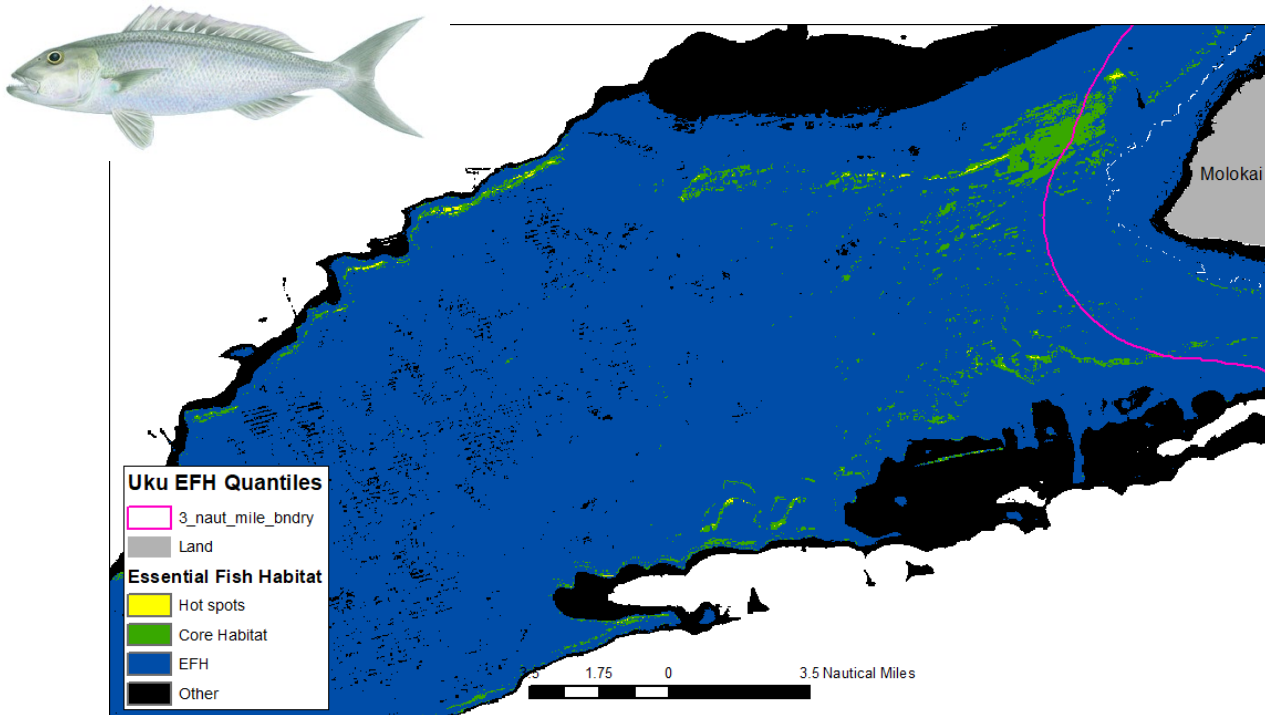


Model-based Essential Fish Habitat Definitions for the Uku *Aprion virescens* in the Main Hawaiian Islands



by

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Executive Summary

The description of essential fish habitat is required for federally managed fishery species. Species distribution models (SDMs) have been utilized in marine science and conservation to identify and predict suitable habitats for many species. SDMs can involve a range of models that vary in structure and complexity. Boosted regression tree models were fit to fishery-independent data to define the geographic extent of essential fish habitat (EFH) of sub-adult/adult life stages of a federally managed snapper species, *Aprion virescens*, commonly called “Uku”, in the main Hawaiian Islands. Due to differences in survey data collection methods, separate SDM models for Uku were constructed for shallow (0-30 m depth) depths using NOAA fish diver surveys and deeper (30-300 m) depths using NOAA and UH baited stereo-video camera arrays.

For shallow models, aspect (i.e., direction that habitat slope faces), depth, and wave heights were strong predictors of Uku occurrence, while depth was the predominant habitat variable for the deep model. Output from the SDMs were used to create maps delineating Uku EFH including continuous probability of occurrence maps as well as categorical maps showing EFH “hot spots”, “core habitats”, and “basic EFH”, based on 25%, 50%, and 95% quantiles of predicted occurrence, respectively. For the shallow habitat range (0-30 m), Uku hot spots represent 0% of the area, core habitats are 0.2%, basic EFH is 55.4%, and other (i.e., non-EFH habitats) are 44.4% of the area. For the deep habitat range (30-300 m), Uku hot spots are 0.1% of the area, core habitats are 2.4%, basic EFH is 60.1%, and other habitats are 37.4% of the area. Most of the hot spot and core habitats are in the deeper depth ranges of Penguin Bank on the N-NW coasts of the islands, such as the Kohala coast of Hawaii Island. Basic EFH habitats cover the majority of both shallow and deep habitats. Total combined EFH (i.e., hot spots, core habitats, and EFH) in shallow and deep habitats is 61.4% of the seafloor between 0-300 m. The “other” habitats (i.e., non-EFH) were predominately either shallow, nearshore habitats adjacent to shorelines or the habitats deeper than ~150 m throughout the main Hawaiian Islands.

A comparison of models using static and dynamic habitat variables suggested that the inclusion of dynamic variables did not significantly improve the model performance although a broader variable set could be further examined in future studies. One strength of dynamic variables is that they may better allow forecasting changes to EFH due to the effects of climate change on environmental variables. One limitation of the study was the lack of sufficient fish length observations from the deep camera surveys necessary to model the sub-adult and adult fish independently. To address this issue, existing videos could be reanalyzed to collect Uku length data for this purpose. Any future video survey analysis from the BFISH project should also include Uku as a priority species to collect length data. These data, coupled with the existing information from the shallow diver surveys, should allow the EFH for the sub-adult (i.e., juvenile) and adult Uku populations to be modeled separately.

The EFH maps are a visual display of the predicted quantitative relationship between Uku and their habitat and can be used to inform marine conservation and management activities in the main Hawaiian Islands. These analyses represent the first model-based approach to delineating EFH for a U.S. Western Pacific stock and could serve as a framework for the EFH descriptions of other managed species in the region.

INTRODUCTION

The description and identification of Essential Fish Habitat (EFH) for all species managed under a US fisheries management plan is mandated by the Magnuson-Stevens Fishery Conservation and Management Act (1996). EFH is generally defined therein as “those waters and substrate necessary for fish for spawning, breeding and growth to maturity”. The National Marine Fisheries Service has provided guidelines to evaluate the quality of available data used to identify EFH should be rated across four levels (Figure 1)(50 CFR Pt. 600.815):

Level 1: All that is known is where a species occurs based on distribution data for all or part of the geographic range of the species.

Level 2: Data on habitat-related densities or relative abundance of the species are available.

Level 3: Data on growth, reproduction, or survival rates within habitats are available.

Level 4: Production rates by habitat are available.

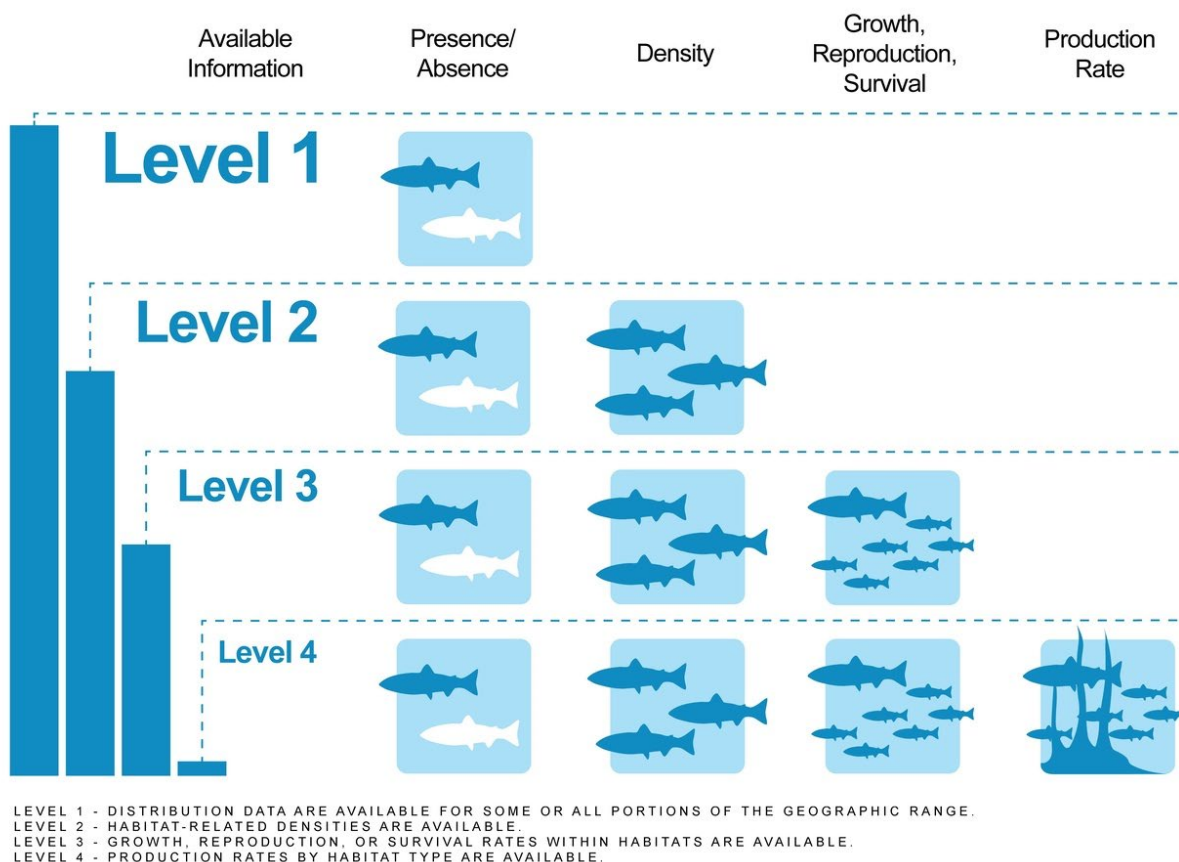


Figure 1. Four levels used to rate information to define Essential Fish Habitat from guidelines provided by the National Marine Fisheries Service (source: NOAA).

In the Hawaiian Archipelago, most EFH definitions for managed species have been primarily qualitative descriptions of the distribution and depth range of the observed life stages (i.e., typically adults, but can include juveniles). For the Green Jobfish, *Aprion virescens* Valenciennes 1830 (Figure 2), or “Uku” as it is known locally in Hawai‘i, the EFH designation

was classified as part of the “Shallow Complex” of bottomfish in the Hawaiian Archipelago by the Western Pacific Regional Fishery Management Council (WPRFMC 2016). Uku is a coastal piscivorous fish observed in the water column and over rocky, coral, and sandy habitats typically between depths of 20 to 200 m (Pyle et al. 2016, Asher et al. 2017). Maximum length is ~100 cm (Sundberg & Undekoffler 2011) with L_{50} maturity at 45 cm (Everson & Williams 1989). Commercial and non-commercial fisheries for Uku operate in the MHI. Based on the most recent stock assessment for the MHI, Uku is not overfished, nor is overfishing occurring (Nadon et al. 2020).

In the Western Pacific region, four life stage categories are defined for EFH: egg, post-hatch pelagic, post-settlement, and sub-adult/adult. For the sub-adult/adult stage of Uku, the EFH was described as “the benthopelagic zone, including all bottom habitats, in depths from the surface to 240 m bounded by the official US baseline and 240 m isobath” and maps to reflect that description were generated. Definitions for the Uku egg, post-hatch pelagic, and post-settlement stages interpreted in aggregate generically identified all water column (out to 50 mi from shore for eggs) and benthic habitats from 0 to 240 m depths as EFH. The current approach used could be classified as “Level 0” EFH since it provides a definition based solely on the potential presence of uku uniformly distributed throughout the entire domain without considering that specific habitat characteristics may disproportionately influence the presence or absence of Uku which, if considered, would lead to a non-uniform geographic distribution of habitats that are more heavily utilized (i.e., are more essential).

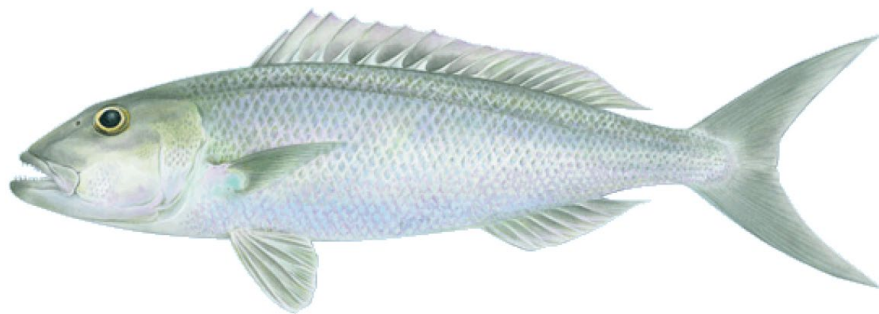


Figure 2. Drawing of adult Green Jobfish or “Uku”, *Aprion virescens*. Source: Hawai‘i DLNR.

To evaluate the non-uniform geographic distribution of Uku associated habitats, this work outlines methods to utilize existing fisheries-independent survey data with geographically-explicit marine habitat information (i.e., GIS data) to identify EFH for the sub-adult/adult phases for *Aprion virescens* in the main Hawaiian Islands (MHI) of the Hawaiian Archipelago (i.e., the Northwestern Hawaiian Islands are not included in this analyses). This work uses statistical and geospatial methods whose complexity depended upon the quality, type, and amount of data available for each species. The approach used would be categorized as Level 1 EFH (Figure 1) based on modeling the presence and absence of Uku from survey observations. Since Uku utilize habitats across a range of depths, it was necessary to utilize different survey data for shallow (0-30 m depths) and deep (30-300 m) depths. NOAA Pacific Island Fisheries Science Center (PIFSC) stationary visual diver surveys were used for shallow depths and baited stereo-video

camera surveys were used for deep depths. Due to the non-overlapping depth and geographic ranges between the different surveys, two separate models were generated to identify EFH, one for shallow habitats (0-30 m) and one for deep habitats (30-300 m). Within the models, “static” habitat variables included seafloor depth (i.e., bathymetry), slope of the seafloor, aspect of the seafloor (i.e., compass direction that slope of seafloor faced), seafloor rugosity (i.e., complexity of the geomorphology of the seafloor) and bottom substrate (i.e., sand or hardbottom) and “dynamic” variables included sea surface temperature (i.e., satellite measurement), sea surface net primary productivity (i.e., satellite derived chlorophyll measurement), and maximum and minimum significant wave height (model derived for the shallow model only). It was not possible to generate separate models for juvenile and adult stages of Uku because of insufficient size information for the deep surveys (i.e., the MOUSS surveys) so models represent combined sub-adult (i.e., juvenile) and adult Uku EFH. Level 2 EFH models based on density of Uku were not possible due to the biases and inaccuracies inherent in directly comparing estimates of relative abundance (i.e., fish per unit area) between the different sampling methods used by shallow visual diver surveys and deep stereo-video surveys (Willis et al. 2000, Harvey et al. 2004) and insufficient intercalibration exists between the survey methods. The current work also did not attempt to delineate EFH for the egg or post-hatch pelagic stages of the fish species due to insufficient information available.

