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ASSESSING HABITAT USE AND POPULATION DYNAMICS OF FISHERIES RESOURCES AT KALOKO FISHPOND

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Assessing habitat use and population dynamics of fisheries resources at Kaloko Fishpond

Final Report to the National Park Service

Contract #G19AC00348

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Abstract: Throughout Hawai'i, fishponds are considered by their local communities as important cultural touchstones, a source of local, sustainably produced food, and an important component to the development of community-based management for nearshore fisheries. Within Kaloko-Honokōhau National Historical Park, the restoration of Kaloko Fishpond for traditional aquaculture management is a goal of both the National Park Service (NPS) and Hui Kaloko-Honokōhau, a community-based group of kia'i, i.e., caretakers and native Hawaiian cultural practitioners. However, existing data on the demographics and condition of the fish populations within the pond, and the fish-habitat quality are poor to non-existent. Therefore, the objectives of this study were to: catalog fish species composition and distribution in the pond; estimate the abundance of focal species/taxonomic groups; and evaluate the occupancy patterns of the invasive algae *Acanthophora spicifera* and Upside-down Jellyfish *Cassiopea andromeda.* As part of these objectives, a survey protocol and analysis framework were designed and evaluated to ensure that the NPS and community group would be able to refine and implement them to continue their monitoring efforts. We conducted dual-observer shore-based visual surveys multiple times per week during September-October 2020 and April-September 2022. A total of 41 species/taxonomic groups were recorded over the course of the surveys. The largest number of species/taxonomic groups were observed at survey stations located on or near the kuapā, or wall separating the fishpond from the ocean. *N*-mixture models fitted to the data estimated a total population of 353 – 392 mullets, 134 – 192 flagtails (āholehole), and 189 – 277 Milkfish (Awa) *Chanos chanos* occurring within the 1.2-ha portion of Kaloko Fishpond that could be surveyed visually from the shoreline. Multi-season occupancy models fitted to the surveyed presence of *A. spicifera* and Upside-down Jellyfish indicted sites throughout most of the pond exhibited moderate and consistent occupancy (ψ = 0.30 – 0.40) throughout much of the pond, except for the northeast corner of the pond (Kaloko Iki) where colonization rates were lower and extinction rates higher than other areas within Kaloko. The visual survey method developed for this study provides a low-cost and effective starting point for the development of methodology that can be used both by NPS personnel and volunteers from the community group. However, we were only able to estimate fish populations for approximately 24% of the area of Kaloko Fishpond with this method. Given that the deeper areas of Kaloko Fishpond are completely inaccessible to the visual survey method used, generating population estimates for the entire pond based on the parameters estimated in the current study is not recommended without further investigation into fish movement and habitat use. Various means to refine this protocol to better meet the needs and abilities of the NPS and community group are proposed.

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Introduction

Prior to European contact in 1778, fishponds were important cultural and economic resources for native Hawaiians as they were a cornerstone of a sophisticated, integrated food production system (Kikuchi 1976; Costa-Pierce 1987). Along the coast, fishponds consisted of embayments or other areas that were enclosed by kuapā (rock walls) and situated to take advantage of groundwater and/or surface water inflows. The kuapā resulted in nutrients arriving with these freshwater inflows not rapidly diffusing into the surrounding ocean, thereby enhancing local productivity (Malone 1969; Kikuchi 1976; Costa-Pierce 1987; Keala 2007). In terms of their hydrology and geomorphology, Hawaiian fishponds were sited and constructed to be artificial estuaries but their ecology remains largely unexamined. Fishponds were stocked both by the natural recruitment of larval and juvenile fishes passing through sluice gates, or mākāhā, built into the kuapā and the transplant of juvenile fishes captured outside of the ponds. While a potentially large number of nearshore species could recruit into fishponds, production focused on several estuarine-dependent nearshore species, such as Striped Mullet ('Ama'ama) *Mugil cephalus*, Hawaiian Flagtail (Āholehole) *Kuhlia xenura*, Pacific Threadfin (Moi) *Polydactylus sexfilis*, Milkfish (Awa) *Chanos chanos*, and Longjaw Bonefish ('Ō'iō) *Albula virgata* (Cobb 1902; Hiatt 1947a, 1947b; Keala et al. 2007). Fishpond maintenance and upkeep included diverse and labor-intensive tasks such as monitoring fish population size and growth within the ponds, control of predatory fish populations within the pond, guarding against poachers, repairing the kuapā when damaged or breached by waves or storms, and sediment management (Sato and Lee 2007); however, traditional practices dictated that all who participated in these tasks gained the right to share in the fish harvested from the pond (Kelly 1975; Sato and Lee 2007).

