both conservation and management challenges. While fleet communication and excluder devices have improved mitigation efforts, effective reduction ultimately depends on anticipating overlap—especially near the seafloor where pollock are targeted. To support context-specific bycatch mitigation strategies, we developed a probabilistic deep learning model that predicts Chinook salmon depth occupancy using fisheries-independent telemetry data and environmental, temporal, and spatial covariates.

**Results**

The best-performing model incorporated season, diel period, and salinity as key predictors of Chinook salmon depth occupancy in the Gulf of Alaska. Seasonal and diel effects formed a repeating annual cycle, with strong diel patterns appearing in late summer and fall. Salinity was also predictive in some months with shallower depth occupancy corresponding to lower surface salinity. Using the model, spatial and temporal patterns in the likelihood of Chinook salmon occupying depths targeted by trawl gear were mapped, revealing seasonal and diel hotspots of overlap. These predictions provide a foundation for context-specific bycatch mitigation strategies that account for both behavioral cycles and environmental gradients.

**Conclusions**

The models developed in this study provide evidence of significant behavioral variability throughout space and time for Chinook salmon. The predictions obtained provide an example of how behavioral models can augment existing bycatch mitigation tools - underscoring the need for broader telemetry coverage to capture the full behavioral gradients that shape Chinook salmon-fishery interactions.

**Keywords**

* Dynamic Ocean Management
* Deep Learning
* Satellite Tags
* Fish Behavior

**Background**

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 walleye pollock fishery is the largest in the United States by volume (NPFMC, 2022). The retained 2020 catch in just the Gulf of Alaska (GOA) totaled 107,000 metric tons and had a first wholesale value of $70.6 million (Monnahan, 2021). Within this fishery, Chinook salmon bycatch is considered prohibited species catch (PSC) meaning it is bycatch that cannot be retained or sold. PSC allowances are granted to the fishery but if those allowances are exceeded, the fishery is shut down regardless of the remaining allowable catch (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). As recently as 2024 two boats accidentally brought in enough Chinook salmon over a single weekend to exceed these allowances (Mapes, 2024). With such limited allowances, bycatch avoidance practices have 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). However, improved understanding of the spatial ecology of Chinook salmon while at sea, including their habitat and depth preferences may improve the efficacy of bycatch mitigation actions by identifying high risk zones.

Adding information on depth occupancy to this toolbox could prove fruitful. Adult walleye 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 50m their overall observed range extends beyond 500m (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 walleye pollock are known to exhibit diel patterns, (Adams, 2009; Miyashita, 2004) the majority of adult walleye pollock are primarily demersal – a pattern reinforced by the fact that the fishery targets them at or near the sea floor (De Robertis, 2006). These differences suggest that bycatch risk could be further mitigated if localized and temporally dynamic information on Chinook salmon depth occupancy was available.

A model of localized, Chinook salmon depth occupancy has not yet been built. Most studies on depth occupancy in Chinook salmon have focused on understanding the factors influencing depth 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 for Chinook salmon along the coast of Washington and British Columbia. However, to assess relative risk with specific depth range, a model would need to estimate the distribution of fish over the entire the water column. Arostegui et al. (2017) did produce such a distributional model but only used season and day/night as features and only used data from a study are in Puget Sound, preventing the model from being amenable to localized and dynamic predictions. Combining these two approaches remains an open opportunity for Chinook salmon.

Our goal is to explore the extent to which probabilistic deep learning can inform Chinook salmon bycatch mitigation strategies, by building a model capable of predicting depth distribution at localized spatial scales. We will do this in three steps. First, we will build a model that leverages environmental and temporal features (such as time of day and/or seasonality) to predict the relative likelihood of depth-bin occupancy by Chinook salmon throughout the water column. The predictor variables or features considered will include oceanographic, biochemical, seasonal, and diurnal characteristics. Second, we will evaluate the model’s predictions against observed depth occupancy and compare it to patterns observed in past research. Finally, we will generate a year's worth of predictions across the spatial domain of 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, at depths proximate to where trawl fishing for pollock often occurs.

**Methods**

**Overview of Model Training**

To predict fish occupation of discrete depth bins using environmental and temporal features (e.g. day of year and time of day), we applied probabilistic deep learning (Durr, 2020) and framed the problem as a classification of fish occupancy within those depth bins. As such, the model was trained over a dataset where each sample in that dataset corresponds to one fish at a specific location and time, and that fish's "classification" is defined as the depth bin it was observed to occupy. Features for each sample are derived from the environmental and/or temporal variables associated with the depth bins at that position. Model training then aimed to reduce categorical cross entropy – a loss function whose negative measures the likelihood of the observed data given the predictions. Deep learning was selected as such models can learn highly non-linear, combinatorial patterns (Durr, 2020).

Broadly, models were built using the following steps. First, we retrieved Chinook salmon movement tracks from prior research in the Gulf of Alaska and Eastern Bering Sea (Seitz, 2024). The position and depth data were then transformed to provide samples for a classification model and split into training (65%) and validation (35%) sets. Environmental data was retrieved from the Copernicus Marine Service and temporal data derived from “ephem” and “suntimes” packages in Python. These data were then aggregated, scaled, and joined to the movement tracks to provide model features. Given the high dimensionality of this feature space, a novel dimensionality reduction technique was applied. Models were trained over a variety of increasingly comprehensive feature sets and the final model selected using loss over the validation set. The following paragraphs describe each of these steps in detail.

**Details of Model Training**

Chinook salmon movement tracks (Seitz, 2024), consisting of daily estimated positions (Figure 1) and depths were used to train and test our models. Fish (62-100cm fork length) were caught and tagged near Dutch Harbor, AK (n=20), Chignik, AK (n=16), Craig, AK (n=8), Homer, AK (n=20), Kodiak, AK (n=13), Yakutat, AK (n=16), Sitka, AK (n=15), and in the Central Bering Sea (n=3). In the EBS they were caught via midwater trawl or by hook whereas all other catches happened by hook and line (Seitz, 2024). Fish were then monitored using pop-up satellite archival tags that collect temperature, ambient light intensity, and depth information at specified (sub day) intervals during deployment and then release from the fish, surface, and transmit collected data over satellite. While the data is sampled at a sub-minute interval, the central tendency of depth occupancy is summarized per (2.5–15-minute) period before being uploaded due to limited battery life. If the tag is recovered, the full dataset is available. To obtain location estimates, the data from the tag is passed through a proprietary hidden Markov model from Wildlife Computers that uses the tag’s data to estimate the likely paths taken by the fish during tag deployment (Wildlife Computers, 2025). An estimate of location for each day can then be derived as the central tendency of those paths on a particular day. In total 7,532 observation days were collected across the fish. These data were especially well suited to our problem as they have the distinct advantage of being fisheries independent and giving a comprehensive view of depth occupancy throughout tag deployment no matter where the fish may go.