To expand on the existing EFH definitions for Uku in the MHI as described in Amendment 4 to the Fishery Ecosystem Plan for the Hawaii Archipelago (WPRFMC 2016), the purpose of this work is to generate species distribution models (SDMs) from shallow and deep surveys documenting the presence and absence of Uku at sub-adult and adult life stages for Level 1 EFH using static and dynamic habitat and environmental covariates. SDMs relate species observations to environmental and habitat covariates and predict the occurrence of the target organism across the study domain. SDMs are commonly used to describe habitat associations for marine organisms (Elith et al. 2008, Franklin et al. 2013, Oyafuso et al. 2017) and have been used previously by NOAA Fisheries to define EFH for federally managed species in the Alaska region (Laman 2017). In this report, the SDMs were constructed by fitting boosted regression tree (BRT) models (Elith et al. 2008) to fishery-independent survey data for models of the shallow (0-30 m) and deep (30 -300 m) Uku habitats. The BRT models provide optimal fits between habitat covariates and *in situ* diver or stereo-video survey data of Uku. Outputs from the SDMs are used to create geographic maps delineating Uku EFH identified as continuous probability of occurrence maps as well as categorical maps of EFH. The probability of Uku occurrence maps describe the possibility between 0% to 100% that the habitat at a particular location, based on the characteristics described by the combination of habitat and environmental covariates, would have an Uku present. The EFH categorical maps allow the geographic identification of “EFH hot spots” (75%-100% probability of Uku occurrence), “EFH core habitats” (50%-74%), and “EFH” (5%-49%) areas for Uku EFH throughout the main Hawaiian Islands, following methods developed for the Alaska EFH delineations (Laman et al. 2017). The categories are hierarchical such that all hot spots are within core habitats and all core habitats are within EFH. The maps also identify areas of low probability of Uku occurrence (<5%) which are described as “other” habitats that are not considered essential for Uku. These analyses represent the first model-based approach to delineating EFH for a U.S. Western Pacific stock and could serve as a framework for the EFH descriptions of other managed species in the region.

MATERIAL AND METHODS

Study Area

The Hawaiian archipelago encompasses a group of volcanic islands and atolls that span 2500 km in the central north Pacific Ocean. The study area included the “shallow” (0 to 30 m depth) and “deep” (30 m to 300 m) benthic habitats around the eight main Hawaiian Islands (MHI) which are Niihau, Kauai, Oahu, Maui, Molokai, Kahoolawe, Lanai, and Hawaii (Figure 3). The geography of these volcanic islands is characterized by prominent coastal capes and headlands that demarcate coastal exposures to different climate and ocean conditions. The north coasts of Kauai, Oahu, and Maui are exposed to large northern hemisphere winter swells (≥ 7 m), while southern hemisphere storms produce waves (3 to 5 m) along Hawaiian south shores in summer (Fletcher et al. 2008). Molokini is a small, partially submerged volcanic cone offshore of Maui with extensive coral reefs within the crater (Figure 3). The eastern or windward side of the islands experience consistent easterly trade winds (10 to 20 knots) that generate steady wind-driven waves (1 m; Fletcher et al. 2008). There are only two large, natural semi-enclosed waters bodies in the MHI, Pearl Harbor and Kaneohe Bay on Oahu. In shallow waters (0 – 30 m), coral reefs are found around the coasts and embayments of all islands (Battista et al. 2007). In deeper waters (30 – 300 m), a mix of softbottom and hardbottom habitats are found through the region with coral reefs less common at these depths.

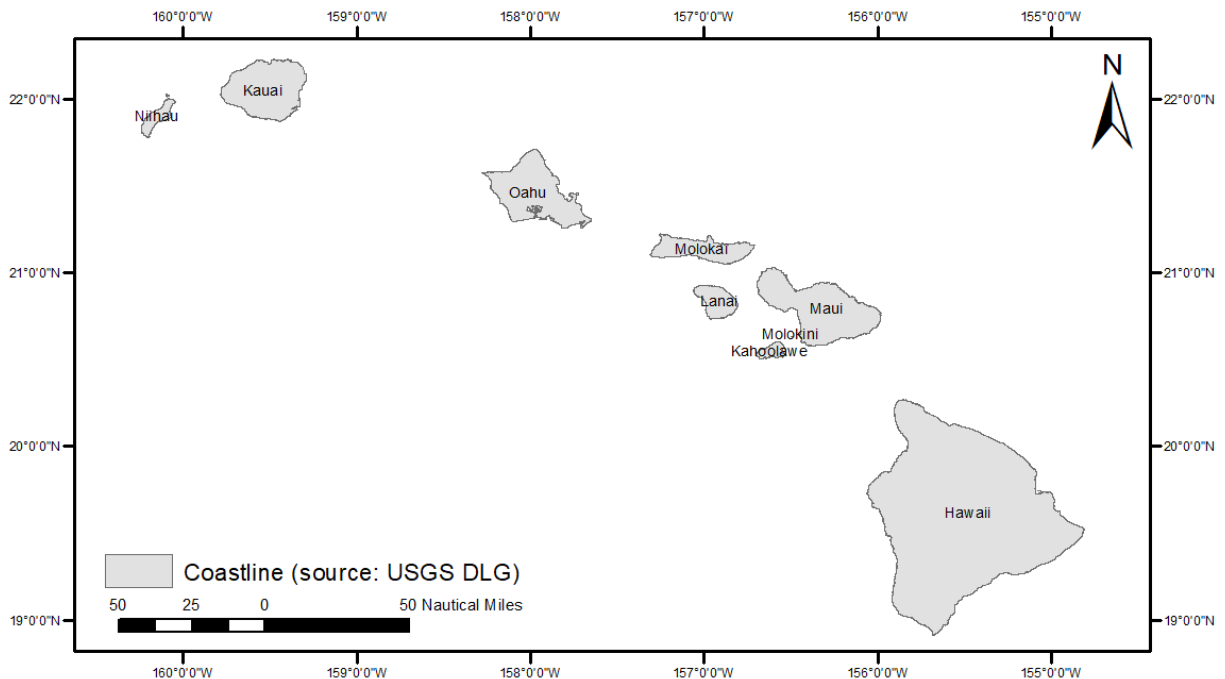


Figure 3. A map of the eight Main Hawaiian Islands.

Literature and Data Search

To collect information and data for the study, I searched the scientific literature (i.e., Google Scholar and Web of Science) and reviewed fishery-independent and fishery-dependent information relevant to the delineation of EFH for Uku *Aprion virescens* in the main Hawaiian Islands. Here, the main Hawaiian Islands are defined as the area of the US EEZ that encompasses the islands of Niihau, Kauai, Oahu, Maui, Molokai, Kahoolawe, Lanai, and Hawaii. Collectively, the islands of Maui, Molokai, Kahoolawe, and Lanai are referred to as “Maui Nui”. GIS bathymetry and habitat layers were provided by the Pacific Islands Benthic Habitat Mapping Center (<https://www.soest.hawaii.edu/pibhmc/cms/>), the Hawaii Mapping Research Group (<http://www.soest.hawaii.edu/HMRG/cms/about-hmrg/>), and the NOAA Centers for Coastal Ocean Science (<https://coastalscience.noaa.gov/research/project-explorer/>). The NOAA Pacific Islands Fishery Science Center (PIFSC) provided diver survey data for Uku. NOAA PIFSC and Jake Asher (formerly of PIFSC) provided baited stereo-video camera survey data for Uku. US federal guidance on EFH mapping requirements is listed as an Appendix.

A number of survey data sources were reviewed for Uku observations in the main Hawaiian Islands between 2010 and 2019. Two primary field methods were used for the direct observation of Uku in fishery-independent surveys, shallow (0-30 m) diver surveys (Heenan et al. 2017) and deep (30-300 m) baited stereo-video cameras (Merritt et al. 2011, Amin et al. 2017, Asher et al. 2017). Diver survey data from the Hawaii Division of Aquatic Resources and The Nature Conservancy were reviewed and considered for the shallow model but were not incorporated into the study due to differences in sampling methodology with the NOAA diver surveys. The details of the final data sources used in the study are provided in the following sections.

Stationary Diver Fish Surveys - NOAA Fisheries Pacific Island Fisheries Science Center (PIFSC)

- Number of surveys: 1,682
- Surveys with *A. virescens* observed: 252 (14.9% of total)
- Year range: 2010-2019
- Island areas surveyed (8): Niihau, Kauai, Oahu, Molokai, Lanai, Maui, Kahoolawe, Hawaii
- Depth range: 1.3 m – 30.0 m
- Median uku length (and range): 54 cm (22 cm – 110 cm) FL
- Methods: Visual observations of fish community by SCUBA divers using the stationary point count method in shallow coral reef habitats (Heenan et al. 2017). Each survey represents data averaged from multiple diver surveys, typically two per site. Uku observations were collected along with observations of multiple species of fish. The number and length of uku were visually estimated by divers, not measured directly.
- Comments: These surveys were performed during 2010, 2012, 2013, 2015, 2016, and 2019. Not all islands and coastlines were surveyed in each year (Figure 4).
- Contact: Tye Kindinger, tye.kindinger@noaa.gov

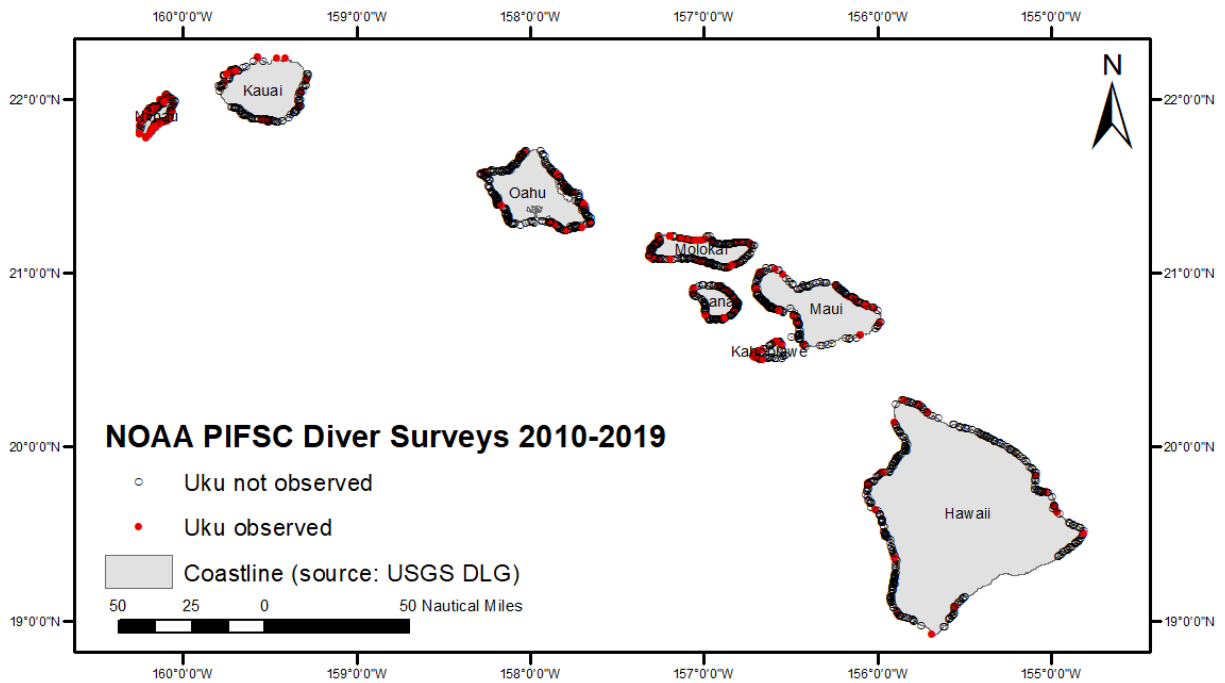


Figure 4. NOAA PIFSC diver surveys for uku (*Aprion virescens*) in the main Hawaiian Islands, 2010-2019. Surveys include those with uku observed (red circles) and those with no uku observed (open circles).

Baited Remote Underwater Video (BRUVs) Surveys – NOAA PIFSC

- Number of surveys: 107
- Surveys with *A. virescens* observed: 28 (26.2% of total)
- Year range: 2010-2013
- Island areas surveyed (4): Oahu, Molokai, Lanai, Maui
- Median depth (and range): 39 m (2.7 m – 96.6 m)
- Uku length range: 22.2 cm – 107.2 cm FL
- Methods: Baited remote underwater video (BRUVs) surveys recorded visual observations of the fish community using stationary stereo-video baited camera arrays in shallow to mesophotic hardbottom and softbottom habitats (Asher et al. 2017). Uku observations were collected along with observations of multiple fish species. The maximum number and length of uku were visually estimated from the videos using software tools (i.e., Event Measure), not measured directly. *Note:* Only surveys deeper than 30 m ($n = 67$) were included in the SDM deep model analysis of the current study.
- Comments: These surveys were performed during 2010-2013 (Figure 5).
- Contact: Jacob Asher, jakeasher@hotmail.com

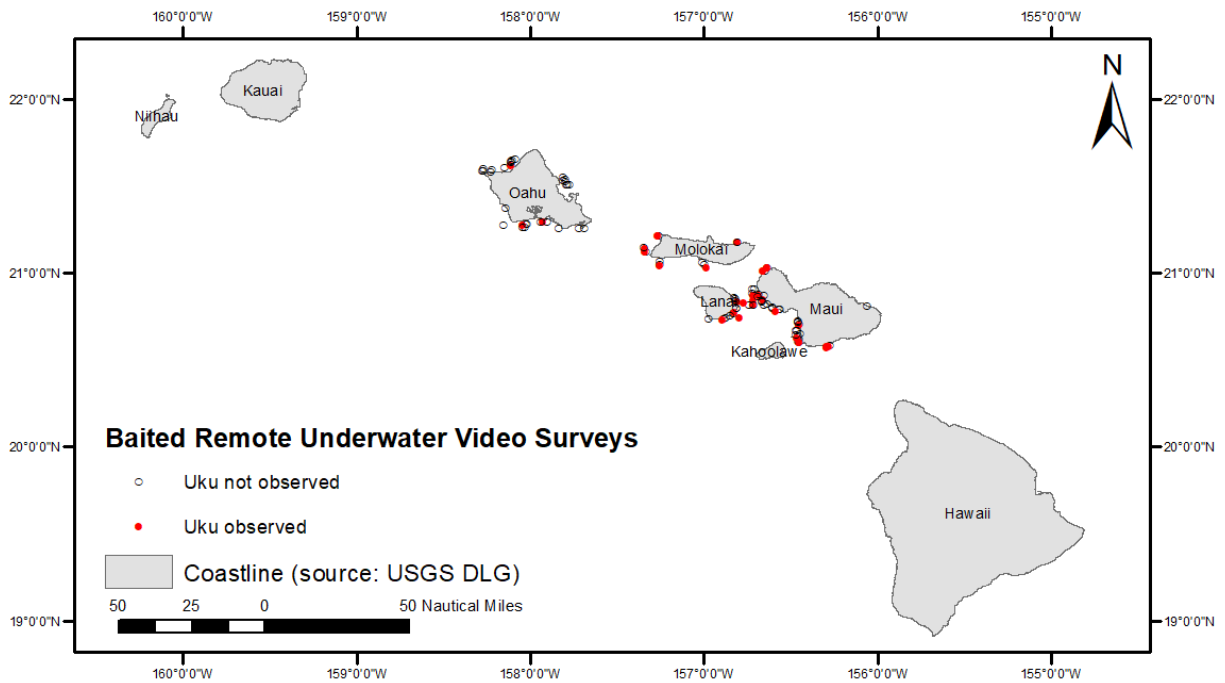


Figure 5. Baited remote underwater videos (BRUVs) for uku (*Aprion virescens*) in the main Hawaiian Islands, 2010-2013. Surveys include those with uku observed (red circles) and those with no uku observed (open circles).