Prior to European contact, an estimated 360-450 fishponds, encompassing > 2,700 ha, were producing an estimated minimum annual yield > 900,000 kg throughout the main Hawaiian Islands (Cobb 1902; Costa-Pierce 1987) or an average production of 200-400 kg ha^{-1} (Cobb 1902; Apple and Kikuchi 1975). This production represented both an important source of protein to people residing in proximity to a fishpond, particularly during times of food insecurity, and easy access to prized species whose consumption was restricted to the upper echelons of native Hawaiian society (Kikuchi 1976, Sato and Lee 2007). However, changing demographics and systems of land ownership resulted in a decline in the use and upkeep of Hawaiian fishponds throughout the 19th century (Kikuchi 1976). Around the state, local community groups have led concerted efforts to restore fishponds since the early 1990s as part of a Hawaiian cultural renaissance (Keala 2007). Yet, to date only a relatively small number of fishponds have been restored and are in active production and few, if any, provide a reliable source of customary food fishes produced following traditional practices (Sato and Lee 2007).

While the legal and financial challenges surrounding fishpond restoration are daunting (Sato and Lee 2007), the most significant impediment to restoring traditional fishpond production is that the knowledge base of traditional fishpond management developed over the 800-1000 years prior to European contact has suffered degradation or outright loss (Keala 2007; Sato and Lee 2007). Further, the baseline environmental conditions under which these traditional practices were developed have shifted dramatically (Sato and Lee 2007). For example, declines in abundance of nearshore fish species have the potential to reduce the pool of larval and juvenile fishes available to recruit into fishponds. Increases in human population densities and changing land-use patterns have reduced groundwater flows and increased nutrient concentrations in many locations throughout the islands (Hunt 2004, 2007, 2014), potentially altering temperature, salinity, and productivity regimes within coastal fishponds. Further, the introduction of non-native species, such as Red Mangrove *Rhizophora mangle*, Kanda *Osteomugil engeli*, the invasive algae *Acanthophora spicifera* (Weijerman et al. 2008) and Upside-down Jellyfish *Cassiopea andromeda* (Most et al. 2009), has altered the physical structure of habitats or food-web dynamics within fishponds. Traditional practices developed under different baseline conditions may not be well-suited to effectively manage fishponds under current conditions. Therefore, assessment and monitoring conducted in collaboration with fishpond managers is necessary to adapt traditional knowledge to meet these new challenges and fill gaps due to knowledge loss.

Kaloko Fishpond is one of the largest intact fishponds in Hawai'i and is part of Kaloko-Honokōhau National Historical Park. Kaloko Fishpond is supplied by groundwater but also has an open connection to the sea through two 'auwai (channels) in the kuapā that act to keep average salinities at approximately 22 PSU. However, changes in freshwater inflows due to nearby development is a particular threat at Kaloko-Honokōhau (Oki et al. 1999, NPS 2013). Several non-native species have invaded the pond and while some, such as Red Mangrove, have been eliminated from the Park (Fronda et al. 2008), others, such as *A. spicifera*, Upside-down Jellyfish, and Kanda, persist and remain a nuisance to pond operations. Even though Kaloko Fishpond was cleared of Red Mangrove in the 1990s, the pond's ability to produce fish may still be degraded due to changes in the quality and quantity of freshwater inflows, the accumulation of sediment, and the presence of invasive species (Nishimoto et al. 2007; Duarte et al. 2010; NPS 2013). The Park's enabling legislation states that it is "...to provide a center for the preservation, interpretation, and perpetuation of traditional native Hawaiian activities and culture, and to demonstrate historic land use patterns…" However, it currently is unknown what level of production following traditional practices is environmentally sustainable and in keeping with the mission of the Park. The National Park Service (NPS) and Hui Kaloko-Honokōhau are jointly in the process of restoring and managing Kaloko Fishpond. However, both parties identified the need to learn first-hand about its resource and develop management practices for the current environmental conditions, threats, and stressors.