After collecting these tag tracks, observations were prepared for use in classification. To prevent over-representing the precision of the uploaded data, we resampled depth measurements from a normal distribution centered at the 15-minute depth summary with a standard deviation equal to 10% of the summary and the mean equal to the reported depth value. We then assigned each sample to a depth bin. Depth bins were divided into increments of 25, 50, 75, 100, 150, 200, 250, 300, 400, and 500 meters. Each number indicates the upper bound of a bin and does not include depths from shallower bins. These depth bins were then normalized to a decimal between 0 and 1, with bin 25 corresponding to 0.1, 50 to 0.2, and so on. Finally, daily fish positions were aggregated to a fixed, hexagonal spatial grid - resolution 4 Uber H3 cells – in order to not over-represent the accuracy of the estimated positions.

Environmental conditions were derived from the Global Ocean Biogeochemistry Hindcast (10.48670/moi-00019) and Global Ocean Physics Reanalysis (10.48670/moi-00021) datasets provided by the E.U. Copernicus Marine Service. Data were drawn for each day between January 2013 and January 2023 in the Northern Pacific and values were aggregated to means per day, depth bin (see above), and Uber H3 cell at resolution 4. Environmental variables chosen for exploration included chlorophyll, net primary production, nitrate, oxygen, phosphate, silicate, bottom elevation, mixed layer thickness, salinity, temperature, and north and easterly current velocity. These were then joined to the fish tracks on location and time.

Seasonality, lunar cycle, and diel features were derived using the datetimes associated with each sample along with the “ephem” and “suntimes” packages in Python for lunar and diel features respectively. In all cases, time 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. Specifically, we constructed temporal features representing the day of year (seasonality), progression through the day or night (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.

To ensure all covariates were on the same scale, chlorophyll, net primary production, and mixed layer thickness were log scaled and then all environmental features were rescaled to be between 0 and 1. Given the range of sines and cosines are -1 to 1, no further normalization was needed for the temporal features.

Next, we made a modification to the typical probabilistic deep learning classification problem to reduce the dimensionality of our feature set. Given we have features for each depth bin, selecting N covariates results in a feature space of dimension 10N (N features across 10 depth bins). The 10x multiplier is an issue because the volume of data required to fit a model effectively can grow exponentially with the dimensionality of the feature space (Verleysen, 2005). Instead, we trained a model that predicts the log odds of occupancy in a specific depth bin. As only one depth bin’s features are needed in this model, our dimensionality drops to N. To train this model using categorical cross entropy we copied the log-odds model weights across all choices, passed depth bin in as a feature to each choice, and then passed the output of each model through a softmax activation layer whose weights are an untrainable identity matrix. This results in a model that still predicts probabilities per depth bin but has an effective dimensionality of N + 1 thereby increasing our odds of a good fit.

However, we arrive at a class imbalance problem because with 10 depth bins most instances of the internal log-odds model are encouraged to report very low log-odds. Therefore, we rebalanced the data by taking advantage of the fact that the log-odds of one choice is independent of the others. As a result, we can down-sample the number of choices in any decision to just two and achieve a balance between the positive and negative classes. To ensure we capture the variety in choices, we then resampled the same decisions repeatedly to get different pairs of selected and unselected choices. We call this process contrast sampling as we are sampling selected vs unselected contrasts. In this specific case 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 35/65 this resulted in 5,550,000 contrasts of which 3,600,000 were used in training and the rest in validation.

Models were implemented in Keras (Chollet, 2015) and trained for 100 epochs using a batch size of 200,000 and an Adam optimizer (Kingma, 2017) with a learning rate of 0.001. A grid search was performed over 2 and 3 hidden layers and 24 and 32 units per hidden layer and the model with the lowest validation over the contrast set was then selected. Amazon Web Service’s Batch Fargate service was used for compute and training was performed on instances with 2 vcpus and 4GB memory.

To facilitate feature selection and investigate the predictive power of different feature sets, several models were trained over feature sets of increasing complexity. All feature sets were subsets of the environmental and temporal features discussed above. The model with the lowest loss over the contrast validation set was selected as the final model. Then, starting from no features, the final model’s features were incrementally added to build additional models used to investigate the importance of each set of features. Each incremental feature was selected according to whichever caused the maximal drop in loss. For each of these models, in order to make comparisons, categorical cross entropy was computed over the validation and training sets for both the contrasts and the original decisions. A related, but more directly interpretable, metric – geometric mean probability (gmp) was also computed to aid comparison. This was computed by taking the geometric mean over the probabilities the model assigned to the observed depth bins in the data and gives a central tendency for the probability of selecting the used bin.

**Evaluation of Model Predictions**

To evaluate the model’s predictions against observed depth occupancy we summarized depth occupancy and predictions across each of the selected features. For seasonal effects we compared the proportion of tagged fish in each depth bin per month (independent of year) in the validation set to the mean probability of fish in each depth bin as predicted by the model. To evaluate diurnal variation, we converted our sin\_sun and cos\_sun features back into radians and then computed the actual proportions of the fish at depths lower than 25m across months for both the training and validation sets. 25m was chosen to distinguish between near surface waters, where Chinook salmon spend most of their time, and waters away from the surface. This was then compared to the mean probability of depth occupancy below 25m across the day as predicted by the model over the validation set. To illustrate the effect of salinity we looked at the predicted proportions of fish near the surface (<25m depth) when salinity was above and below 31.3ppt (25th percentile of surface salinity over the tagging dataset). As well as the change in model loss across month when adding the feature to the model.

**Informing Bycatch Mitigation**

To illustrate how the model predictions can guide mitigation of incidental capture near the seafloor we back predicted depth occupancy over the entire domain of the Gulf of Alaska in the year of 2022 and then used the predictions to explore how our features drive risk of overlap with fishing gears deployed near the bottom. First, in the same manner as described for model training, we built a dataset of model features that included each depth bin, over every single H3 resolution 4 cell in the Gulf of Alaska and Eastern Bering Sea, for each hour over the full year of 2022. This resulted in over 96 million individual predictions in space and time. Using AWS Batch, we then ran model inference over these points to determine the likelihood associated with each of the entries. We then subset this data to just the GOA and removed entries where the average depth was greater than 600m as Chinook are rarely seen deeper than 500m.