BotCAM Video Surveys – NOAA PIFSC / University of Hawaii

- Number of surveys: 465
- Surveys with *A. virescens* observed: 24 (5.2% of total)
- Year range: 2011-2014
- Island areas surveyed (3): Lanai, Maui, Kahoolawe
- Median depth (and range): 164.5 m (63.7 m – 314.0 m)
- Uku length range: 52.7 cm – 75.3 cm FL
- Methods: Baited underwater video surveys recorded visual observations of the fish community using stationary stereo-video baited camera arrays in mesophotic hardbottom and softbottom habitats (Merritt et al. 2011).
- Comments: These surveys were performed annually during 2011-2014 (Figure 6). Uku observations were collected along with observations of multiple fish species. Surveys with “at least 1” uku were given a value of 1 for Nmax. Survey records with a *Species* identification of “Lutjanid/ae”, “Perciformes”, “Teleost”, or “too dark to annotate” were not included in the analysis.
- Contact: Audrey Rollo, audrey.rollo@noaa.gov

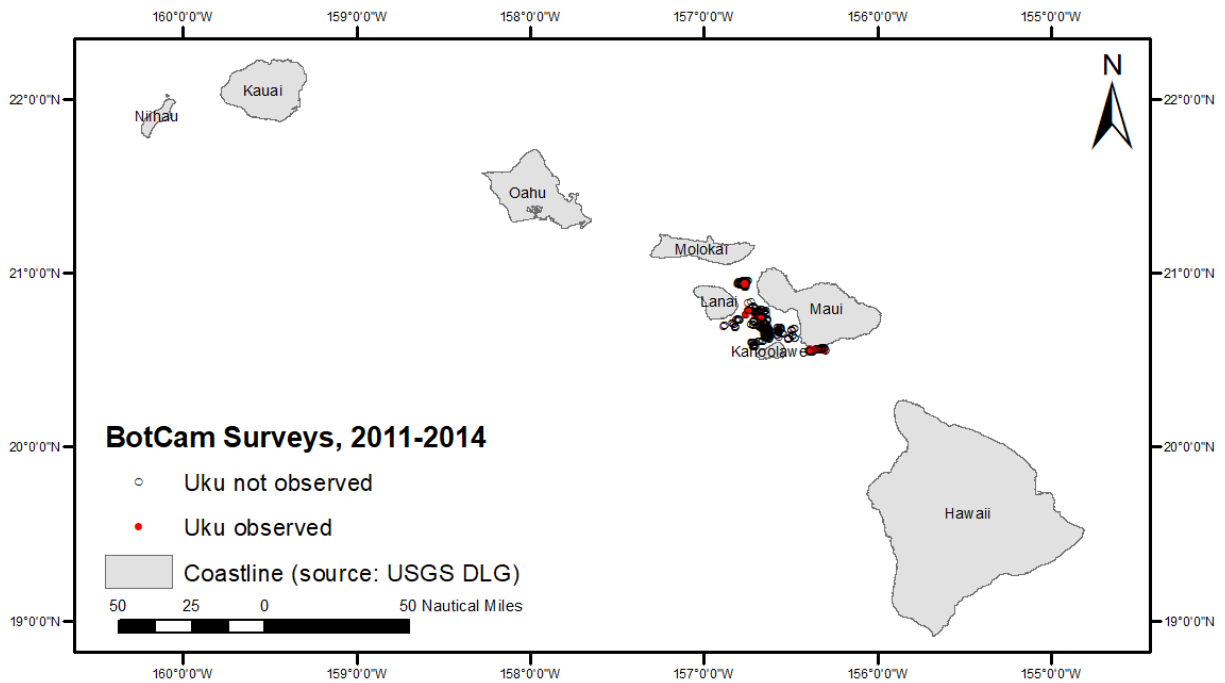


Figure 6. BotCam underwater video surveys for uku (*Aprion virescens*) in the main Hawaiian Islands, 2011-2014. Surveys include those with uku observed (red circles) and those with no uku observed (open circles).

MOUSS Video Surveys – NOAA PIFSC

- Number of surveys: 951
- Surveys with *A. virescens* observed: 105 (11.0% of total)
- Year range: 2016-2019
- Island areas surveyed (8): Niihau, Kauai, Oahu, Molokai, Lanai, Maui, Kahoolawe, Hawaii
- Median depth (and range): 159.5 m (44.8 m – 291.7 m)
- Uku length range: NA
- Methods: Baited underwater video surveys recorded visual observations of the fish community using stationary stereo-video camera arrays in shallow to mesophotic hardbottom and softbottom habitats (Amin et al. 2017).
- Comments: These surveys were performed annually during 2016-2019 (Figure 7). Uku observations were collected along with observations of multiple fish species. Surveys with “at least 1” uku were given a value of 1 for Nmax. Survey records with a *Species* identification of “Lutjanidae”, “Perciformes”, “Teleost”, or “too dark to annotate” were not included in the analysis.
- Contact: Audrey Rollo, audrey.rollo@noaa.gov

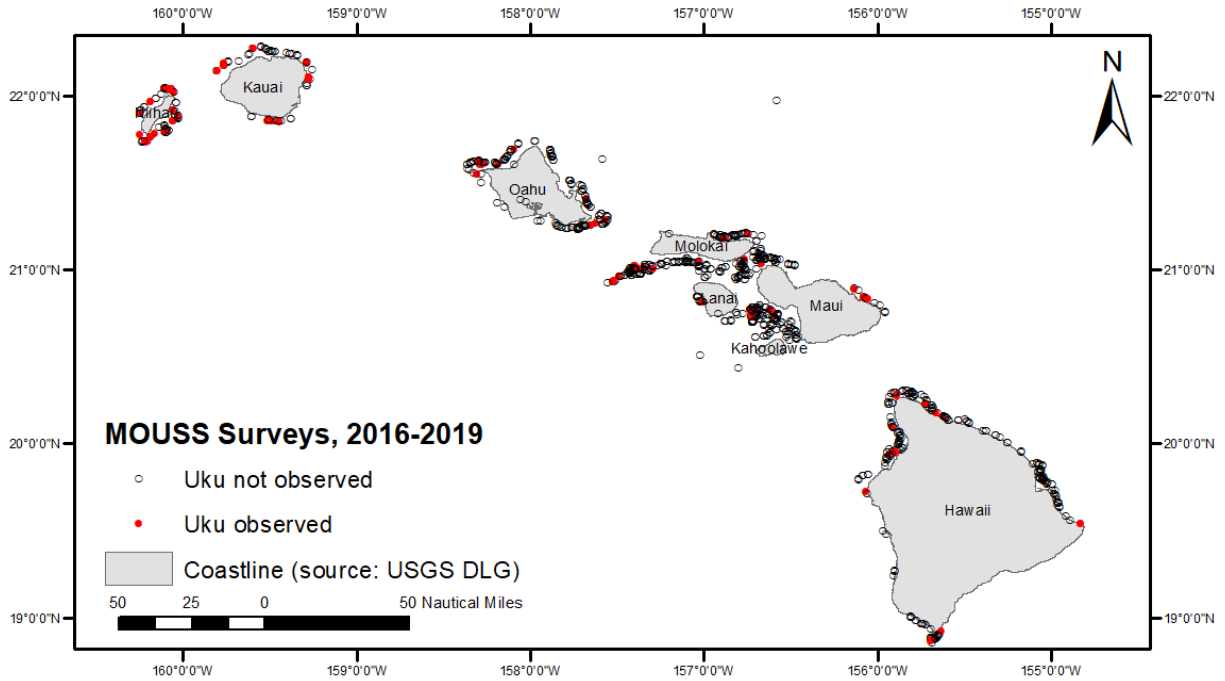


Figure 7. MOUSS underwater video surveys for uku (*Aprion virescens*) in the main Hawaiian Islands, 2016-2019. Surveys include those with uku observed (red circles) and those with no uku observed (open circles).

Survey Data Used for SDM Models

While several potential survey data sources were evaluated for inclusion in the SDMs (including data from Hawaii Division of Aquatic Resources and The Nature Conservancy), only the NOAA PIFSC SPC diver surveys for shallow habitats and NOAA/UH baited remote underwater stereo-video surveys (i.e., BotCam, MOUSS, & BRUVs) for deep habitats were used. These surveys were selected based on their methodological consistency, well-documented field techniques, and data collection QA/QC procedures by NOAA scientists (Merritt et al. 2011, Amin et al. 2017, Asher et al. 2017, Heenan et al. 2017). Due to differences in the survey data collection methods and a lack of geographic and depth overlap between diver surveys and stereo-video camera surveys, separate SDM models for Uku were constructed for shallow (0-30 m depth) depths using stationary visual diver surveys and deep (30-300 m) depths using baited stereo-video camera arrays. Shallow diver surveys included information on fish lengths but most of the deep video surveys (i.e., MOUSS surveys) did not include length information for observed Uku. The lack of length data for most of the surveys meant that sufficient information was not available to create separate EFH maps for sub-adult and adult fish for the majority of the study domain (i.e., 30-300 m). Thus, the EFH analyses and maps that follow are for aggregated sub-adult/adult life stages. In addition, Level 2 EFH models based on density of Uku were not possible due to the biases and inaccuracies inherent in directly comparing estimates of relative abundance (i.e., fish per unit area) between the different sampling methods used by shallow visual diver surveys and deep stereo-video surveys (Willis et al. 2000, Harvey et al. 2004) and insufficient intercalibration exists between the survey methods. Some stereo-video camera surveys were performed in depths shallower than 30 m but these surveys were not included in the SDMs. A few surveys had bad

geographic coordinates that were located on land or in water much deeper than 300 m. These were not included in the models. Shallow and deep survey sites were present around Niihau and Kauai (Figure 8), Oahu (Figure 9), Maui Nui (Figure 10), and Hawaii (Figure 11).

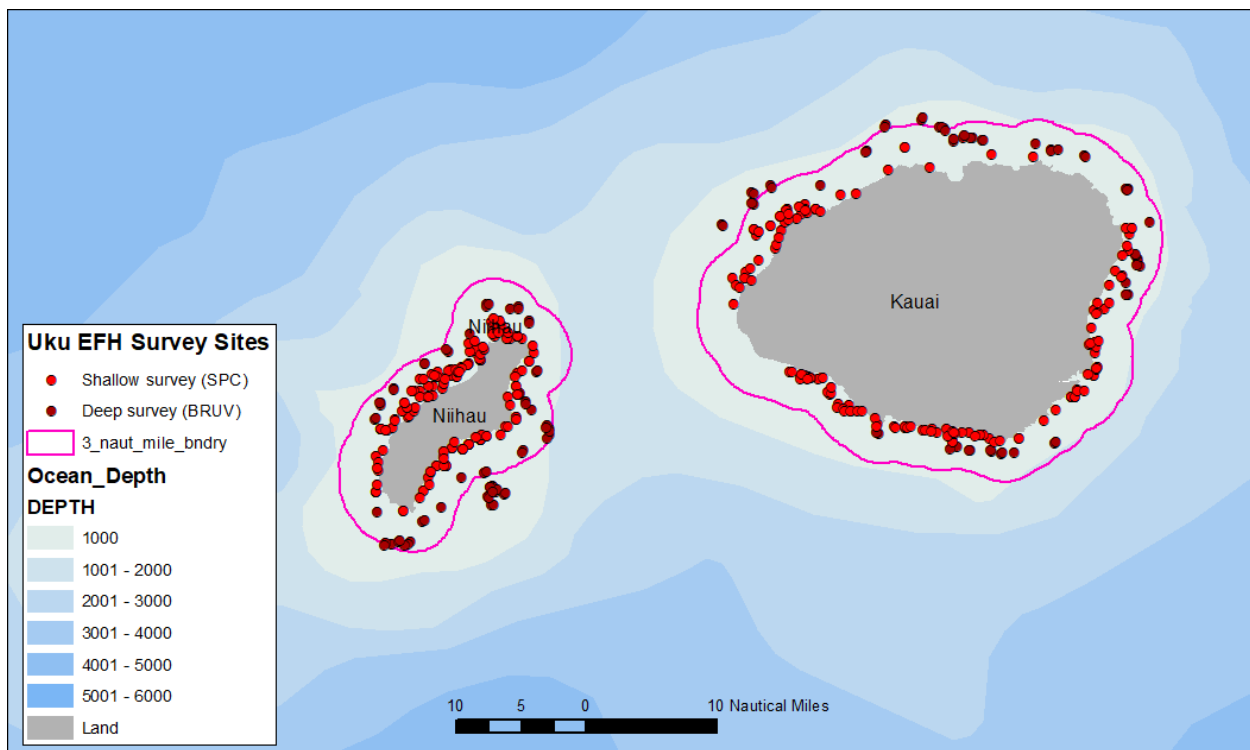


Figure 8. Shallow and deep survey sites for Uku (*Aprion virescens*) in Niihau and Kauai.