Throughout Hawai'i, fishponds are considered important cultural touchstones, a source of local, sustainably produced food, and an important component to the development of community-based management for nearshore fisheries (Sato and Lee 2007). However, existing data on the demographics and condition of the fish populations within a pond, and how habitat quality influences habitat use by fishes are poor to non-existent. Furthermore, the combination of gaps in traditional knowledge and Hawai'i's significantly altered environmental conditions have made initiating sustainable fishpond management based on the traditional methods established prior to European contact challenging. Therefore, an understanding of the ecology of Kaloko Fishpond, particularly as it pertains to the population dynamics of its fish species, is critical to adapting traditional pond management practices to respond to already altered and continually changing environmental conditions. Grounding these practices in defensible science and traditional knowledge is necessary to move forward with the restoration and traditional management of Kaloko Fishpond. Therefore, the objective of this study was to develop and test a fish monitoring protocol that was compatible with traditional management practices and community values that could be implemented by volunteers yet would still produce statistically robust estimates of fish abundance and distribution in Kaloko Fishpond. Secondarily, this study evaluated the ability of the monitoring protocol to serve as a means of detecting and evaluating changes in the distribution and occupancy of invasive species, as well as tracking trends in fish species diversity within Kaloko Fishpond. The final requirement for the study was that the data analyses and modeling tools necessary to draw conclusions from the monitoring protocol had to be able to be implemented by both NPS personnel and the community.

Methods

Study area.—Kaloko Fishpond is located along the west coast of the island of Hawai'i (Figure 1) in the moku, or district, of Kona and ahupua'a, (land and cultural subdivision approximately analogous to a watershed) of Kaloko. Kaloko translates from Hawaiian as "The Pond" suggesting that it held particular importance over other fishponds on Hawai'i Island, all of which have more specific names (Kelly 1971). The fishpond consists of an approximately 4.5-ha natural embayment separated from the sea by a 244-m long, 3 – 6-m wide man-made kuapā with two 'auwai o ka mākāhā, or openings in the wall with a sluice channel. Traditionally the fishpond would also include a mākāhā, to prevent the exit of larger fishes. However, neither of the two 'auwai at Kaloko Fishpond currently have mākāhā in place. The kuapā is composed of stacked basalt rocks and boulders and has been rehabilitated by the Park's Hawaiian masonry specialists following traditional construction practices. Secondary walls located within the pond itself partially isolate small coves, traditionally referred to as Kaloko Nui along the southeast corner and Kaloko Iki in the northwest corner (Maly 2000; Peterson and Orr 2005), where fingerlings were raised and different species of fish were kept. There are numerous freshwater springs within the pond, most of which are concentrated along the back edge of the pond, particularly in the northwest and southeast corners (Kikuchi 1972).

Visual fish surveys.—Initial consultations between project personnel, NPS biologists, and local community members indicated that standard fisheries survey methods to assess fish populations and habitats, such as mark recapture and sidescan sonar surveys, would not be practicable or acceptable due to regulatory concerns or because they conflicted with local traditions, beliefs, or cultural practices. In addition, community members expressed a desire to develop a methodology that ultimately could be used by volunteers to both collect and analyze data following traditional kilo methods to the extent possible. Kilo is a Hawaiian word meaning to watch, observe, examine, or forecast. While the definition as applied to ecological and natural resource surveys and monitoring is not universally agreed upon (Nakachi 2021), kilo typically is used in reference to traditional methods of acquiring and cultivating place-based knowledge that recognizes the observer and their mindset as a part of the phenomena being observed.

To meet the survey design requirements set forth by the NPS and local community, we developed an unreconciled, dual-observer shore-based monitoring protocol. In an unreconciled survey design, observers are not required to match or otherwise reconcile observations of individuals (Riddle et al. 2010). A series of stations (n = 30) were established around the perimeter of Kaloko Fishpond (Figure 1). Each station was centered on a 20-m length of shoreline that constituted the observation area. The area covered by the stations was approximately 4,700 m^2 or about 40% of the approximately 12,000 m^2 that could be visually surveyed. The area of the pond that was surveyable was 24% of the total area of Kaloko Fishpond. Therefore, all reported population estimates, population densities, and model parameters are for this surveyable area unless otherwise noted.