Using this dataset we then explored the effect each of our features had on depth occupancy in the lowest depth bin available to each H3 cell. First, to look at seasonality, we computed the 5th percentile risk in the lowest depth bin per H3 cell across the months of February and August (examples from winter and summer respectively). Then to better understand seasonal and diurnal variation we plotted the risk per depth bin across the entire year for one H3 cell (index=840ccebffffffff, lat=55.9N, lon=-158.2E) near Chignik where a number of the fish in this study were caught. To further understand variation in depth occupancy as a function of time of day, we computed, per H3 cell on August 15 and February 15, the average of our sin\_sun feature where depth occupancy was below its 5th percentile for that day and H3 cell. Positive values of this aggregate indicate that occupancy is minimized during the day, negative values indicate a minimization at night.

**Results**

**Model Evaluation**

The model with the lowest validation loss (providing the highest likelihood of the data) included depth\_bin, season, diel, and salinity as features (model D in Table 1). Starting from a null model with a loss of 1.740 (geometric mean probability [gmp] of 17.6%), adding depth\_bin (model A) reduced the loss to 1.457 (gmp 23.3%). Including season (model B) brought it to 1.368 (gmp 25.5%), and adding the diel features (model C) lowered it again to 1.352 (gmp 25.9%). With salinity included (model D), the final validation loss reached 1.340 (gmp 26.2%).

Depth occupancy, as observed by the tags and predicted by the model, skewed toward relatively shallow water. Nearly half (46.4%) of the observations were near the surface in the 0–25 m depth bin, and 85.6% were within 100 m of the surface (Table 2). The predictions paralleled this with predicted proportions of 45.6% and 85.5% respectively.

In both the observations and the predictions, Chinook salmon depth occupancy varied seasonally (Figure 2). The proportion of observations near the surface (0-25m) was at a maximum in June, at ~68% (~66% in predictions). The proportion of time spent in the top 25m of the water column decreased throughout the fall to only 30% of observations (26% predicted) being near the surface by November. Depth occupancy remained skewed toward deeper waters throughout the winter months (35–40% above 25m) before beginning to shift back toward the surface again in early spring (March-April).

Diel variation in depth occupancy also appeared, with notable seasonal shifts (Figure 3). During the summer, fall, and most of winter fish in the validation set tended to be closer to the surface at night. August had the largest swing in observed depth occupancy with nearly three quarters (73%) of observations in the validation set near the surface (0-25m) at night but only around a quarter (27%) near the surface during the day. This diel swing of 46% weakened throughout fall and winter (37% by October and 17% by January) and in February the pattern reversed with fish more likely to be near the surface during the day.

The diel patterns of the individual fish themselves were quite variable. For example, out of 28 fish observed in August, four spent over 70% of their time near the surface during the day while six had 85% of their daytime observations below 25m. At night a similar degree of variation was observed with four fish spending most of their time (>50%) at depth (>25m) whereas seven fish were near the surface in more than 85% of observations.

Corresponding to this individual variability was considerable variation in diel patterns between the validation and training sets (Figure 3). The most extreme case occurred in May with fish being near the surface far more often (37-52% of observations) in the training set as compared to the validation set (12-31%). Likewise, in October the validation set showed a clear diel pattern with fish being closer to the surface at night (49%) than during the day (15%), but in the training set for October fish were just as likely to be near the surface throughout the day.

In terms of the final feature – salinity – after controlling for depth, model predictions indicated that less saline (<31.3ppt) surface waters had higher occupancy than more saline surface (>31.3ppt) waters in all months except August and September (Figure 4). This pattern was strongest during the winter (30% difference in February) and weaker during the spring (6-14% difference). During the months of August and September the pattern switched and occupancy near the surface was predicted to be higher in the more saline areas.

However, the effect of salinity on model loss differed between the training and validation sets (Figure 5). From December to February, the two sets showed opposing trends. In December and January, the model with salinity better represented the fish in the training set than the model without salinity (with a drop in loss of 0.03 and 0.05 respectively). However, the fish in the validation set were more poorly represented (with an increase in loss of 0.02 and 0.05). In February the salinity feature made no difference for the fish in the training set but made for a much better representation of fish in the validation set (here a drop in loss of 0.14 was observed). During the remaining months, changes in loss were smaller (up to 0.03), yet discrepancies in magnitude between the validation and training sets persisted even though the direction of the change was aligned.

**Informing Bycatch Mitigation**

Likelihood near the seafloor was assessed to understand the model’s implications for Chinook salmon occupancy in the portion of the water column often occupied by both pelagic and non-pelagic trawl gear. Specifically, we were interested in where and when the likelihood of Chinook salmon occupying the deepest depth present at a given point in space, were minimized over time.

The minimum predicted likelihood of occupancy in the deepest bin varied across space and season (Figure 6). In February (example month from winter), the lowest likelihood of Chinook salmon occupying the deepest bin occurred along the shelf edge, where they dropped below 1%. Across the shelf, these values varied considerably, with neighboring cells often differing by 10% or more. In August (example month from summer), minimum likelihoods remained low (<1%) except for several persistent hotspots that were shared with February. One such hotspot, located just west of Kodiak, showed a minimum likelihood of 15%, roughly three times higher than the surrounding areas.

The time of day in which Chinook were least likely to be near the seafloor varied across space and season as well (Figure 7). In August, fish had the lowest probability of being near the seafloor at night in nearly all locations, with only one exception. In contrast, February showed much more spatial variation. Along the shelf edge, like in August, Chinook salmon were least likely to be near the seafloor at night. However, on the shelf, depending on which area was considered, fish were most likely to be away from the seafloor at dusk, dawn, or even during the day indicating that diel variation during February depends on location.

In a specific H3 cell near Chignik (Figure 8), both depth occupancy and diel variation changed considerably over the year. During winter, Chinook salmon were at greater depths, with ~50% of samples deeper than 25 m. At the same time, diel variability (the difference between maximum and minimum likelihood over the day) decreased during the winter, from nearly 20% in the 100 m depth bin (near seafloor) in November to 10% in January. Beginning in March, Chinook salmon shifted toward shallower water, with only ~30% of predicted observations deeper than 25 m by May. Diel variation increased again in July and August reaching ~15% (in the 100m bin). As a result of this high daily variation in summer as compared to spring, Chinook salmon were most likely to be found near the surface (0-25m) at night during the summer.