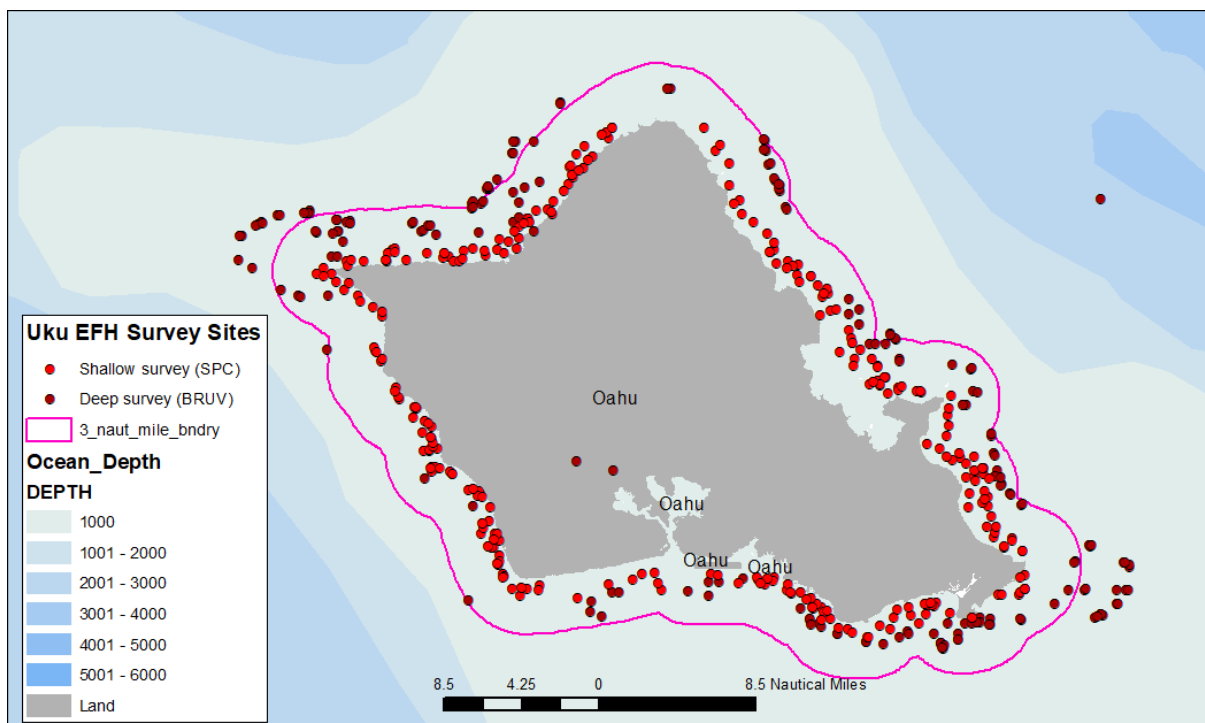


Figure 9. Shallow and deep survey sites for Uku (*Aprion virescens*) around Oahu.

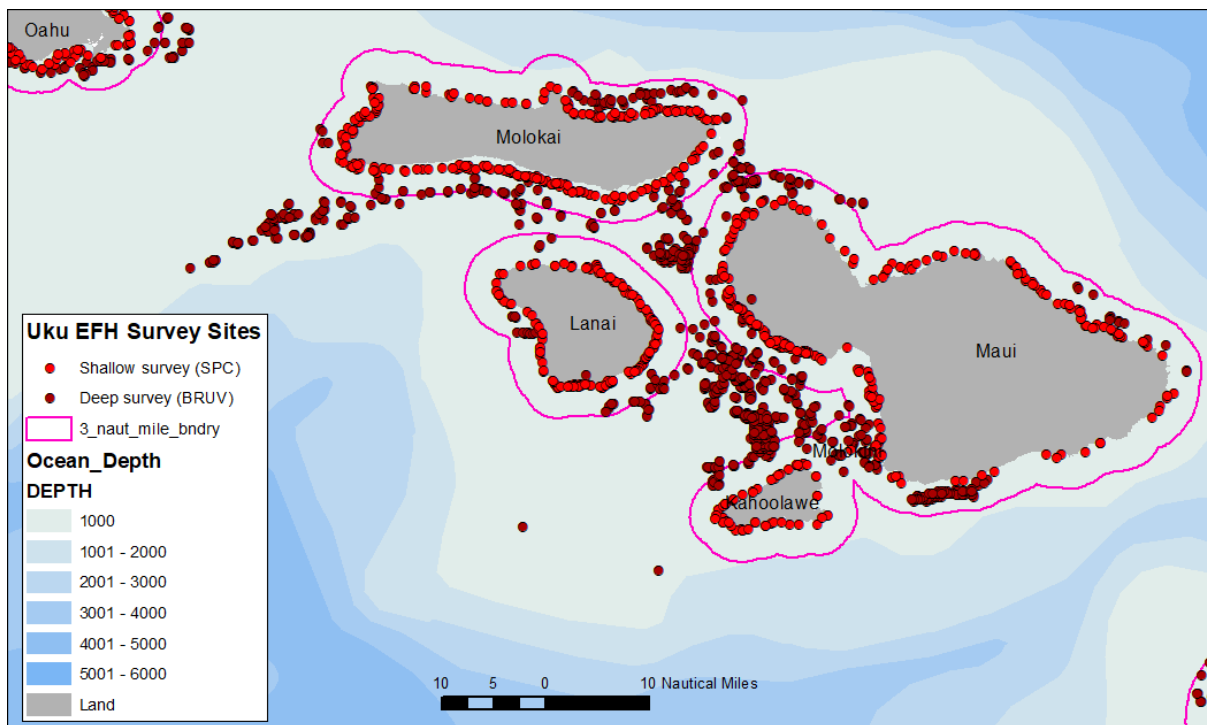


Figure 10. Shallow and deep survey sites for Uku (*Aprion virescens*) around Maui Nui.

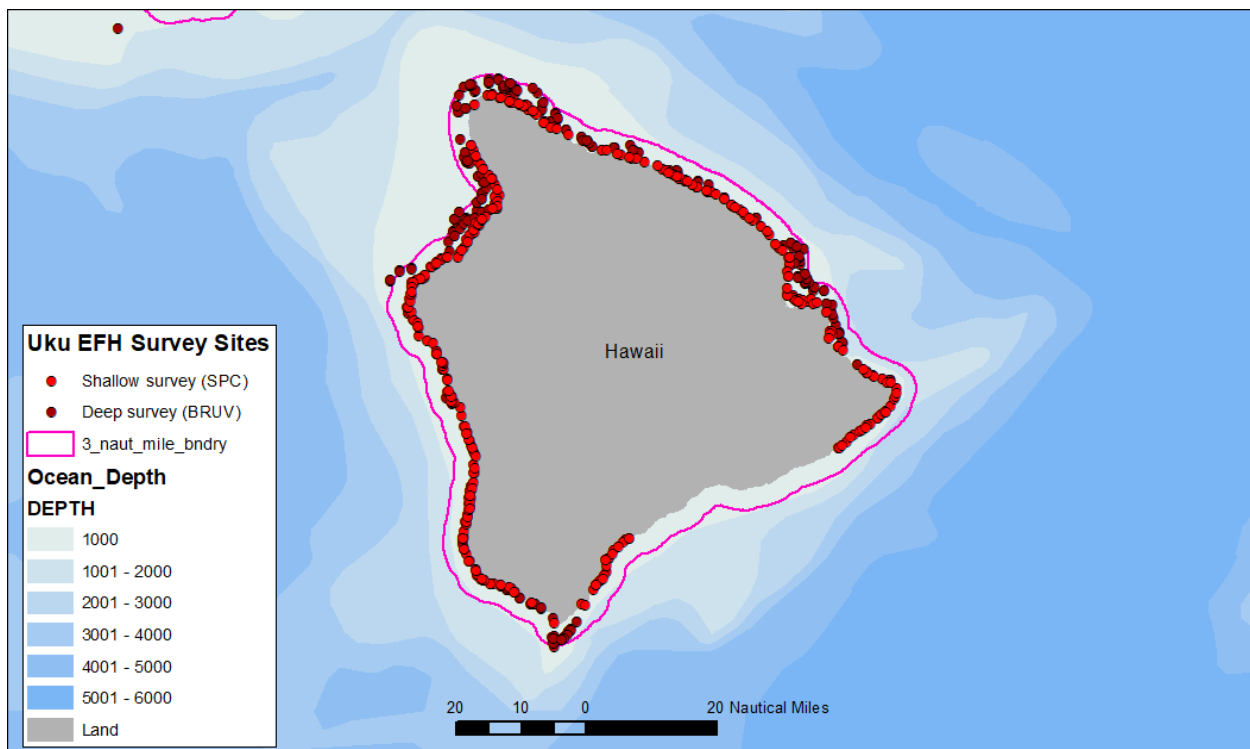


Figure 11. Shallow and deep survey sites for Uku (*Aprion virescens*) around Hawaii Island.

Habitat Covariates

A set of habitat covariates were used to parameterize and select the best fit SDMs. The covariates represented observed, calculated, and modeled variables that were expected to influence the distribution of Uku. For all covariates, the values were resampled to regular spatial raster grids of 50 m x 50 m resolution. Bathymetry-derived variables—slope, aspect, and rugosity—were calculated in ArcGIS (V.10.7.1) with an eight-cell neighborhood (Burrough and McDonnell, 1998). Terrain ruggedness, referred to as rugosity hereafter, was calculated with an eight-cell neighborhood using ArcGIS Benthic Terrain Modeler (Wright et al., 2005) and ranged from 0 (no variation) to 1 (complete variation). Bathymetry-derived variables were calculated at 50-m resolution of bathymetry provided by the Hawaii Mapping Research Group’s bathymetry synthesis. The bathymetry derived variables are considered “static” variables that don’t change often. In contrast to static variables, three dynamic variables were included in the analyses for the shallow models only. SWAN wave model output provided maximum significant wave height and mean significant wave height for the climatology from 2010-2019 (Franklin et al. 2013). The 8-day composite sea surface temperature (SST) and net primary productivity (NPP) from the Aqua MODIS sensor (NASA 2021) were extracted to match the location and time of each Uku survey using *rerddap* in R (Chamberlin 2021) from the NOAA PFEG ERDDAP server (<https://coastwatch.pfeg.noaa.gov/erddap/index.html>). Collinearity among covariates was examined prior to using them in the SDMs. Paired correlations for all covariates were below $r = 0.6$, an acceptable threshold for boosted regression tree models (Elith et al. 2008). Records with no data values for any variables were dropped from the analyses.

Species distribution modeling

SDM modeling adapted methods used by Franklin et al. (2013) and Oyafuso et al. (2017). Boosted regression tree (BRT) models were constructed for Uku occurrence (i.e., presence/absence) using the routines *gbm* (generalized boosted regression models) v2.1.8 (Ridgeway 2020) and *gbm.step* (Elith et al. 2008) in the R statistical program V4.03 (R Development Core Team, www.r-project.org). BRT models combine regression trees that fit environmental predictors to response variables with a boosting algorithm that assembles an ensemble of trees in an additive, stage-wise fashion (Hastie et al. 2001, Elith et al. 2008). Within the BRT models, 3 terms were used to optimize predictive performance: tree complexity, learning rate, and bag-fraction. Tree complexity (*tc*) determined the number of nodes in a tree that should reflect the true interaction order on the response being modeled, although this is often unknown, and learning rate (*lr*) was used to shrink the contribution of each tree as it is added to the model (Elith et al. 2008). The bag-fraction determined the proportion of data to be selected at each step and, therefore, the model stochasticity (Elith et al. 2008). For each species, the BRT model training dataset was a one-time random selection of 70% of the original total dataset of model grid cells (Table 1). The remaining 30% was held out for independent validation of each optimal BRT model. I determined optimal settings for these parameters by examining the cross-validation deviance over *tc* values 1–5, *lr* values of 0.01, 0.05 and 0.001, and bag fractions of 0.5 and 0.75. All possible combinations were run, with the optimal number of trees in each case being determined by *gbm.step* (Elith et al. 2008). Each model run included 10-fold cross-validation using training data sets. The combination of the 3 parameter settings with the lowest cross-validation deviance was then selected to produce the optimal BRT model for each species

fit with the entire training dataset (Elith et al. 2008). Finally, the deviance of the optimal model was evaluated on the test (30%) dataset. All models were run with binary measures of Uku presence (i.e., 0 or 1) which were treated as a binomial response distribution. For the final BRT models, the relative contribution of each predictor was based on the number of times the variable was selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees (Friedman & Meulman 2003, Elith et al. 2008). Partial dependency plots were used for interpretation and to quantify the relationship between each predictor variable and response variable, after accounting for the average effect of all other predictor variables in the model. I used *gbm.interactions* (Elith et al. 2008) to quantify interaction effects between predictors. The relative strength of interaction fitted by BRT was quantified by the residual variance from a linear model, and the value indicates the relative relative degree of departure from a purely additive effect, with zero indicating no interaction effects fitted (Elith et al. 2008). I defined a threshold interaction value and reported the interactions with values ≥ 0.1 . Example code used for the SDM modeling is included as in the Appendix.

Comparing SDMs With Static and Dynamic Habitat Variables

Two broad categories of habitat and environmental variables that can be used to describe EFH are “static” and “dynamic” variables. Static variables are typically geomorphological benthic structures and substrates that don’t change rapidly such as depth, slope, and rugosity. Dynamic variables represent environmental elements that can change on hourly and diurnal timescales like seawater temperature and wave energy. To evaluate, the relative contribution of static and dynamic variables, I compared shallow (0-30 m) SDMs constructed from (1) only static variables, (2) only dynamic variables, and (3) a full model of all static and dynamic variables. Models were evaluated using standard procedures and metrics described in the next section.

SDM Evaluation

A set of common evaluation metrics of predictive performance was calculated on the models fitted to the test datasets. Area Under the Receiving Operating Curve (AUC) calculates the ability of a model to discriminate between a presence or absence observation. Values of AUC are coarsely interpreted as: bad: 0.50–0.59; poor: 0.60–0.69; fair: 0.70–0.79; good: 0.80–0.89; excellent: 0.90–1.0 (Hosmer et al., 2013). Specificity, Sensitivity and the True Skill Statistic (TSS) were calculated using a probability threshold that balances sensitivity and specificity similar to Schröder and Richter (2000). True Skill Statistic values range from –1 to +1 where values <0 indicating a predictive model worse than random, zero indicating an indiscriminate predictive model, and +1 indicating a perfect predictive model. Lastly, percent deviance explained was calculated as: $\% \text{ Deviance Explained} = 100\% * (1 - \text{Residual Deviance} / \text{Null Deviance})$.