Observers worked in two-person teams with each observer equipped with a pair of polarized sunglasses to eliminate surface glare and aid in fish identification. Observers were provided a brief orientation focused on the survey methodology, use of the survey equipment, and briefed on NPS and local community protocols associated with entering Kaloko. Observers were also provided with survey data sheets (Appendix 1) that led them through the survey protocol and provided space for recording kilo, as well as a fish identification guide containing pictures of fishes commonly encountered in Kaloko Fishpond as they appear *in situ* from the surface (Appendix 1). Observers walked around the pond locating each station using a Garmin GPS 73 handheld GPS units (Garmin, LTD., Olathe, Kansas). Upon arrival at a station, the observers started a 5-minute observation period during which time the observers recorded the presence of all fish species that could be observed and identified, and estimated the number of mullets, flagtails (āholehole), Pacific Threadfin (Moi), Milkfish (Awa), and bonefishes ('o'io) within the station. Multiple species of mullets (Striped Mullet, Sharpnose Mullet [Uouoa] *Neomyxus leuciscus*, and Kanda), flagtails (Reticulated Flagtail *Kuhlia sandvicenis* and Hawaiian Flagtail), and bonefishes (Longjaw Bonefish and Shortjaw Bonefish *Albula glossodonta*) could have been present within Kaloko at the time of the surveys. However, there are no reliable methods for visually discriminating between the species within these groups from shore-based surveys, necessitating that mullets, flagtails, and bonefishes be considered taxonomic categories that potentially included multiple species for purposes of analysis. In addition to counting the number of individuals of each focal species/taxonomic category, observers recorded the presence or absence of all other identifiable fish species and the presence or absence of Green Sea Turtles

(Honu) *Chelonia mydas*, Upside-down Jellyfish, the invasive algae *A. spicifera*, and avian predators, such as Black-crowned Night Heron *Nycticorax nycticorax*.

At the completion of the 5-minute observation period, observers measured water temperature to the nearest 0.1°C and salinity to the nearest 0.1 PSU using a YSI Pro 2030 handheld water quality meter (YSI, Inc., Yellow Springs, Ohio). Dissolved oxygen (DO) was also recorded to the nearest 0.1 mg L^{-1} during the 2020 surveys; however, DO measurements were only collected for the initial survey events during 2022 due to a sensor malfunction. Supply chain shortages brought on by the global COVID-19 pandemic prevented the acquisition of a replacement sensor in time to complete the surveys. Visibility was estimated as the distance from the shoreline at which the bottom of the pond was no longer visible. In 2020, this was assessed using a set of five bricks painted black and white and placed 1 m apart along a 5-m transect extending perpendicular to the shore into the water at four stations around the pond. These bricks were placed in the pond and left there for the duration of the study. The observers were instructed to report the number of bricks that they were able to count. A change was made to the 2022 surveys because algae and sediment built up on the bricks over time in 2022 reducing their visibility. Therefore, observers were asked to estimate the maximum distance at which they could discern the bottom of the pond in 2022. Weather conditions, i.e., air temperature, cloud cover, and wind speed, were collected post-survey for each station at the start time of the visual observation period from the weather station data at the Kona International Airport, approximately 5.0 km north of Kaloko. This weather station was selected rather than the one in the Park because data were available at 15-minute time intervals rather than daily summaries, enabling changes in cloud cover or wind speed that occurred during a survey to be incorporated as covariates. Tidal stage was also recorded post-survey for each station.