**Discussion**

**Chinook Salmon Behavior**

Born in freshwater streams that drain into the Pacific Ocean they then may travel vast distances - thousands of kilometers – in the ocean, with many stocks occurring throughout this species’ US west coast range, spending considerable time (1-5 years) in the Gulf of Alaska. Here they remain until they mature and make the journey back to their natal rivers to spawn and then die (Quinn, 2018). By applying probabilistic deep learning to a multiyear tagging dataset, we were able to uncover fine-scale patterns in the depths occupied by near-mature Chinook salmon in the Gulf of Alaska. Specifically, we found that Chinook salmon appear to demonstrate predictable seasonal patterns in depth occupancy, diel patterns in depth occupancy that vary among seasons, and that the depths occupied appear to correlate with the salinity of surface waters but this pattern depends on season as well.

Our analyses revealed considerable and predictable seasonal variation in Chinook salmon depth occupancy. In parallel with prior research (Arostegui, 2017) (Freshwater, 2024) we identified a pattern of deeper depth occupancy during the fall and winter as compared to spring and summer seasons. However, by taking using day of year instead of a categorical season feature we were able to identify the specific transitions between these two observed modes, similar to past research (Freshwater et al. 2023). Akin to the seasonal depth distributions described for Chinook salmon near British Columbia and the Washington/Oregon coasts (Freshwater, 2024) we saw a dramatic shift at the end of September to increased occupancy of deeper waters - a result that puts Chinook salmon deepest in mid to late fall rather than in winter. However, our results suggest a different pattern in the shift back toward shallower waters. Specifically, while Chinook salmon near British Columbia shifted abruptly back to shallower water occupancy in April, we observed a more gradual shift in Chinook depth occupancy beginning in February and extending all the way through June. These subtle differences in the timing of the spring transition toward shallower depth distribution are perhaps not surprising, given the important differences in the timing of the onset of the spring primary and secondary production between the Gulf of Alaska and location of prior research further south.

The observed and predicted seasonal patterns and variation in Chinook salmon depth occupancy has considerable alignment with seasonal shifts in productivity in the Gulf of Alaska. For example, primary and secondary productivity is lowest in the GOA during the late fall and winter months due to wind driven mixing and short photoperiods (Stabeno, 2004). This is the same period of time in which we observed minimum Chinook salmon occupancy near the surface. However, in the spring, as the photoperiod increases and mixing decreases, a cascade of phytoplankton blooms begin that culminate in August. This period of primary productivity aligns with increased shallow water occupancy that we observed. Then in August strong surface stratification sets in and remains until October when winds and ensuing mixing begin to increase again - the same period in which we see Chinook salmon return to deeper overall occupancy.

In a similar vein, the prediction that Chinook occupy near-surface waters with low salinity may also be a result of productivity differentials in the GOA. Due to its lower density, freshwater is known to enhance surface stratification – an important condition for increased local productivity (Miller, 2012). Freshwater also supplies key limiting nutrients such as iron and silicate used by phytoplankton (Miller, 2012). This combined with the alignment with productivity cycles in the Gulf of Alaska suggests that one potential hypothesis to explain our model results is that Chinook tend to occupy areas of higher productivity.

Chinook salmon diets provide a plausible ecological link between these shifts in primary production and their observed behavior. While variable across their range and through the seasons, Chinook diets tend to center on prey such as squid, euphausiids, and small pelagic fishes (Davis, 2009; Kaeriyama, 2004; Hunt, 1999) - organisms whose abundance and availability are closely tied to primary productivity.

The hypothesis also gains some support from studies of other highly mobile, predatory species. While largely surface oriented, the diving depths of Atlantic salmon have been noted to be directly correlated with stratification of the surface layer (Strøm, 2018) and yellowfin tuna are known to occupy deeper depths during the winter in the Pacific when the mixed layer is deeper at that time (Schaefer, 2007).

While patterns in marine productivity appear to be a plausible hypothesis for the realized depth occupation for these species, thermoregulation may influence diving behavior as well. There is evidence that the diving behavior of many fishes, including billfishes and tunas, is regulated as a behavioral warming mechanism after diving into much colder, deeper water (Abascal, 2010) (Rohner, 2022) (Schaefer, 2007) (Howell, 2010). In contrast, there is evidence that chum salmon attempt to occupy cooler waters during migration to reduce metabolic demands as they try to maintain their body condition by reducing energy expenditure prior to spawning (Tanaka, 2000). While in this study temperature did not improve model performance, its impact cannot be discounted due to the strong correlation between temperatures, depth, and time of year in the Gulf of Alaska. As such, further investigation into the relationships between productivity, thermoregulation, and the environment would likely be a valuable source of further insight.

Beyond observed seasonal patterns of in depth occupancy, our results indicate significant diel variation. Specifically we found that during the summer, fall, and most of the winter, GOA Chinook salmon occupy shallower depths at night, and are deeper during the day. However, there was some evidence that this diel pattern in depth occupancy reversed in late winter (February). The presence of predictable day/night patterns have been explored in prior research (Arostegui, 2017) (Freshwater, 2024) but the results and interpretation have been varied. For example Arostegui’s et al. (2015) documented acoustically tagged Chinook salmon near the Salish Sea and Puget sound, found fish to occupy shallower depths during the day for most of the year (except in winter). In contrast, Freshwater et al. (2024) study near the B.C and WA/OR coast, found the opposite behavior with Chinook salmon tending to occupy shallower depths at night. Our results corroborate these past studies for the fall and summer seasons, however, Chinook salmon were found to be closer to the surface during the day during the late winter and early spring seasons.

Beyond just categorizing behaviors as occurring in day/night, by using a time-of-day feature in our models, as we were able to capture when the shift between day-like behavior and night-like behavior occurs as well as the speed of these transitions. The results of these analyses suggest two overall modes of behavior with only a small portion of the day spent in transition. Such time-of-day shifts (e.g., day, night, crepuscular) have been observed in other many species of mobile, predatory fishes, including Billfishes, tuna, and Pacific and Atlantic salmon. For example, Black (*Istiompax indica*) and Striped marlin (*Kajikia audax*) (Rohner, 2022), Bigeye tuna (*Thunnus obesus*) (Howell, 2010), Yellowfin tuna (*Thunnus albacares*) (Shaefer, 2007) have all been demonstrated to have shallower distributions during the day than at night. Additionally, Atlantic salmon (*Salmo salar*) both dive deeper during the day and tend to be much more surface oriented during the long polar night (Strom, 2018).