RESULTS

Uku was a habitat generalist found in both hardbottom and softbottom habitats with most observations occurring in depths between 30-120 m. The species seems to be a solitary predator, with most positive observations of only single fish (e.g., only 18 of 156, 12%, of deep camera

observations had more than one Uku). The final optimal BRT models for shallow and deep habitats predicted the habitat suitability of combined sub-adult/adult Uku probability of occurrence for the MHI. Model parameter settings for the optimal BRT models were selected from a set of possible combinations of bag fraction, tree complexity, and learning rate (Table 1). The optimal models for shallow and deep habitats had “good” model fits based on AUC and the Total Skill Statistic with acceptable performances in model specificity and sensitivity (Table 2). The occurrence of Uku was higher on N-NW and SE-SW facing habitats and increased with decreasing depths and increasing wave heights in the shallow model (0-30 m) (Figure 12). Ranked relative importance of variables for the optimal shallow model was aspect (25.2% of relative importance), depth (24.4%), maximum wave height (16.8%), mean wave height (12.3%), slope (9.7%), rugosity (8.4%), and sand (3.2%) (Figure 12). For the deeper model (30-300 m), the occurrence of Uku was higher in depths shallower than 100 m and hard-bottom habitats (Figure 13). Ranked relative importance of variables for the optimal deep model was depth (44.9%), sand (17.2%), slope (13.1%), aspect (12.7%), and rugosity (12.2%) (Figure 13).

Table 1. Surveys with Uku observed, model sample sizes, and parameter values selected for shallow and deep optimal BRT models. Abbreviations are for bag fraction (bf), tree complexity (tc), learning rate (lr), number of trees (trees), and mean deviance for cross validated model runs (devmean)

Model	Samples with Uku present	Total Sample size	bf	tc	lr	trees	devmean
<i>Shallow</i>	159	1198	0.5	4	0.001	4400	0.537
<i>Deep</i>	138	1423	0.5	4	0.001	3300	0.488

Table 2. Model performance values for the shallow and deep optimal BRT models. Abbreviations are for proportion of deviance explained (Environ_DEV), area under curve-receiver operating characteristic (AUC), total skill statistic (TSS), and model specificity and sensitivity.

Model	Environ_DEV	AUC	TSS	Specificity	Sensitivity
<i>Shallow</i>	0.42	0.82	0.43	0.83	0.61
<i>Deep</i>	0.39	0.86	0.55	0.76	0.79

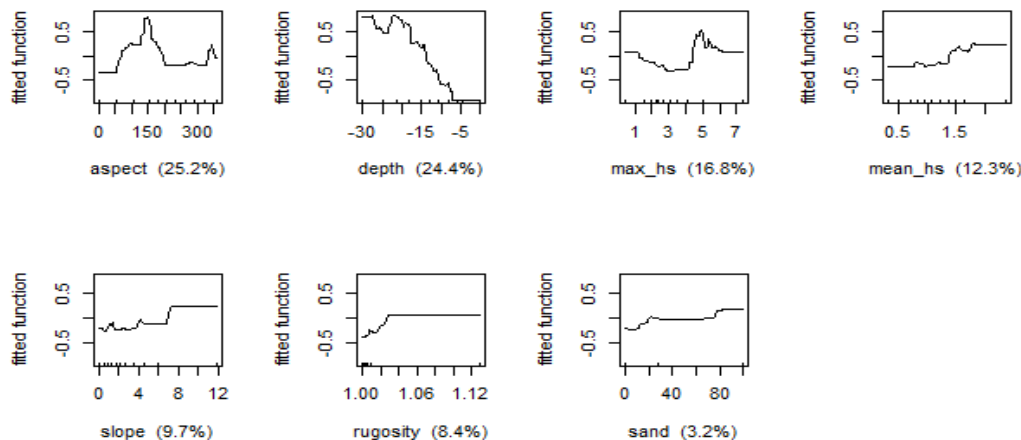


Figure 12. Partial regression plots for covariates in the optimal “shallow” BRT model.

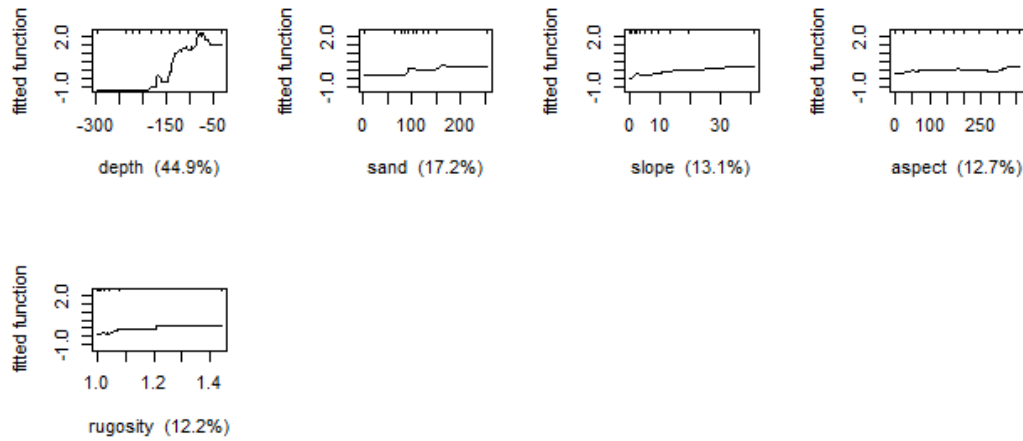


Figure 13. Partial regression plots for covariates in the optimal “deep” BRT model.

In a comparison between SDMs, the “only static variables” model outperformed the “only dynamic variables” model but performed similarly to the full model that incorporated all the static and dynamic habitat variables (Table 3). Overall, the model performances were not good compared to the prior optimal shallow BRT model most likely due to a smaller set of samples being used in the comparison. The data set used for the comparison was trimmed to 1,018 samples (1,198 samples) from to eliminate records that had no data values from the dynamic SST and NPP variables (Table 4). A disproportionate number of the trimmed records had positive Uku observations (57 of the 180) which most likely contributed to the diminished model performance compared to the prior optimal shallow model.

Table 3. Model performance values for the shallow and deep optimal BRT models.

Abbreviations are for proportion of deviance explained (Environ_DEV), area under curve-receiver operating characteristic (AUC), total skill statistic (TSS), and model specificity and sensitivity.

Model	Environ_DEV	AUC	TSS	Specificity	Sensitivity
<i>Static only</i>	0.26	0.75	0.27	0.72	0.55
<i>Dynamic only</i>	0.11	0.59	0.09	0.74	0.35
<i>Static and Dynamic</i>	0.32	0.74	0.27	0.75	0.52

Table 4. Surveys with Uku observed, model sample sizes, and parameter values selected for optimal BRT models using static variables only, dynamic variables only, and a full model with both sets of variables. Abbreviations are for bag fraction (bf), tree complexity (tc), learning rate (lr), number of trees (trees), and mean deviance for cross validated model runs (devmean).

Model	Samples with Uku present	Total Sample size	bf	tc	lr	trees	devmean
<i>Static only</i>	102	1018	0.5	2	0.001	2950	0.584
<i>Dynamic only</i>	102	1018	0.75	2	0.001	1700	0.646
<i>Static and Dynamic</i>	102	1018	0.75	4	0.001	3200	0.564

Uku EFH Habitat Suitability Maps

The optimal shallow (0-30 m) and deep (30-300 m) BRT models were used to predict Uku sub-adult/adult occurrence to the waters around the main Hawaiian Islands. The GIS maps were generated by using the optimal models fit to the values of habitat covariates from each geographic location in the main Hawaiian Islands domain (in R) to generate a predicted probability of Uku occurrence. Across the shallow habitat range, the mean probability of occurrence per habitat cell was 0.09 (range = 0.02 – 0.71, sd = 0.09, n = 477,795 habitat cells). For the deeper habitat range, the mean probability of occurrence per habitat cell was 0.12 (range = 0.01 – 0.88, sd = 0.12, n = 2,259,733 habitat cells). The maps show the model-predicted probability of occurrence for sub-adult/adult Uku for Kauai and Niihau (Figure 14), Oahu (Figure 15), Maui Nui (Figure 16), and Hawaii island (Figure 17). A visual comparison of the probability of Uku occurrence model output and the total commercial Uku catch in fishery reporting grids for 2010-2019 showed generally good geographic correspondence between them (Figure 18). In particular, there appeared to be good correspondence between the model output and catch records from Niihau, Kaena Pt (Oahu), Penguin Bank, and the Kohala coast (Hawaii Island). For Kauai and south Lanai, there was a mismatch between the model and recorded catch. Near Kauai, the higher relative catches are reported on the east and south shores while the model predicted higher probability of Uku occurrence on the north shore (Figure 14). For the southeast coast of Lanai, the model predicted very low probability of Uku occurrences but the catch records were relative high from that area.

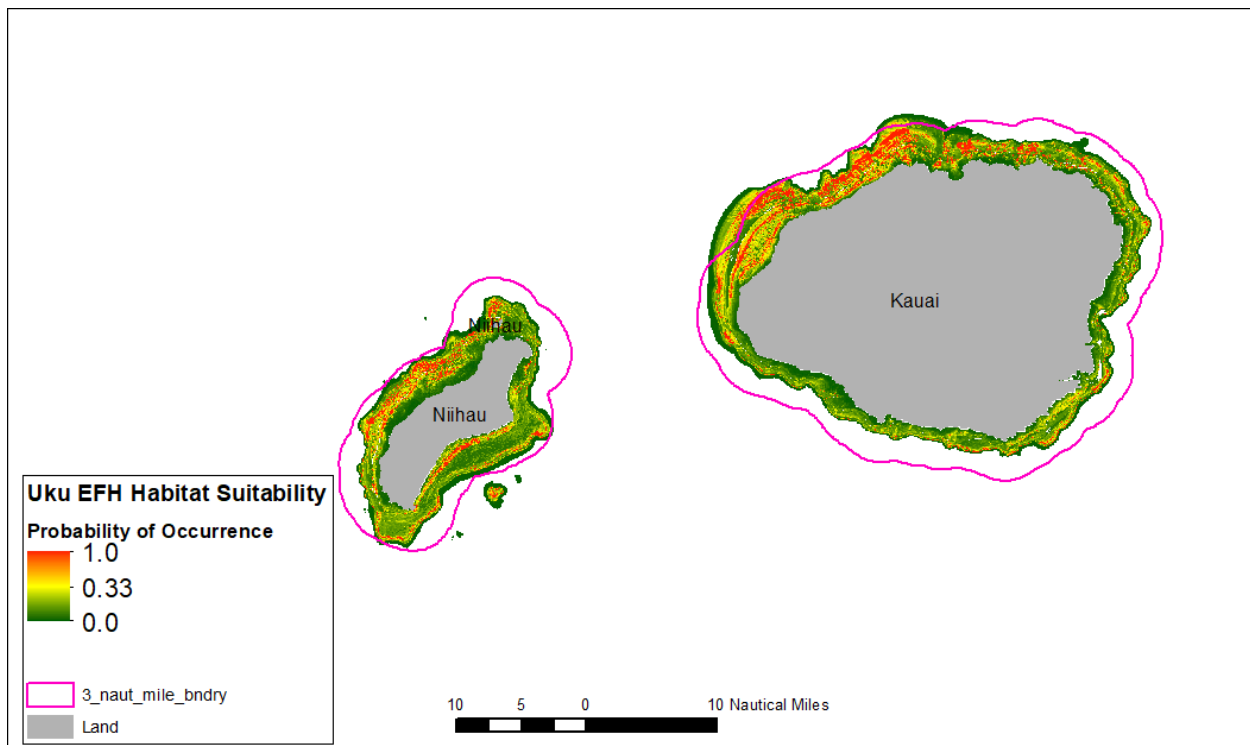


Figure 14. Uku (*Aprion virescens*) predicted probability of occurrence around Kauai and Niihau from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

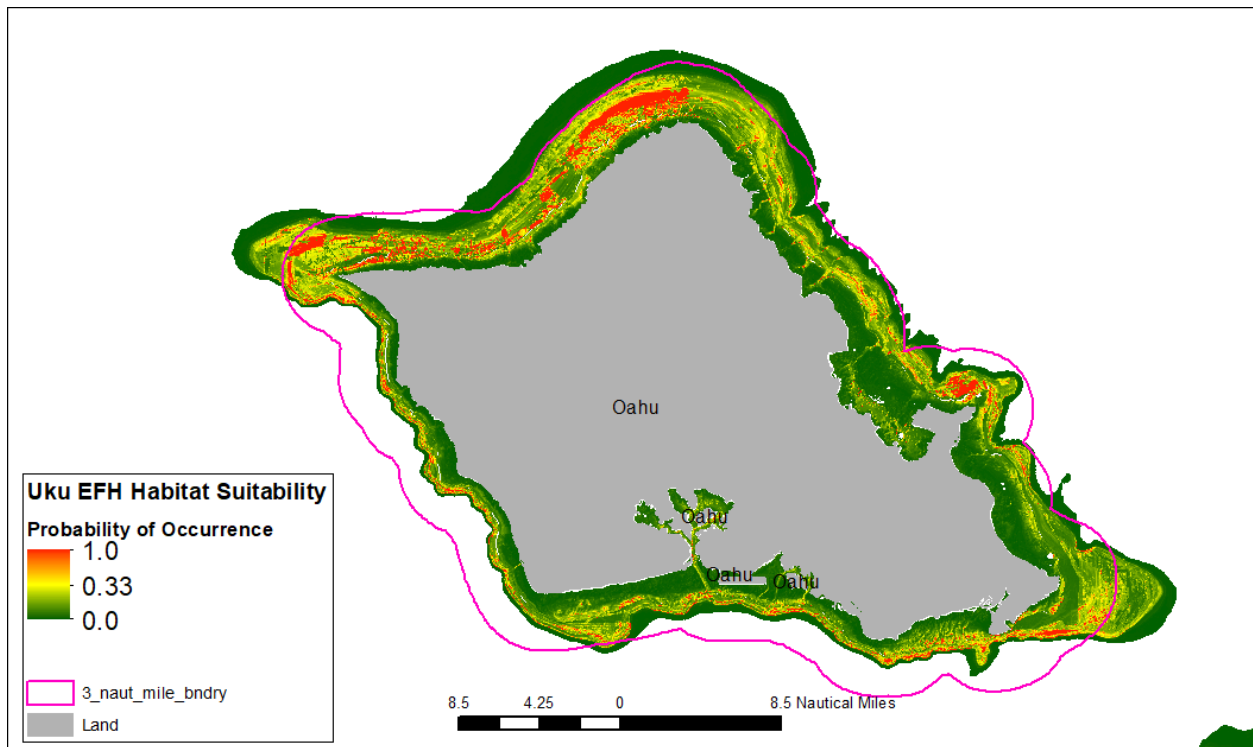


Figure 15. Uku (*Aprion virescens*) predicted probability of occurrence around Oahu from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