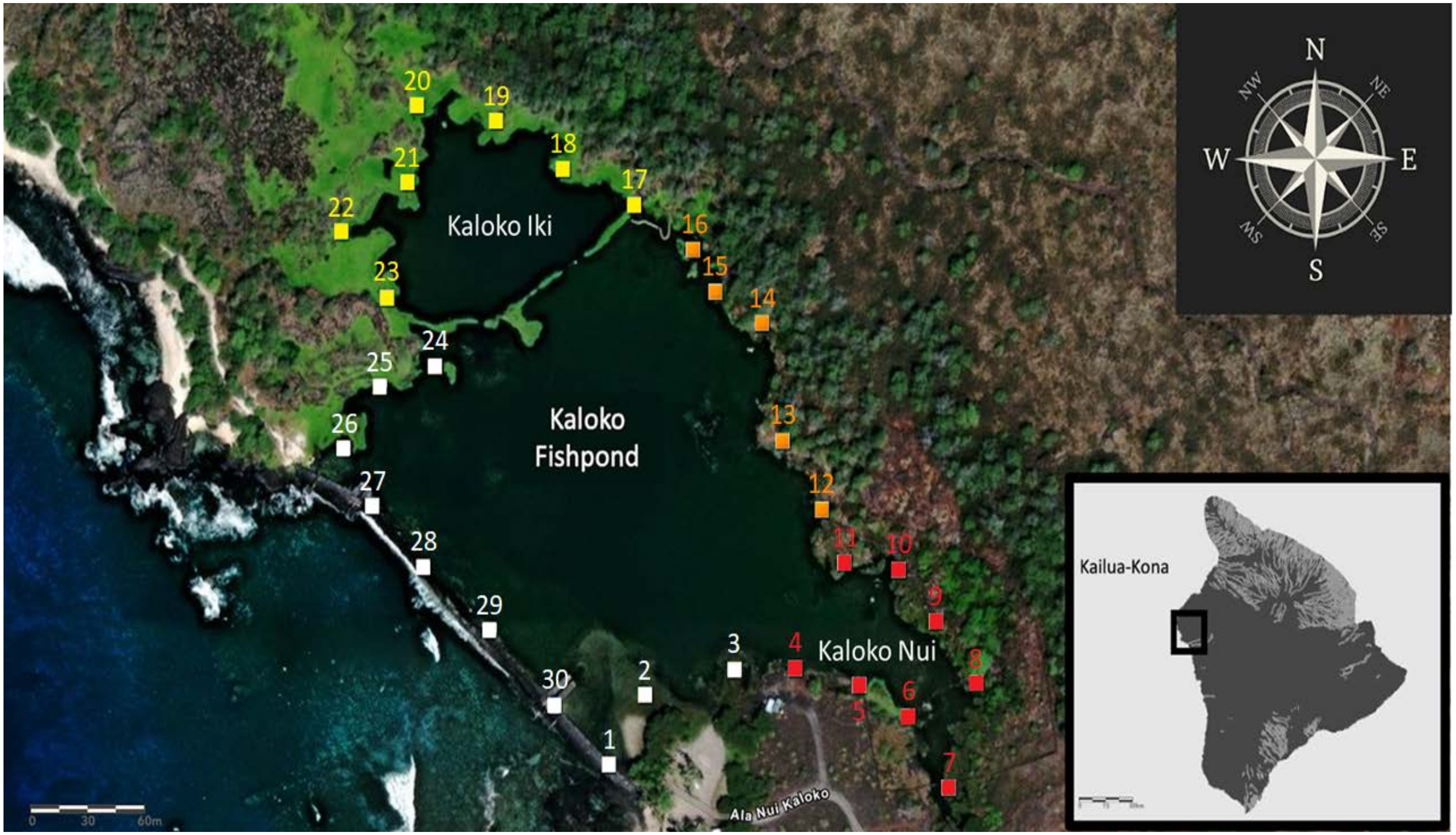

Figure 1. Map of sites where shore-based visual surveys of Kaloko Fishpond in Kailua-Kona, Hawai'i (inset map) were conducted during September-October 2020 and April-September 2022. White squares indicate sites classified as makai, red squares indicate sites classified as Kaloko Nui, orange squares indicate sites classified as mauka, and yellow squares indicate sites classified as Kaloko Iki. The 'auwai o ka mākāhā, or sluice gates in the wall, are located at stations 27 and 30. Aerial imagery from Google Earth.

Modeling focal species abundance.—We estimated the abundance of the focal species/taxonomic categories using an *N*-mixture modeling framework as described by Royle (2004). *N*-mixture models are a class of models that allow for the estimation of population size from count data. Assuming a closed population, count data from location (*i*) at time (*t*) can be treated as independent random variables that can be estimated as:

$$n_{it} \sim Binomial\ (N_i, p) \text{ [Eq. 1]}$$

where *N* is the total number of individuals available to be counted at a site and *p* is the detection probability (Royle 2004). Spatial and temporal replication in the survey design provides additional information that allows for *n* to be corrected for imperfect detection of the focal species/taxonomic category. However, the N_i are ultimately unmeasurable and are likely to be zero for a large proportion of the survey sites leading to instability in estimating population parameters due to the large number of unknowns. The *N*-mixture modeling framework handles this instability issue by treating N_i as independent random nuisance variables following a Poisson density distribution:

$$f(N;\ \lambda) = \frac{e^{-\lambda}\lambda^N}{N!} \text{ [Eq. 2]}$$

where λ is the overall population density (Royle 2004). The maximum likelihood estimate (MLE) can now be generated by integrating Eq. 1 and Eq. 2:

$$MLE(p, \lambda \mid \{n_{it}\}) = \left\{\sum_{N_i=max_t\, n_{it}}^{\infty} \left(\prod_{t=1}^{T} Binomial\ (n_{it};\ N_i, p)\right) f(N_i;\ \lambda)\right\} \text{ [Eq. 3]}$$