It is not unexpected that the depths occupied by Chinook salmon depend on the depth of the water column, and the tendency for Chinook salmon to shift deeper as the water column depth increases is well documented (Freshwater, 2024) (Arostegui, 2017) (Orsi, 1995) (Walker, 2007). This finding was also demonstrated in our analysis - even without the explicit inclusion of overall depth as a feature. Because our model produces an odds of occupancy per depth bin, the addition of deeper and more depth bins has the effect of reducing the likelihood of occupying shallower depth bins. Nonetheless it was surprising that this simple fact of math captured enough of the bathymetry effect on Chinook salmon that depth as a feature was unnecessary. Perhaps this is related to the finding in a prior study (Freshwater et. al) that the relative position in the water column was a more predictive feature than the actual depth.

Together, these findings highlight the value of probabilistic deep learning for resolving fine-scale ecological patterns across time and space. By capturing both known and previously unresolved structure in Chinook salmon depth distribution, our model not only reinforces existing knowledge but also refines key timelines that shape depth occupancy by this species within the Gulf of Alaska. Furthermore, because the model provides estimates across the entire water column, it enables detailed examination of behavior within specific depth ranges of interest from the perspective of overlap with fishing gears within the region.

**Bycatch Mitigation**

Our model reveals that Chinook salmon occupancy at depth is anything but static: it shifts with season, time of day, and location. These results are directly applicable for strategies seeking to improve selectivity by anticipating overlap between target species and Chinook salmon, ultimately reducing bycatch. For the pollock fishery, which utilizes pelagic gear but primarily targets fish the near seafloor (De Robertis, 2006), this means focusing on the water column immediately above the seafloor. That is, risk can be partly assessed by understanding the likelihood of Chinook salmon occupying the region near the seafloor, where they are likely to overlap with pollock trawl gear and are therefore at risk for capture. By helping to resolve and describe these dynamics, the model provides insight into how and when risk can be reduced—and where it cannot.

First mapping the minimum likelihood over time of Chinook salmon occupancy near the seafloor illustrates that risk mitigation is shaped by space and time. For example, in February (season A), the landscape is variegated: some areas allow risk to be reduced to 5% or less, while others only allow a reduction to approximately 25%. As a result, in February, spatial selection of where to fish is a powerful tool for managing encounters with Chinook salmon. However, by August, minimum risk is much lower—near zero—and more uniform, suggesting that time of day becomes the stronger lever. Still, key hotspots persist where risk never falls below ~15% in our model. Given the sharp contrast with surrounding areas, these hotspots are likely best avoided.

Our findings echo work in the U.S. West Coast Pacific hake (*Merluccius productus*) fishery, where trends in Chinook salmon bycatch shift across time and space (Sabal 2023) (Shirk 2023). For example, in this fishery, risk increased as Chinook salmon sought thermal refuge, specifically, when surface waters exceeded 18 °C, salmon moved deeper and overlapped more with hake, resulting in higher bycatch. Bycatch risk thus became a function of shifting sea surface temperatures. Archival tagging data off the coasts of Oregan and California has also shown a tendency for Chinook salmon to move to deeper water in order to stay within a specific thermal habitat (8 – 12 °C ) (Hinke, 2005). Temperature was not a predictor of Chinook salmon depth occupancy in our study, but this does not actually contradict the findings in the Pacific hake fishery as the thermal refuge pattern occurred only in southern populations exposed to such high temperatures, weakening and disappearing further north. This suggests a gradient of Chinook behavior along the Pacific coast shaped by local temperature regimes.

Our findings underscore that risk identification is inherently dynamic a pattern that has been observed across a variety of other fisheries as well. In Lake Huron, Lake Trout (*Salvelinus namaycush*) are more often caught in the Lake Whitefish (*Coregonus clupeaformis*) fishery during spring and summer (Bergstedt 2016). Turtles are more likely to be hooked on pelagic longlines near weather fronts (Gilman 2006). Whale entanglements rose sharply in the Dungeness crab (*Metacarcinus magister*) fishery during a heatwave (Santora 2020).

In addition to spatial selection, time of day can also be leveraged in bycatch mitigation – especially in summer and fall. Our results from the GOA document that during August there is a strong diel pattern: Chinook tend to rise toward the surface at night, thereby reducing the probability of interaction with bottom trawls. In contrast, in southern portions of the Pacific Hake fishery of the WA/OR coast, Chinook salmon show the opposite pattern, with Chinook more surface-oriented by day and descending at night (Sabal 2023; Shirk 2023). This diel gradient weakens northward, suggesting that our “opposite” pattern may be a northern extension of a behavioral continuum. Yet the diel behavior also shifts with season: in February, weak or inverted diel patterns result in lower risk by adopting daytime or crepuscular fishing. These results further support the conclusion that bycatch mitigation strategies must be tuned to their spatiotemporal context.

Our results suggest that diel patterns are not only important locally but also part of a broader principle. These observations add to mounting evidence that time-of-day behaviors can inform effective targeting strategies for highly mobile marine predators. In the Gulf of Mexico, for instance, pelagic longline bycatch studies revealed strong diel and lunar patterns across blue (*Makaira nigricans*) and white marlin (*Kajikia albida*), wahoo (*Acanthocybium solandri*), dolphinfish (*Coryphaena hippurus*), swordfish (*Xiphias gladius*), and several tuna species—patterns that could be exploited to reduce bycatch (Orbesen 2017). Fishermen have long drawn on similar rhythms to target swordfish and yellowfin. Even in freshwater, Lake Trout displayed diverse diel behaviors across individuals (Bergstedt 2016). Across these studies a central theme emerges, namely that understanding diel patterns can benefit harvester efficacy, but fish behavior is always a moving target, shaped by space, season, lunar cycles, and location (Orbesen 2017; Goodyear 2008; Sabal 2023; Shirk 2023; Bergstedt 2016).

While choosing to fish at specific times of day and spatial selectivity are powerful levers for risk mitigation, zooming in on specific locations shows that other timing strategies matter as well. At Chignik, for example, risk at depth drops by nearly 10% between mid-January and March. By late February, the diel pattern itself becomes increasingly useful, adding another layer of leverage in this area. More broadly, these interactions between space and time mean that models cannot be read as static maps of risk. Monthly shifts, daily rhythms, and environmental variability all change the risk of fishing at particular times and places. As Goodyear (2008) noted for another highly mobile pelagic predator - blue marlin - habitat use is a four-dimensional problem. Dynamic, practical visualizations are therefore essential so that fishermen can take full advantage of this 4D habitat.