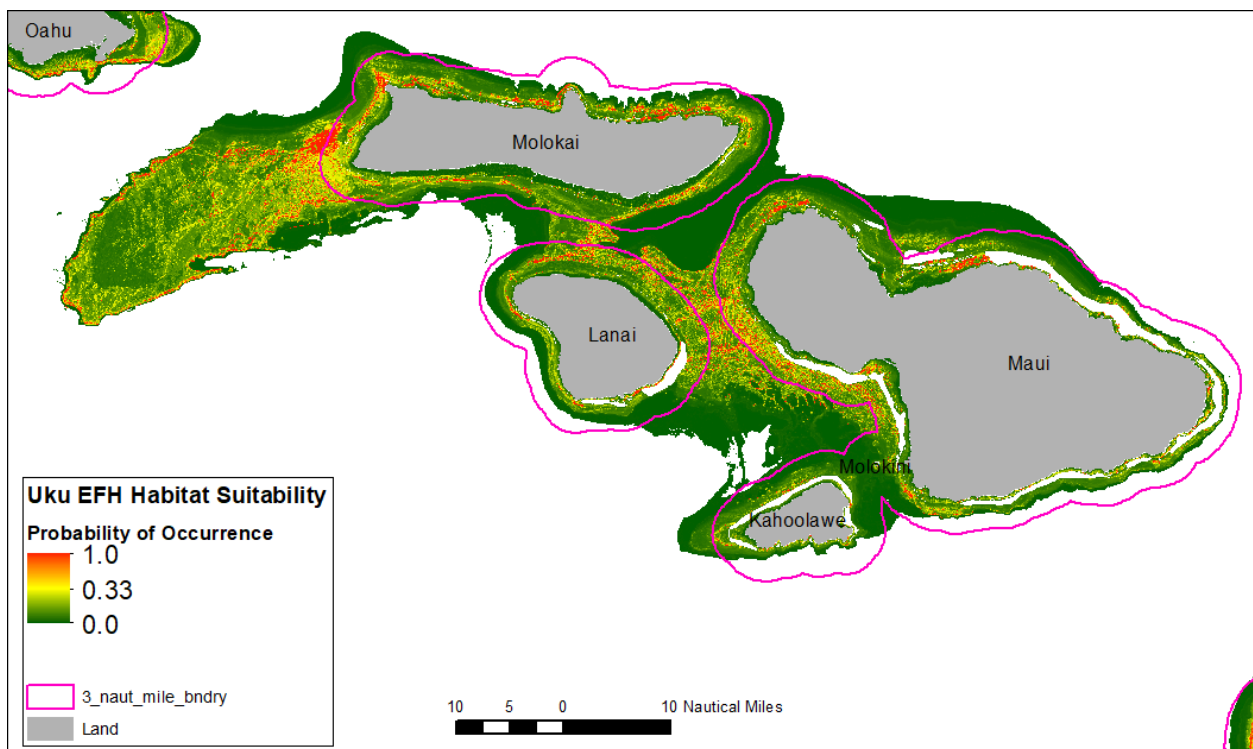


Figure 16. Uku (*Aprion virescens*) predicted probability of occurrence around Maui Nui from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

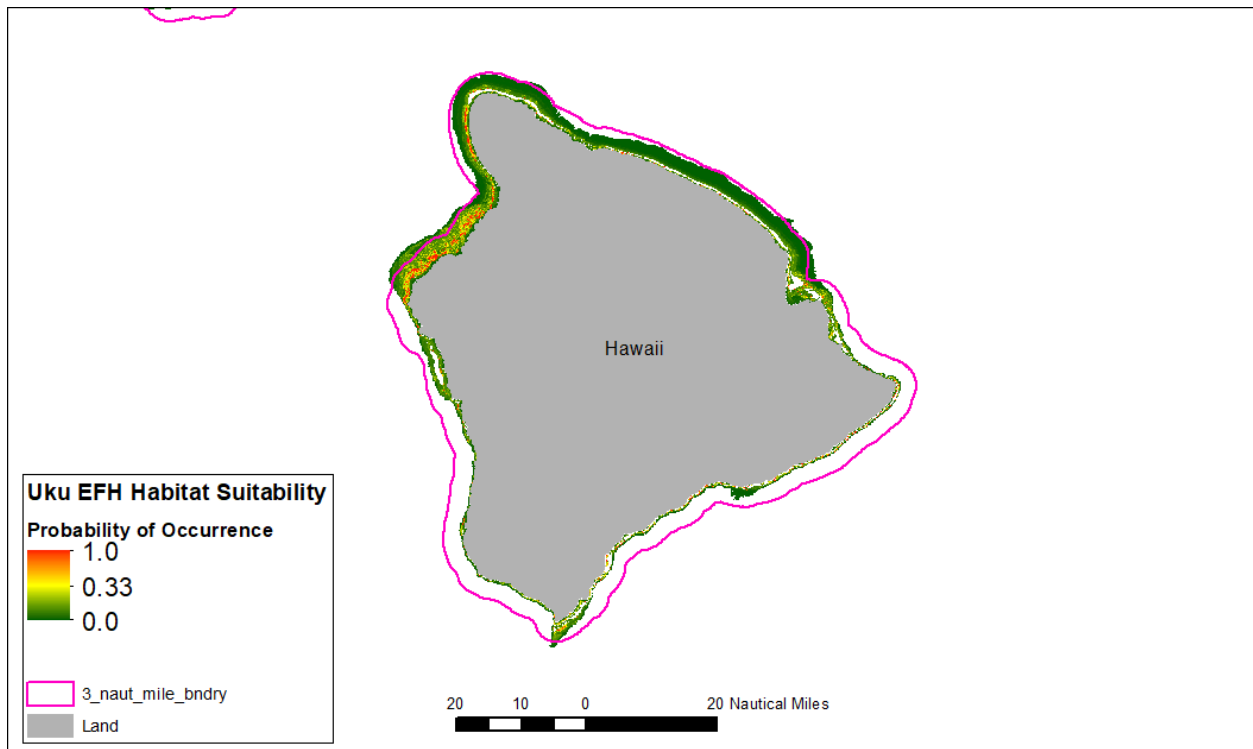


Figure 17. Uku (*Aprion virescens*) predicted probability of occurrence around Hawaii island from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

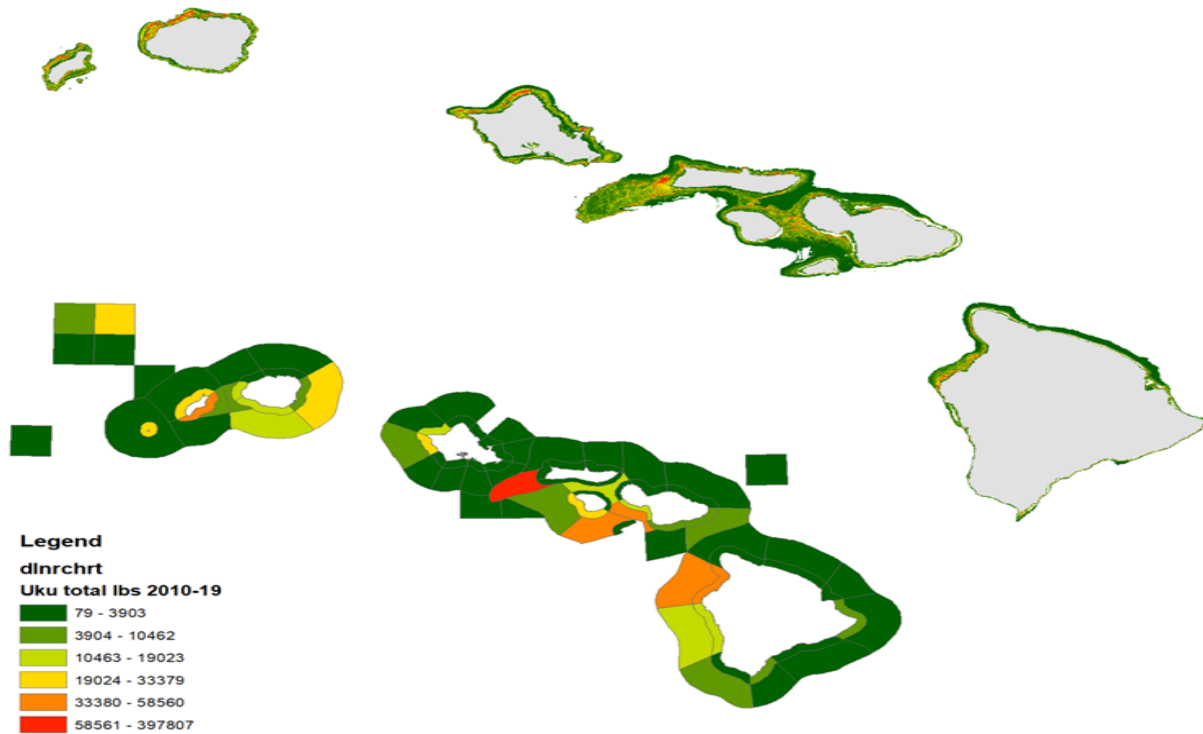


Figure 18. Uku predicted probability of occurrence in the main Hawaiian Islands and the total commercial Uku catch in fishery reporting grids for 2010-2019.

Uku EFH Categorical Maps

Maps of the predicted probability of occurrence from habitat suitability models display a continuous scale of the response variable that is difficult to interpret for decision making. To better visualize the relative importance of different habitat areas, a categorical method for EFH using the absolute 25%, 50% and 95% quantiles of the Uku probability of occurrence is introduced. This approach has been utilized for delineation of EFH in other US Fishery Management Regions such as the North Pacific (Pirtle et al. 2020). The quantiles identified “hot spots” (predicted probability of occurrence: 1.0 – 0.75), “core habitats” (0.75 – 0.50), and basic “EFH” (0.50 – 0.05) for waters around Kauai and Niihau (Figure 18), Oahu (Figure 19), Maui Nui (Figure 20), and Hawaii island (Figure 21). For the shallow habitat range (0-30 m), Uku hot spots represent 0% of the area, core habitats are 0.2%, basic EFH is 55.4%, and other (i.e., non-EFH habitats) are 44.4% of the area. For the deep habitat range (30-300 m), Uku hot spots are 0.1% of the area, core habitats are 2.4%, basic EFH is 60.1%, and other habitats are 37.4% of the area. Most of the hot spot and core habitats are in the deeper depth ranges of Penguin Bank (Figure 22) on the N-NW coasts of the islands, such as the Kohala coast of Hawaii Island (Figure 23). Basic EFH habitats cover the majority of both shallow and deep habitats. Total combined EFH (i.e., hot spots, core habitats, and EFH) in shallow and deep habitats is 61.4% of the seafloor between 0-300 m. The “other” habitats (i.e., non-EFH) were predominately either shallow, nearshore habitats adjacent to shorelines or the habitats deeper than ~150 m throughout the main Hawaiian Islands. An ESRI ArcGIS layer package is provided with this report that includes the map files for the Uku EFH categorical maps (efh_sh_dp.lpk).

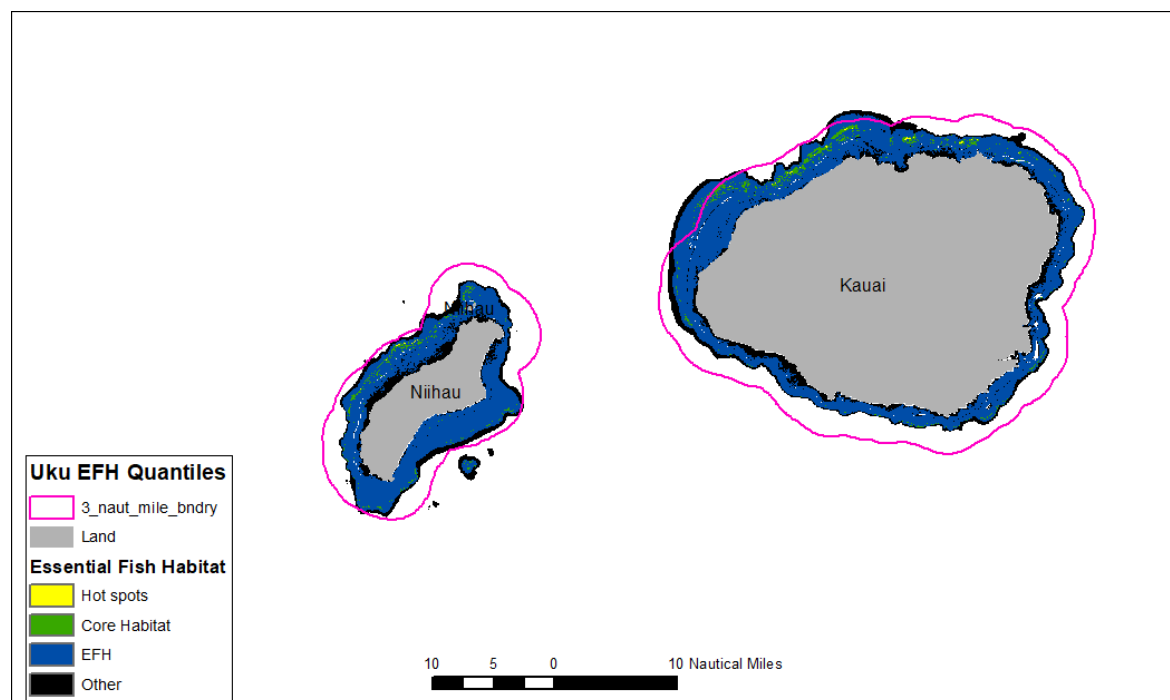


Figure 18. Uku (*Aprion virescens*) EFH hot spots (predicted occurrence probability of 0.75-1.0), core habitats (0.5-0.75), and basic EFH (0.05-0.5) around Kauai and Niihau from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