Further, the effects of site covariates, such as habitat composition or distance to the nearest ‘auwai which are considered constant across survey events, on estimates of site-specific population density (λ_i) using a log-linear link function:

$$log(\lambda_i) = \sum_{j=1}^{r} x_{ij}\beta_j \text{ [Eq. 4]}$$

where x_{ij} is the mean value of covariate *j* at site *i* and r is the number of measurable covariates for site *i* (Royle 2004). The effect of survey covariates of detection probability, such as observer experience, water quality parameters, weather conditions, or tidal stage which can vary across survey events, can also be assessed using a log-likelihood function (Royle 2004). We developed a set of six candidate models and used Akaike information criterion (AIC) to select the model best explaining the effects of covariates on fish abundance in Kaloko Fishpond during each of five survey intervals: A: 9/15/2020-10/11/2020, B: 4/11/2022-6/29/2022, C: 6/30/2022-8/10/2022, D: 8/12/2022-9/2/2022, and E: 9/5/2022-9/27/2022. Each interval contained an equal number of survey events. This partitioning was done to evaluate the model performance with datasets of a size comparable to what NPS personnel and local community volunteers would be able to generate. Model selection has several advantages to single model testing including identification of the most parsimonious model, ability to make inferences on covariate influence, and providing weights for model averaging (Anderson and Burnham 2004). Competing models were scored based on their difference of AIC to the top model (ΔAIC) with models having ΔAIC ≤ 2.0 considered to be performing equally (Anderson and Burnham 2004). The population estimate was then used to calculate the population density for the surveyable area within Kaloko Fishpond. All *N*-mixture models were implemented in R v. 4.2.2 (R Core Team 2022) using the "unmarked" package (Fiske and Chandler 2011). In addition to the files provided to NPS and the local community as part of the deliverables for this package, all code used for running *N*-mixture models to estimate fish abundance in Kaloko Fishpond are included in Appendix 2.

Modeling invasive species occupancy.—Because observers only recorded the presence or absence of invasive species, we modeled occupancy using a single-species multi-season occupancy modeling framework for each species. Occupancy models use presence/absence data to model the probability of the species of interest being present within a patch of habitat. Similar to *N*-mixture models described above, occupancy models rely on repeated surveys, such as dual observers surveying a site at the same time, at replicated sites to estimate detection probability in order to better interpret observations of zero individuals (MacKenzie et al. 2018). The occupancy coefficient (ψ) for each invasive species was estimated using the detection history generated from the survey methodology described above using a two-part conditional model as described by MacKenzie et al. (2006; 2018). In this model, a species that has not been observed at time *i*, i.e., $y_i = 0$, will have an unknown occupancy state at that site but it can be estimated by the sum of two conditional probabilities where the species is either not present ($y_i = 0$) or present ($y_i = 1$) but undetected ($p_i < 1.0$). This can be mathematically represented as:

$$Pr(y_i = 0) = \psi_i(1 - p_i) + (1 - \psi_i) \text{ [Eq. 5]}$$

whereas, a species that has been observed at time *i*, i.e., y_i=1, can be represented as:

$$Pr(y_i = 1) = \psi_i(1 - p_i) \text{ [Eq. 6]}$$

These two equations are the basis of a static occupancy model; which can be generalized to provide MLE estimates of occupancy and detection probability for full set of survey data thusly:

$$MLE(\psi, p \mid data) = \left[\psi^{N_d} \prod_{j=1}^{j} p_j^{s_j} (1 - p_j)^{N_d - s_j}\right] \left[\psi \prod_{j=1}^{j} (1 - p_j) + (1 - \psi)\right]^{N - N_d} \text{ [Eq. 7]}$$

where N is the total number of sites, N_d is the total number of sites at which the species was detected at least once, and s_j is the number of sites where the species was detected during survey *j* (McKenzie et al. 2018; Gerber et al. 2022). This model assumes a constant occupancy rate across sites and a constant detection probability across surveys and sites. Covariates explaining variations in ψ and p across sites can be incorporated into the model in the same manner to how they were added to the *N*-mixture model described above.

Table 1. Candidate set of *N*-mixture models used to evaluate the abundance of mullets, flagtails, and Milkfish (Awa) *Chanos chanos* from shore-based visual surveys of Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022. λ represents the initial population within each survey area, ψ represents the probability of the species occupying a site, and *p* is the detection probability of the species.