To be useful, tools that capture 4D habitat must also fit within the strategies already used by the GOA pollock fleet to mitigate Chinook salmon bycatch. The fishery already employs excluder devices (Gauvin 2016; Lomeli 2019), fleet communication protocols through SeaState (Gilman 2006), test trawls, and—most importantly—the fishermen’s own knowledge of where and when to fish (Gilman 2006). Our model and the tools built from it are intended to augment these approaches. Excluders, for instance, can reduce but not eliminate bycatch when Chinook are encountered; lowering the likelihood of encounter remains essential. Fleet communication protocols are reactive, while this framework could support more proactive decision-making. And by offering a new perspective grounded in telemetry, these models can enhance—and perhaps even catalyze—the on-the-water knowledge the fleet already holds.

Finally, beyond making results more accessible, there is a need to improve the models themselves through additional data collection. Gradients in salmon behavior—from the southernmost portions of the Pacific Hake fishery to the Gulf of Alaska—variation among individuals, and complex ties to environmental parameters, prey fields, and temperature tolerance all point to how much remains unresolved about Chinook behavior. Only with broader coverage across space and time can the turning points and gradients in that behavior be illuminated. Greater clarity will not only advance understanding but also strengthen efforts to reduce overlap between Chinook salmon and the fisheries that share their range.

Taken together, these results underscore that bycatch mitigation is not governed by fixed rules but by a shifting landscape. Overlap between Chinook salmon and the pollock fishery unfolds across gradients of space, season, and time of day, shaped further by environmental and behavioral variability still being resolved.

**Conclusion**

This study set out to develop a probabilistic depth model for Chinook salmon that could support context-specific bycatch mitigation strategies in the Gulf of Alaska. By leveraging fisheries-independent telemetry data and framing depth occupancy as a probabilistic classification problem, we created a model that resolved fine-scale vertical distribution across environmental, seasonal, and diel gradients. Crucially, by providing explicit spatiotemporal predictions, our model demonstrates that bycatch risk is not a static condition but a dynamic intersection of behavior, oceanography, and fishing activity. Furthermore, by using the flexibility of deep learning, this framework provides a consistent set of tools that can evolve as more data become available. As such, models such as the one built here can complement existing bycatch mitigation strategies such as fleet communication, excluder use, and fishermen's own experiential knowledge.

**Abbreviations**

* GOA: Gulf of Alaska
* PSC: Prohibited Species Catch
* EBS: Eastern Bering Sea
* GMP: Geometric Mean Probability
* WA: Washington
* OR: Oregon

**Declarations**

**Ethics** **Approval**

**Consent for Publication**

Not Applicable

**Availability of Data and Materials**

The packages built for this study can be found at:

* Zenodo: <https://zenodo.org/account/settings/github/repository/networkearth/mimic>
* Zenodo: <https://zenodo.org/account/settings/github/repository/networkearth/haven>
* Zenodo: <https://zenodo.org/account/settings/github/repository/networkearth/watercycle>

The training/inference data and models can be found at:

* <https://s3.us-east-1.amazonaws.com/networkearth-shared>

Note: The authors are more than willing to use another data storage facility if this does not suit the purpose.

**Competing Interests**

The authors declare that they have no competing interests.

**Funding**

Tag deployments were funded by Arctic-Yukon-Kuskokwim Sustainable Salmon Initiative, Pollock Conservation Cooperative Research Center, Pacific States Marine Fisheries Commission, and the US Navy, Commander Pacific Fleet, under the Navy’s Marine Species Monitoring Program, through a Cooperative Ecosystems Studies Unit agreement (Cooperative Agreement #N62473-20-2-0001) administered by Naval Facilities Engineering Systems Command Southwest.

**Author’s Contributions**

MG, AS, MC, and CC were all participant in the design of the work. MC provided all the tag tracks and significant guidance on the use of the data. MG acquired all other data, built the models, wrote the code, performed the analyses, and wrote the initial drafts of this manuscript. AS, MC, and CC provided significant review and substantiative revisions. All authors read and approved the final manuscript.