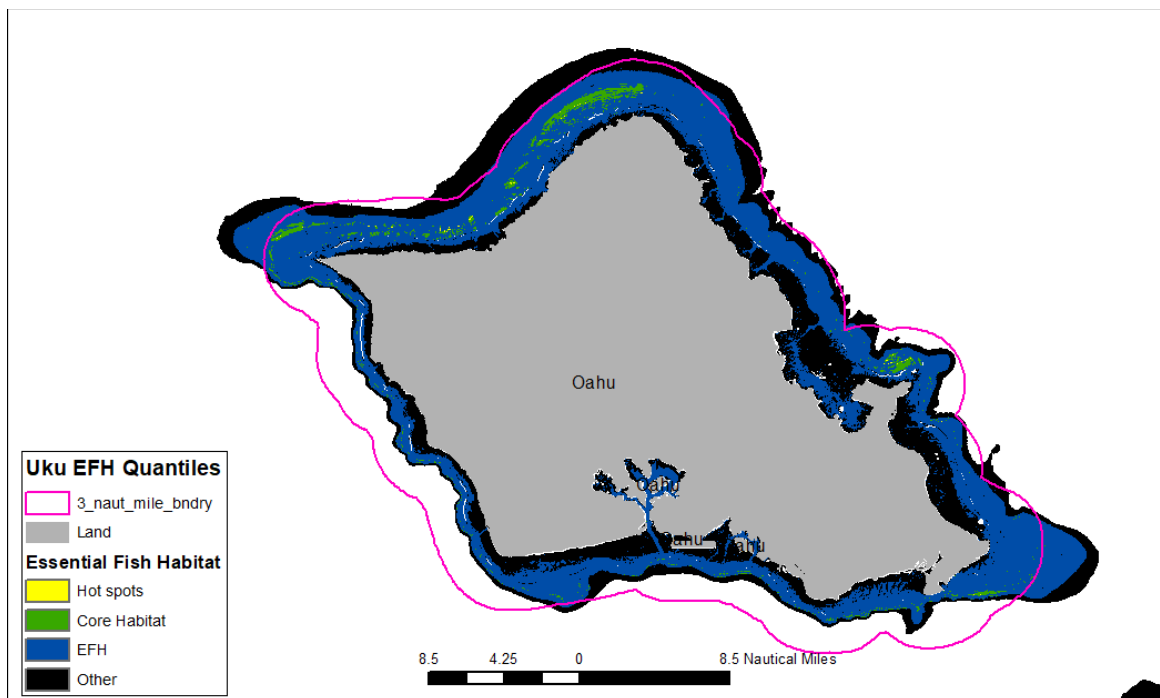


Figure 19. Uku (*Aprion virescens*) EFH hot spots (i.e., predicted occurrence probability of 0.75-1.0), core habitats (0.5-0.75), and basic EFH (0.05-0.5) around Oahu from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

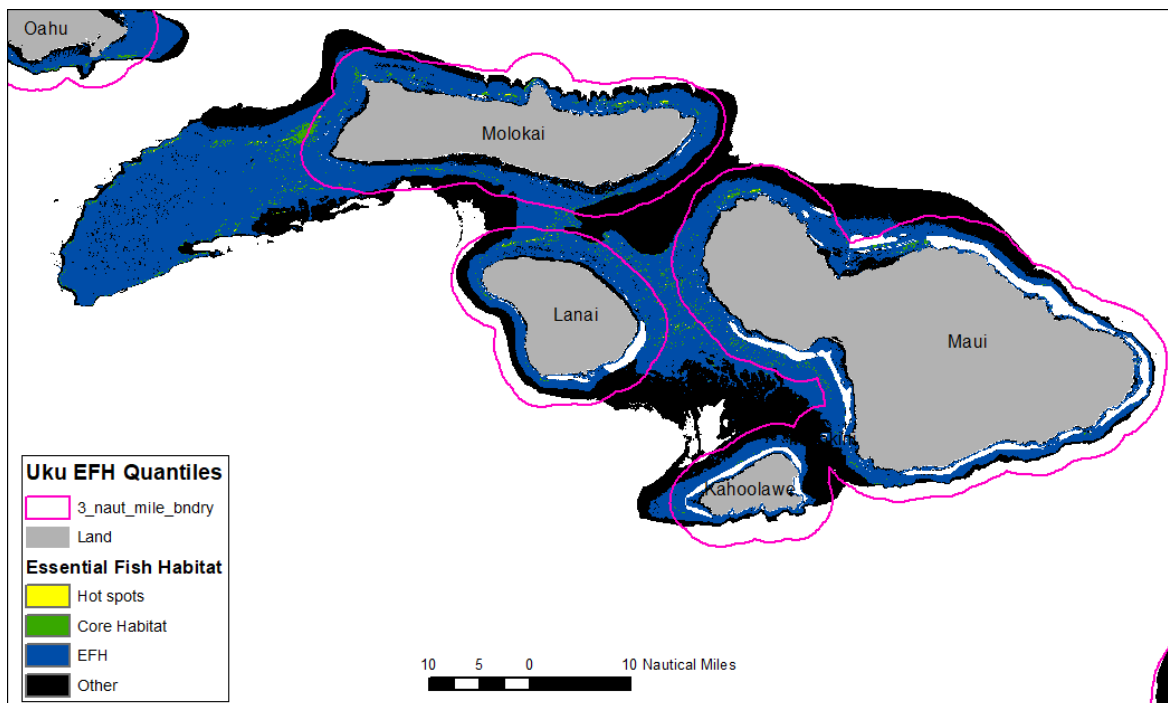


Figure 20. Uku (*Aprion virescens*) EFH hot spots (i.e., predicted occurrence probability of 0.75-1.0), core habitats (0.5-0.75), and basic EFH (0.05-0.5) around Maui Nui from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

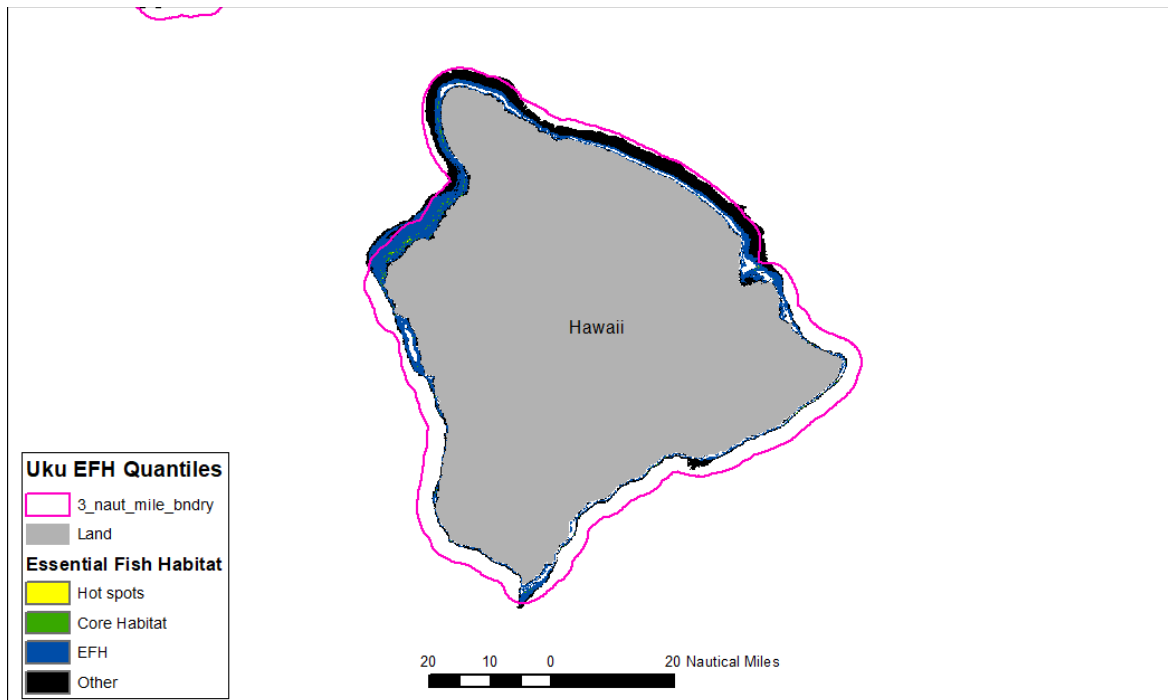


Figure 21. Uku (*Aprion virescens*) EFH hot spots (i.e., predicted occurrence probability of 0.75-1.0), core habitats (0.5-0.75), and basic EFH (0.05-0.5) around Hawaii island from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

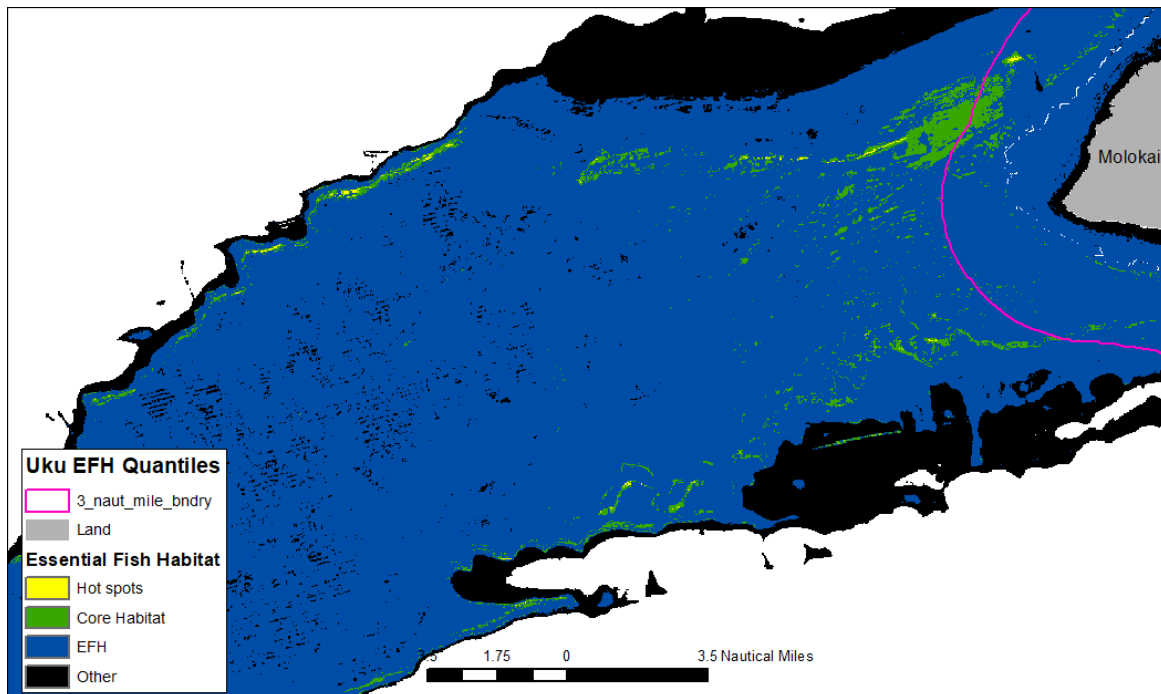


Figure 22. Uku (*Aprion virescens*) EFH hot spots (i.e., predicted occurrence probability of 0.75-1.0), core habitats (0.5-0.75), and basic EFH (0.05-0.5) on Penguin Bank from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

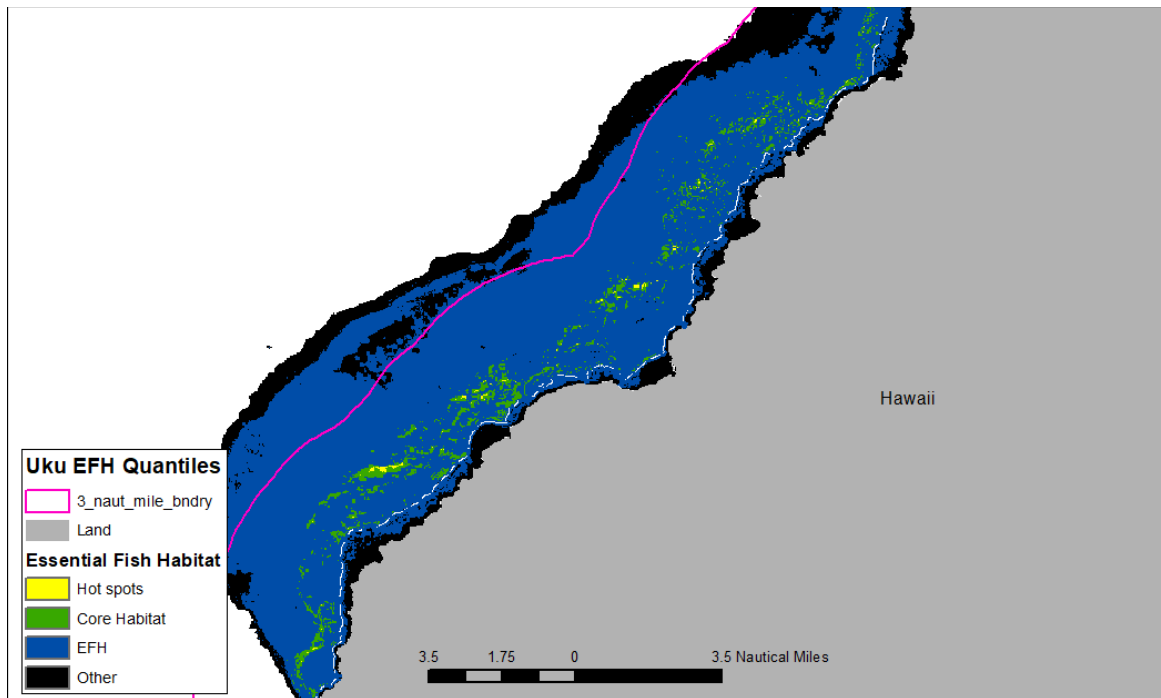


Figure 23. Uku (*Aprion virescens*) EFH hot spots (i.e., predicted occurrence probability of 0.75-1.0), core habitats (0.5-0.75), and basic EFH (0.05-0.5) on Penguin Bank from optimal BRT models for shallow (0-30 m) and deep (30-300 m) habitats.

CONCLUSIONS

A species distribution modelling approach was successfully demonstrated for the delineation of EFH for sub-adult/adult Uku (*Aprion virescens*) in the main Hawaiian Islands. The availability of fisheries-independent diver surveys for shallow (0 – 30 m) habitats and stereo-video camera surveys for deeper (30 – 300 m) provided sufficient observations to model the predicted occurrence of Uku across the entire spatial domain. Output from the SDMs were used to create maps delineating Uku EFH including continuous probability of occurrence maps as well as EFH categorical maps. The resulting categorical maps allowed the geographic identification of “hot spot”, “core habitat”, and “EFH” areas for Uku EFH to facilitate management and permitting activities. These approaches provided geographically-explicit delineations of hierarchically structured EFH categories that can be used by managers to evaluate the relative potential impacts of activities in particular locations. As an improvement to the existing EFH definitions based primarily on depth ranges, these EFH maps allow a quantitative assessment of Uku habitat value for specific sites relative to other habitats.

A comparison of models using static and dynamic habitat variables suggested that the inclusion of dynamic variables did not significantly improve the model performance although a broader variable set could be further examined in future studies. One strength of dynamic variables is that they may better allow forecasting changes to EFH due to the effects of climate change on environmental variables. One limitation of the study was the lack of sufficient fish length observations from the deep camera surveys necessary to model the sub-adult and adult fish

independently. To address this issue, existing videos could be reanalyzed to collect Uku length data for this purpose. Any future video survey analysis from the BFISH project should also include Uku as a priority species to collect length data. These data, coupled with the existing information from the shallow diver surveys, should allow the EFH for the sub-adult (i.e., juvenile) and adult Uku populations to be modeled separately. Even with these potential improvements, the analyses in this report represent the first model-based approach to delineating EFH for a U.S. Western Pacific stock and could serve as a framework for the EFH descriptions of other managed species in the region.