Candidate model	Number of parameters
λ(.), ψ(.), *p*(.)	3
λ(site), ψ(.), *p*(.)	6
λ(.), ψ(.), *p*(salinity)	4
λ(.), ψ(.), *p*(tide)	4
λ(.), ψ(.), *p*(turbidity)	4
λ(site), ψ(.), *p*(salinity, tide, turbidity)	9

Additional parameters can be added to the model to account for extirpation at a site (ε_t), i.e., the probability that a site occupied during season *t* is unoccupied during season *t* + 1, and colonization of a site (γ_t), i.e., the probability that an unoccupied site during season *t* is occupied during season *t* + 1 (McKenzie et al. 2018). The addition of these two parameters forms the basis of the multi-season occupancy model (Fig. 2). In this model, season is defined as the unit of time to which the survey was conducted and the population of individuals at each survey site is assumed to be closed (Gerber et al. 2014; MacKenzie et al. 2018). The closure assumption can be relaxed; therefore, for the purposes of the present study, each survey event, consisting of paired observations at the 30 stations around Kaloko Fishpond, represented a single "season" during which the population was considered closed to recruitment, mortality, and migration. The population was considered open to these processes during the intervals between survey events. We used PRESENCE v. 2.13.6 (Hines 2006) to assess a set of six candidate models describing covariates influencing occupancy, detection, extirpation, and colonization. Models were assessed for fit as described above for the *N*-mixture models using AIC (Anderson and Burnham 2004).