**Acknowledgements**

Not Applicable

**References**

1. Abascal FJ, Mejuto J, Quintans M, Ramos-Cartelle A. Horizontal and vertical movements of swordfish in the Southeast Pacific. ICES Journal of Marine Science. 2010 Apr 1;67(3):466–74.
2. Adams CF, Foy RJ, Kelley JJ, Coyle KO. Seasonal changes in the diel vertical migration of walleye pollock (Theragra chalcogramma) in the northern Gulf of Alaska. Environ Biol Fish. 2009 Oct;86(2):297–305.
3. Arostegui MC, Essington TE, Quinn TP. Interpreting vertical movement behavior with holistic examination of depth distribution: a novel method reveals cryptic diel activity patterns of Chinook salmon in the Salish Sea. Anim Biotelemetry. 2017 Dec;5(1):2.
4. Bergstedt RA, Argyle RL, Taylor WW, Krueger CC. Seasonal and Diel Bathythermal Distributions of Lake Whitefish in Lake Huron: Potential Implications for Lake Trout Bycatch in Commercial Fisheries. North American Journal of Fisheries Management. 2016 Aug 1;36(4):705–19.
5. Chollet F. and others. Keras. 2015. <https://keras.io>
6. Copernicus Marine Service. Global Ocean Biogeochemistry Hindcast. 2024. 10.48670/moi-00019
7. Copernicus Marine Service. Global Ocean Physics Reanalysis. 2024. 10.48670/moi-00021
8. Courtney MB, Evans MD, Strøm JF, Rikardsen AH, Seitz AC. Behavior and thermal environment of Chinook salmon Oncorhynchus tshawytscha in the North Pacific Ocean, elucidated from pop-up satellite archival tags. Environ Biol Fish. 2019 Aug;102(8):1039–55.
9. Courtney MB, Evans M, Shedd KR, Seitz AC. Understanding the behavior and ecology of Chinook salmon (Oncorhynchus tshawytscha) on an important feeding ground in the Gulf of Alaska. Environ Biol Fish. 2021 Mar;104(3):357–73.
10. D’agrosa C, Lennert‐Cody CE, Vidal O. Vaquita Bycatch in Mexico’s Artisanal Gillnet Fisheries: Driving a Small Population to Extinction. Conservation Biology. 2000 Aug 15;14(4):1110–9.
11. Davies RWD, Cripps SJ, Nickson A, Porter G. Defining and estimating global marine fisheries bycatch. Marine Policy. 2009 July;33(4):661–72.
12. Davis ND, Myers KW, Fournier WJ. Winter Food Habits of Chinook Salmon in the Eastern Bering Sea. North Pacific Anadromous Fish Commission. 2009 (5):243-253.
13. De Robertis A, Wilson CD. Walleye pollock respond to trawling vessels. ICES Journal of Marine Science. 2006 Jan 1;63(3):514–22.
14. Duffy-Anderson JT, Ciannelli L, Honkalehto T, Bailey KM, Sogard SM, Springer AM, et al. Distribution of age-1 and age-2 walleye pollock in the Gulf of Alaska and eastern Bering Sea: sources of variation and implications for higher trophic levels. Institute of Marine Research. 2003
15. Durr O, Sick B. Probabilistic Deep Learning. Manning. 2020
16. Estes JA, Terborgh J, Brashares JS, Power ME, Berger J, Bond WJ, et al. Trophic Downgrading of Planet Earth. Science. 2011 July 15;333(6040):301–6.
17. Freshwater C, Anderson SC, Huff DD, Smith JM, Jackson D, Hendriks B, et al. Chinook salmon depth distributions on the continental shelf are shaped by interactions between location, season, and individual condition. Mov Ecol. 2024 Mar 15;12(1):21.
18. Gauvin J. Bering Sea Salmon Excluder EFP 15-01 Final Report. North Pacific Fisheries Research Foundation. 2016
19. Gilman EL, Dalzell P, Martin S. Fleet communication to abate fisheries bycatch. Marine Policy. 2006 July;30(4):360–6.
20. Goodyear C, Luo J, Prince E, Hoolihan J, Snodgrass D, Orbesen E, et al. Vertical habitat use of Atlantic blue marlin Makaira nigricans: interaction with pelagic longline gear. Mar Ecol Prog Ser. 2008 Aug 18;365:233–45.
21. Hall MA, Alverson DL, Metuzals KI. By-Catch: Problems and Solutions. Marine Pollution Bulletin. 2000 Jan;41(1–6):204–19.
22. Hinke J, Foley D, Wilson C, Watters G. Persistent habitat use by Chinook salmon Oncorhynchus tshawytscha in the coastal ocean. Mar Ecol Prog Ser. 2005;304:207–20.
23. Howell EA, Hawn DR, Polovina JJ. Spatiotemporal variability in bigeye tuna (Thunnus obesus) dive behavior in the central North Pacific Ocean. Progress in Oceanography. 2010 July;86(1–2):81–93.
24. Hunt S, Mulligan T. Oceanic feeding habits of chinook salmon, Oncorhynchus tshawytscha, off northern California. Fishery Bulletin. 1999; 97:717–721
25. Kaeriyama M, Nakamura M, Edpalina R, Bower JR, Yamaguchi H, Walker RV, et al. Change in feeding ecology and trophic dynamics of Pacific salmon ( Oncorhynchus spp.) in the central Gulf of Alaska in relation to climate events. Fisheries Oceanography. 2004 May;13(3):197–207.
26. Kingma DP, Ba J. Adam: A Method for Stochastic Optimization. ICLR. 2017.
27. Lomeli MJM, Wakefield WW, Herrmann B, Dykstra CL, Simeon A, Rudy DM, et al. Use of artificial illumination to reduce Pacific halibut bycatch in a U.S. West Coast groundfish Bottom trawl. Fisheries Research. 2021 Jan;233:105737.
28. Mapes L. Bycatch of nearly 20,000 Chinook salmon shuts down Alaska trawl fishery. The Seattle Times. 2024
29. Miller C, Wheeler P. Biological Oceanography. Wiley-Blackwell. 2012
30. Miyashita K, Tetsumura K, Honda S, Oshima T, Kawabe R, Sasaki K. Diel changes in vertical distribution patterns of zooplankton and walleye pollock ( Theragra chalcogramma ) off the Pacific coast of eastern Hokkaido, Japan, estimated by the volume back scattering strength (Sv) difference method. Fisheries Oceanography. 2004 Dec;13(s1):99–110.
31. Monnahan CC, Thorson JT, Kotwicki S, Lauffenburger N, Ianelli JN, Punt AE. Incorporating vertical distribution in index standardization accounts for spatiotemporal availability to acoustic and bottom trawl gear for semi-pelagic species. Godo OR, editor. ICES Journal of Marine Science. 2021 Sept 7;78(5):1826–39.
32. North Pacific Fishery Management Council. Bering Sea salmon bycatch update. 2022. Retrieved from <https://www.npfmc.org>
33. North Pacific Fishery Management Council. Fisheries Management Plan for the Groundfish fisheries of the Gulf of Alaska. 2024. Retrieved from <https://www.npfmc.org>
34. Orbesen E, Snodgrass D, Shideler G, Brown C, Walter J. Diurnal patterns in Gulf of Mexico epipelagic predator interactions with pelagic longline gear: implications for target species catch rates and bycatch mitigation. bms. 2017 Apr 1;93(2):573–89.
35. Orsi JA, Wertheimer AC. Marine Vertical Distribution of Juvenile Chinook and Coho Salmon in Southeastern Alaska. Transactions of the American Fisheries Society. 1995 Mar;124(2):159–69.
36. Quinn T. The behavior and ecology of Pacific salmon and trout. Second Edition. University of Washington Press, Seattle, Washington. 2018.
37. Rohner C, Bealey R, Fulanda B, Prebble C, Williams S, Pierce S. Vertical habitat use by black and striped marlin in the Western Indian Ocean. Mar Ecol Prog Ser. 2022 June 2;690:165–83.
38. Sabal MC, Richerson K, Moran P, Levi T, Tuttle VJ, Banks M. Warm oceans exacerbate Chinook salmon bycatch in the Pacific hake fishery driven by thermal and diel depth‐use behaviours. Fish and Fisheries. 2023 Nov;24(6):910–23.
39. Santora JA, Mantua NJ, Schroeder ID, Field JC, Hazen EL, Bograd SJ, et al. Habitat compression and ecosystem shifts as potential links between marine heatwave and record whale entanglements. Nat Commun. 2020 Jan 27;11(1):536.
40. Schaefer KM, Fuller DW, Block BA. Movements, behavior, and habitat utilization of yellowfin tuna (Thunnus albacares) in the northeastern Pacific Ocean, ascertained through archival tag data. Mar Biol. 2007 Sept;152(3):503–25.
41. Seitz AC, Courtney MB. Telemetry and Genetic Identity of Chinook Salmon in Alaska: Final Report. 2024
42. Shirk PL, Richerson K, Banks M, Tuttle V. Predicting bycatch of Chinook salmon in the Pacific hake fishery using spatiotemporal models. Zhou S, editor. ICES Journal of Marine Science. 2023 Jan 25;80(1):133–44.
43. Squires D, Ballance LT, Dagorn L, Dutton PH, Lent R. Mitigating Bycatch: Novel Insights to Multidisciplinary Approaches. Front Mar Sci. 2021 Mar 19;8:613285.
44. Stabeno PJ, Bond NA, Hermann AJ, Kachel NB, Mordy CW, Overland JE. Meteorology and oceanography of the Northern Gulf of Alaska. Continental Shelf Research. 2004 May;24(7–8):859–97.
45. Strøm JF, Thorstad EB, Hedger RD, Rikardsen AH. Revealing the full ocean migration of individual Atlantic salmon. Anim Biotelemetry. 2018 Dec;6(1).
46. Tanaka H, Takagi Y, Naito Y. Behavioural Thermoregulation of Chum Salmon During Homing Migration in Coastal Waters. Journal of Experimental Biology. 2000 June 15;203(12):1825–33.
47. Verleysen M, François D. The Curse of Dimensionality in Data Mining and Time Series Prediction. In: Cabestany J, Prieto A, Sandoval F, editors. Computational Intelligence and Bioinspired Systems. Berlin, Heidelberg: Springer Berlin Heidelberg; 2005. p. 758–70. (Hutchison D, Kanade T, Kittler J, Kleinberg JM, Mattern F, Mitchell JC, et al., editors. Lecture Notes in Computer Science; vol. 3512).
48. Walker RV, Sviridov VV, Urawa S, Azumaya T. Spatio-Temporal Variation in Vertical Distributions of Pacific Salmon in the Ocean. (4).
49. Wallace BP, Kot CY, DiMatteo AD, Lee T, Crowder LB, Lewison RL. Impacts of fisheries bycatch on marine turtle populations worldwide: toward conservation and research priorities. Ecosphere. 2013 Mar;4(3):1–49.
50. Wildlife Computers. Minipat. 2025
51. Zeller D, Cashion T, Palomares M, Pauly D. Global marine fisheries discards: A synthesis of reconstructed data. Fish and Fisheries. 2018 Jan;19(1):30–9.