References Cited

- Amin R, Richards BL, Misa WFXE, Taylor JC, Miller DR, Rollo AK, Demarke C, Singh H, Young GC, Childress J, Ossolinski JE, Reardon RT, Koyanagi KH (2017) The Modular Optical Underwater Survey System. *Sensors* 17: 2309.
- Asher J, Williams ID, Harvey ES (2017) An assessment of mobile predator populations along shallow and mesophotic depth gradients in the Hawaiian Archipelago. *Scientific Reports* 7: 3905 DOI:10.1038/s41598-017-03568-1
- Battista TA, Costa BM, Anderson SM (2007) Shallow-water benthic habitats of the main eight Hawaiian Islands (DVD). NOAA Technical Memorandum NOS NCCOS 61, Biogeography Branch. Silver Spring, MD
- Burrough, P.A., McDonnell, R.A., 1998. Principals of Geographic Information Systems (revised Edition). Clarendon Press, Oxford, pp. p.333.
- Scott Chamberlain (2021). rerddap: General Purpose Client for 'ERDDAP' Servers. R package version 0.7.6. <https://CRAN.R-project.org/package=rerddap>
- Elith J, Leathwick JR, Hastie T (2008) A working guide to boosted regression trees. *Journal of Animal Ecology* 77: 802-813.
- Fletcher CH, Bochicchio C, Conger CL, Engels MS and others (2008) Geology of Hawaii reefs. In: Riegl BM, Dodge RE (eds) Coral reefs of the USA. Springer, New York, NY
- Franklin EC, Jokiel PL, Donahue MJ (2013) Predictive modeling of coral distribution and abundance in the Hawaiian Islands. *Mar. Ecol. Prog. Ser.* 481, 121–132.
- Harvey E, Fletcher D, Shortis MR, Kendrick GA (2004) A comparison of underwater visual distance estimates made by scuba divers and a stereo-video system: implications for underwater visual census of reef fish abundance. *Marine and Freshwater Research* 55: 573-580.
- Hastie T, Tibshirani R, Friedman JH (2001) The elements of statistical learning: data mining, inference and prediction. Springer-Verlag, New York, NY
- Heenan A, Williams ID, Acoba T, DesRochers A, Kosaki RK, Kanemura T, Nadon MO, Brainard RE (2017) Long-term monitoring of coral reef fish assemblages in the Western central Pacific. *Scientific Data* 4: 170176. DOI: 10.1038/sdata.2017.176
- Hosmer, J.D.W., Lemeshow, S., Sturdivant, R.X., 2013. Applied Logistic Regression. John Wiley & Sons, Inc., Hoboken, NJ p.528.
- Laman EA, Rooper CN, Turner K, Rooney S, Cooper DW, Zimmermann M (2017) Using

- species distribution models to describe essential fish habitat in Alaska. *Canadian Journal of Fisheries and Aquatic Sciences* 75: 1230-1255
- Merritt D, Donovan MK, Kelley C, Waterhouse L, Parke M, Wong K, Drazen JC (2011) BotCam: a baited camera system for nonextractive monitoring of bottomfish species. *Fishery Bulletin* 109: 56-67.
- Nadon MO, Sculley M, Carvalho F (2020) Stock assessment of uku (*Aprion virescens*) in Hawaii, 2020. U.S. Dept. of Commerce, NOAA Technical Memorandum NOAA-TM-NMFS-PIFSC-100, 120 p.
- NASA Goddard Space Flight Center, Ocean Ecology Laboratory, Ocean Biology Processing Group (2021) Moderate-resolution Imaging Spectroradiometer (MODIS) Aqua SST and NPP Data; NASA OB.DAAC, Greenbelt, MD, USA. Accessed on 06/20/2021
- Oyafuso ZS, Drazen JC, Moore CH, Franklin EC (2017) Habitat-based species distribution modelling of the Hawaiian deepwater snapper-grouper complex. *Fisheries Research* 195: 19-27.
- Pirtle J, Laman N, Thorson J (2020) Discussion paper on advancing essential fish habitat descriptions and maps for the 2022 5-year review. Report to North Pacific Regional Fishery Management Council. 150 pp.
- Ridgeway G (2012) Generalized boosted regression models. Documentation on the R package ‘gbm’, version 2.18, www.r-project.org/
- Schröder, B., Richter, O., 2000. Are habitat models transferable in space and time. *J. Nat. Conserv.* 8, 195–205.
- Sundberg, M., and K. Underkoffler. 2011. Size composition and length-weight data for bottomfish and pelagic species sampled at the United Fishing Agency Fish Auction in Honolulu, Hawaii from October 2007 to December 2009. Pacific Islands Fish. Sci. Cent., Natl. Mar. Fish. Serv., NOAA, Honolulu, HI 96822-2396. Pacific Islands Fish. Sci. Cent. Admin. Rep. H-11-04, 34 p
- Western Pacific Regional Fishery Management Council [WPRFMC] (2016) Amendment 4 to the Fishery Ecosystem Plan for the Hawaii Archipelago: Revised Descriptions of Essential Fish Habitat and Habitat Areas of Particular Concern for Bottomfish and Seamount Groundfish of the Hawaiian Archipelago. 243 pp.
- Willis TJ, Millar RB, Babcock RC (2000) Detection of spatial variability in relative density of fishes: comparison of visual census, angling, and baited underwater video. *Marine Ecology Progress Series* 198: 249-260.
- Wright, D., Lundblad, E., Larkin, E., Rinehart, R., Murphy, J., Cary-Kothera, L., Draganov, K.,

2005. ArcGIS Benthic Terrain Modeler (BTM), v. 3.0. Environmental Systems Research Institute, NOAA Coastal Services Center, Massachusetts Office of Coastal Zone Management.

Appendix: EFH Mapping Requirements

Paragraphs from the Code of Federal Regulations that are relevant to the geographic representations of EFH are excerpted below (source: NOAA NMFS Habitat Conservation EFH Mapper: <https://www.habitat.noaa.gov/application/efhmapper/index.html>) . The full text of this section of the CFR can be accessed [here](#)

**(50 CFR Ch. VI (10-1-02 Edition)
Subpart J-Essential Fish Habitat**

EFH)§ 600.815 Contents of Fishery Management Plans.

(a) Mandatory contents

(1) Description and identification of EFH

(i) Overview. FMPs must describe and identify EFH in text that clearly states the habitats or habitat types determined to be EFH for each life stage of the managed species. FMPs should explain the physical, biological, and chemical characteristics of EFH and, if known, how these characteristics influence the use of EFH by the species/life stage. FMPs must identify the specific geographic location or extent of habitats described as EFH. FMPs must include maps of the geographic locations of EFH or the geographic boundaries within which EFH for each species and life stage is found.

(iv) EFH determination.

(B) FMPs must describe EFH in text, including reference to the geographic location or extent of EFH using boundaries such as longitude and latitude, isotherms, isobaths, political boundaries, and major landmarks. If there are differences between the descriptions of EFH in text, maps, and tables, the textual description is ultimately determinative of the limits of EFH. Text and tables should explain pertinent physical, chemical, and biological characteristics of EFH for the managed species and explain any variability in habitat usage patterns, but the boundaries of EFH should be static.

(v) mapping requirements.

(A) FMPs must include maps that display, within the constraints of available information, the geographic locations of EFH or the geographic boundaries within which EFH for each species and life stage is found. Maps should identify the different types of habitat designated as EFH to the extent possible. Maps should explicitly distinguish EFH from non-EFH areas. Councils should confer with NMFS regarding mapping standards to ensure that maps from different Councils can be combined and shared efficiently and effectively. Ultimately, data used for mapping should be incorporated into a geographic information system (GIS) to facilitate analysis and presentation.

(B) Where the present distribution or stock size of a species or life stage is different from the historical distribution or stock size, then maps of historical habitat boundaries should be included in the FMP, if known.

(C) FMPs should include maps of any habitat areas of particular concern identified under paragraph (a)(8) of this section.

Appendix: Species distribution modeling (SDM) software code

Example code in the R statistical software language used to perform species distribution modeling using boosted regression trees for Uku EFH delineation in the main Hawaiian Islands.

```
#####  
## Aprion virescens Species Distribution Modeling  
## Erik Franklin, Zack Oyafuso  
## Boosted Regression Trees  
#####  
setwd("") #need to set working directory  
  
#####  
## Import Libraries  
#####  
library(dismo); library(gbm)  
library(PresenceAbsence)  
library(corrplot)  
source("brt.functions.R")  
  
#####  
## Import Data  
#####  
uku_data = read.csv("") # need to set data file  
  
#####  
## correlation matrix for covariates  
#####  
corrplot(cor(uku_data[,]),  
          method = "number",  
          type = "upper" # show only upper  
          )  
  
#####  
## For BRTs, test BRT heuristic using different three types of model settings  
## All records are used for this section  
## bag: bagging fraction (50% or 75%)  
## tcomp: tree complexity (2, 3, 4, or 5)  
## lrs: learning rate (0.001, 0.005, 0.01)  
#####  
spp_name <- "Aprvire"  
brt_settings <- expand.grid(species = spp_name,  
                             bag = c(0.75, 0.50),  
                             tcomp = 2:5,  
                             lrs = c(0.001, 0.005, 0.01),  
                             ntrees = NA, #Number of trees
```



```

devmean = NA, #mean cv deviance
stringsAsFactors = FALSE)

# split datasets into 70% train and 30% test (i.e., independent)
splitdf <- function(dataframe, seed=NULL) {
  if (!is.null(seed)) set.seed(seed)
  index <- 1:nrow(dataframe)
  trainindex <- sample(index, trunc(length(index)*0.7))
  trainset <- dataframe[trainindex, ]
  testset <- dataframe[-trainindex, ]
  list(trainset=trainset, testset=testset)
}

uku_splits <- splitdf(uku_data, seed=105)
uku_train <- uku_splits$trainset
uku_test <- uku_splits$testset
dim(uku_train); dim(uku_test); dim(uku_data)

for (i in 1:nrow(brt_settings)) {
  temp_fit = dismo::gbm.step(data = uku_train,
    #Column ids of covariates in argument data
    gbm.x = c(
      #4, #lat
      #5, #long
      6, #depth
      7, #aspect
      8, #sand
      9, #rugosity
      10), #slope
    #name of column that contains response
    gbm.y = spp_name,
    family = "bernoulli",
    tree.complexity = brt_settings$comp[i],
    learning.rate = brt_settings$lrs[i],
    bag.fraction = brt_settings$bag[i],
    verbose = TRUE)

  brt_settings[i, c("ntrees", "devmean")] <-
    c(temp_fit$n.trees, temp_fit$cv.statistics$deviance.mean)
}

#####
## Trim settings that used less than 1500 trees
## Choose settings with the lowest mean deviance
#####

```

```

brt_settings_trimmed <- subset(x = brt_settings,
                             subset = ntrees > 1500)

(best_settings <- brt_settings_trimmed[which.min(brt_settings_trimmed$devmean), ])

#####
## Setup up training models with the optimized BRT settings
#####
train_uku = gbm.step(data = uku_train,
                     gbm.x = c(6:10),
                     gbm.y = spp_name,
                     family = "bernoulli",
                     tree.complexity = best_settings$stcomp,
                     learning.rate = best_settings$lrs,
                     bag.fraction = best_settings$bag)

#####
## Parsimonious Models on Test Dataset
#####
test_uku = gbm.step(data = uku_test,
                    gbm.x = c(6:10),
                    gbm.y = spp_name,
                    family = "bernoulli",
                    tree.complexity = best_settings$stcomp,
                    learning.rate = best_settings$lrs,
                    bag.fraction = best_settings$bag)

#####
## Evaluation Metrics
#####
AUC_return = function(model.name, sp_code, thres) {

  preds <- predict.gbm(model.name,
                       uku_test,
                       n.trees=model.name$gbm.call$best.trees,
                       type="response")

  d <- cbind(uku_test[,sp_code], preds)
  pres <- d[d[,1]==1, 2]
  abs <- d[d[,1]==0, 2]
  e <- evaluate(p=pres, a=abs, tr = thres)
  return(round(e@auc,2))

}

output_df = data.frame(species = spp_name)

```

```

#output_df$Raw_I <- round(ape::Moran.I(x = uku_test[, spp_name], w =
test.dists.inv)$observed, 3)
test_pred <- predict.gbm(object = train_uku,
                        newdata = uku_test,
                        n.trees = train_uku$gbm.call$best.trees,
                        type = "response")
#residual = test_pred - uku_test[, spp_name]

#output_df$Environ_I = round(ape::Moran.I(x = residual, w = test.dists.inv)$observed, 3)

tv = sum(uku_data[, spp_name]) / nrow(uku_data)
name_assign = paste('cmx_', spp_name, sep = ")
assign(name_assign,
      PresenceAbsence::cmx(cbind(1:nrow(uku_test), uku_test$Aprvire,
                                predict.gbm(train_uku,
                                              uku_test,
                                              type = 'response',
                                              n.trees = train_uku$n.trees)), threshold = tv))

output_df$Environ_DEV = 1 - (test_uku$self.statistics$mean.res /
                             test_uku$self.statistics$mean.null)
output_df$AUC = AUC_return(train_uku, spp_name, tv)
output_df$TSS = PresenceAbsence::sensitivity(get(name_assign), st.dev = FALSE) +
PresenceAbsence::specificity(get(name_assign), st.dev = FALSE) - 1
output_df$kappa = PresenceAbsence::Kappa(get(name_assign), st.dev = FALSE)
output_df$specific = PresenceAbsence::specificity(get(name_assign), st.dev = FALSE)
output_df$sens = PresenceAbsence::sensitivity(get(name_assign), st.dev = FALSE)
output_df

#####
## Percent Variable Importance
#####
train_uku$contributions

#####
## Plot fitted functions
#####
gbm.plot(train_uku)#, write.title=TRUE)

gbm.plot.fits(train_uku)

#####
## Interactions
#####
find.int = gbm.interactions(train_uku)

```

```

find.int$interactions
find.int$rank.list

## plot largest interaction size
gbm.perspec(train_uku, 3, 1)

#####
## Predict to grids
#####

eval.data <- read.csv("deep_covars.csv", as.is=T)
names(eval.data) = c("FID", "pointid", "depth", "sand", "surf_ratio", "slope", "aspect",
"rugosity", "lat", "long")
eval.data = eval.data[, c("lat", "long", "depth", "aspect", "sand", "rugosity", "slope")]

gbm.predict.grids(train_uku, eval.data, want.grids = FALSE, sp.name = "aprville_pred")

aprville.out = cbind(eval.data, aprville_pred)
write.csv(aprville.out, "pred\\aprville_deep_total.csv")

```