**Tables and Figures**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Features | Loss Train | Loss Validation | Geometric Mean Probability  Validation |
| Null |  | 1.835 | 1.740 | 17.6% |
| A | depth\_bin | 1.412 | 1.457 | 23.3% |
| B | A + season | 1.330 | 1.368 | 25.5% |
| C | B + diel | 1.313 | 1.352 | 25.9% |
| D | C + salinity | 1.308 | 1.340 | 26.2% |

**Table 1: Model Improvements over Features.** Deep learning was used to train on and then predict the depth bins occupied by individual Chinook salmon at 15 minute intervals in the Gulf of Alaska and Eastern Bering Sea. The objective of the training was to optimize the overall likelihood of the data given the predictions by minimizing a categorical cross entropy loss function. Beginning with a null model - predicting equal probabilities across all depth bins – each new model (A – D) demonstrates the improvement in loss each new feature brings to our selected model D. Training loss represents the loss over the data the model saw during training, validation loss is the loss over a holdout set. Geometric mean probability is the geometric mean of the probability of the data given the model.

|  |  |  |
| --- | --- | --- |
| Depth Bin | Proportion of Samples | Predicted Proportion of Samples |
| [0, 25] | 46.4% | 45.6% |
| (25, 50] | 16.6% | 16.4% |
| (50, 75] | 13.0% | 12.6% |
| (75, 100] | 9.6% | 10.8% |
| (100, 150] | 10.1% | 9.8% |
| (150, 200] | 3.1% | 3.8% |
| (200, 250] | 0.6% | 0.8% |
| (250, 300] | 0.3% | 0.2% |
| (300, 400] | 0.1% | <0.1% |
| (400, 500] | <0.1% | <0.1% |

**Table 2: Depth Skew.** Over 15 minute interval observations of depth occupancy across tagged Chinook salmon in the Gulf of Alaska and Eastern Bering Sea, the proportion of samples in each of our depth bins (units in meters) as well as the proportions predicted by a deep learning model.

A map of the world

AI-generated content may be incorrect.**Figure 1: Chinook Salmon Tag Tracks.** Estimated positions, colored by month of year, of all Chinook salmon tag tracks used in this study. **A chart of different colors

AI-generated content may be incorrect.**

**Figure 2: Seasonal Shifts in Depth Occupancy.** (Top) Using observations of depth at 15-minute intervals from individual Chinook salmon (GOA and EBS), the proportions of samples in each depth bin across all months. (Bottom) For those same samples, mean predicted probability of the occupied depth from a deep learning model binned across all months.

A graph of different colored lines

AI-generated content may be incorrect.

**Figure 3: Diel Variation** Using observations taken at 15-minute intervals from Chinook salmon in the GOA and EBS, the proportions of samples deeper than 25m as a function of time of day across all months. Validation is the proportion over the validation data; train is the proportion over the training data and predicted is the mean predicted probability of the occupied depth over the validation data. The radians on the x-axis indicate time of day with negative numbers indicating nighttime and positive numbers indicating daytime.

A graph of different colored bars

AI-generated content may be incorrect.

**Figure 4: Effect of Salinity** Using predictions of depth occupancy at 15-minute intervals for Chinook salmon using a deep learning model, predicted proportions of fish within 25m of the surface when surface salinity is above (high) and below (low) 31.3ppt. Predictions were made over the validation dataset.

A graph with different colored squares

AI-generated content may be incorrect.

**Figure 5: Variation in Performance of Salinity as a Feature** Change in loss across months when adding salinity as a feature to a deep learning model of Chinook salmon depth occupancy. Red indicates the training dataset whereas blue indicates the validation dataset.

A screenshot of a map

AI-generated content may be incorrect.

**Figure 6:** **Spatial Distribution of Minimum Likelihood.** Minimum likelihood of Chinook salmon occupancy in the deepest bin over each hour in the months of February (left) and August (right) as predicted by our deep learning model.

A screenshot of a map

AI-generated content may be incorrect.

**Figure 7: Time of Day Minimization.** Time of day when the predicted likelihood, from our selected model, in the deepest bin for Chinook salmon is minimized on February (left) and August (right) 15. Negative values indicate nighttime whereas positive values indicate daytime.

A graph showing the growth of the company's sales

AI-generated content may be incorrect.

**Figure 7: Full Year of Likelihoods** Predicted likelihood, using our selected model, of occupancy per depth bin for Chinook salmon across all hours in 2022 for an H3 cell near Chignik, AK. The apparent width of the time series indicates the degree of diel variation at that point in time.