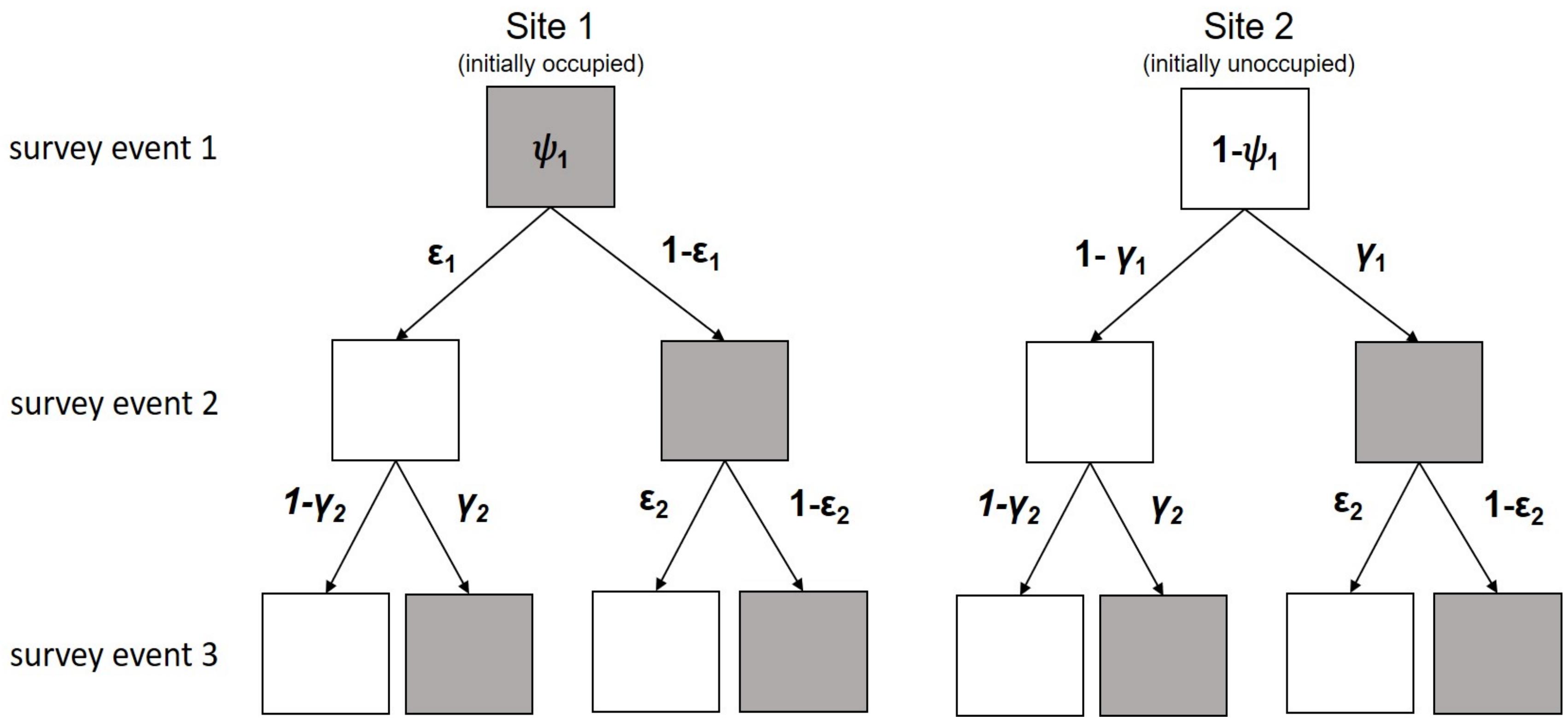

Figure 2. Conceptual framework of a single-species, multi-season occupancy model showing how the probability of potential changes in occupancy (ψ) occurring between seasons through local extinction (ε) and colonization (γ) are represented. Redrawn from Gerber et al. (2022).

Table 2. Candidate set of multi-season occupancy models used to evaluate the occurrence of two invasive species, Upside-down Jellyfish *Cassiopeia andromeda* and the algae *Acanthophora spicifera*, from shore-based visual surveys of Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022. ψ represents the probability of the species occupying a site, γ represents the probability of the species colonizing a previously unoccupied site between survey events, ε represents the probability of a species going extinct at a previously occupied site between survey events, and *p* is the detection probability of the species.

Model	Number of parameters
ψ(.), γ(.), ε(.), p(.)	4
ψ(area), γ(area), *p*(.)	9
ψ(mean_salinity, mean_temperature, distance), γ(area), *p*(survey)	135
ψ(distance), γ(area), *p*(season)	133
ψ(area), γ(area), *p(*survey)	135
ψ(area, mean_salinity, mean_temperature, distance), γ(area, survey), *p*(survey)	266

Results

A total of eight surveys were conducted in September – October 2020 during the initial development of the sampling protocol. The sampling protocol was fully implemented in 2022 and we conducted 248 surveys during April – September. As expected, there were strong and consistent temperature and salinity gradients across the stations related to their distance to the freshwater springs concentrated along the back edge of the pond and the kuapā and 'auwai along the coast (Figure 3). Mean temperatures and salinities were consistently higher at the stations along or adjacent to the kuapā and tended to be lower with increasing distance from the ocean. In contrast, there was little evidence for a comparable gradient in DO across the stations based on limited sampling (Figure 4); however, mean DO ranged between 6.0 – 10.0 mg O_2 L^{-1} but hypoxic conditions, i.e., ≤ 2.0 mg O_2 L^{-1}, were recorded occasionally at stations 15, 17, and 21 along the back edge of Kaloko. In contrast, turbidity was a factor that varied considerably across the survey and among sites. Visibility was generally best at stations along or adjacent to the kuapā and decreased with increasing distance from the kuapā.

A total of 41 fish species/taxonomic units were identified during surveys of Kaloko Fishpond with 11 occurring in ≥ 50% of the surveys (Table 3). Only three of the four focal species/taxonomic groups, mullets, flagtails, and Milkfish, occurred with sufficient regularity in the surveys to model their abundance and both groups were recorded at ≥ 22 of the stations. Many species, particularly predatory fishes, such as carangids, barracudas, and moray eels, were recorded from a low proportion of surveys but a large proportion of stations (Table 3). Green Sea Turtle was only recorded once during the survey. In general, the highest species diversity was observed at the stations along or adjacent to the kuapā and lower at the stations along the back edge of the pond in the mauka and Kaloko Nui and Kaloko Iki regions (Figure 5). Milkfish, Pacific Threadfin, and flagtails were recorded at > 20 stations, but appeared infrequently in the surveys. Bonefishes were recorded in approximately 26% of the surveys but only from the 12 stations near the kuapā and along the southeastern edge of Kaloko Fishpond. Reef fishes, such as surgeonfishes (Acanthuridae), damselfishes (Pomacentridae), butterflyfishes (Chaetodontidae), and wrasses (Labridae), comprised the bulk of the species observed in Kaloko, but their distribution was largely restricted to stations 1-3 and 24-30 near the kuapā (Figure 5). Convict Surgeonfish (Manini) *Acanthurus triostegus* was a notable exception that was widely distributed throughout the pond. Western Mosquitofish *Gambusia affinis*, an invasive euryhaline species, along with other invasive species, such as Blacktail Snapper (To'au) *Lutjanus fulvus*, Upside-down Jellyfish, and *A. spicifera* were recorded from a relatively large proportion of surveys and were also widely distributed throughout Kaloko Fishpond.

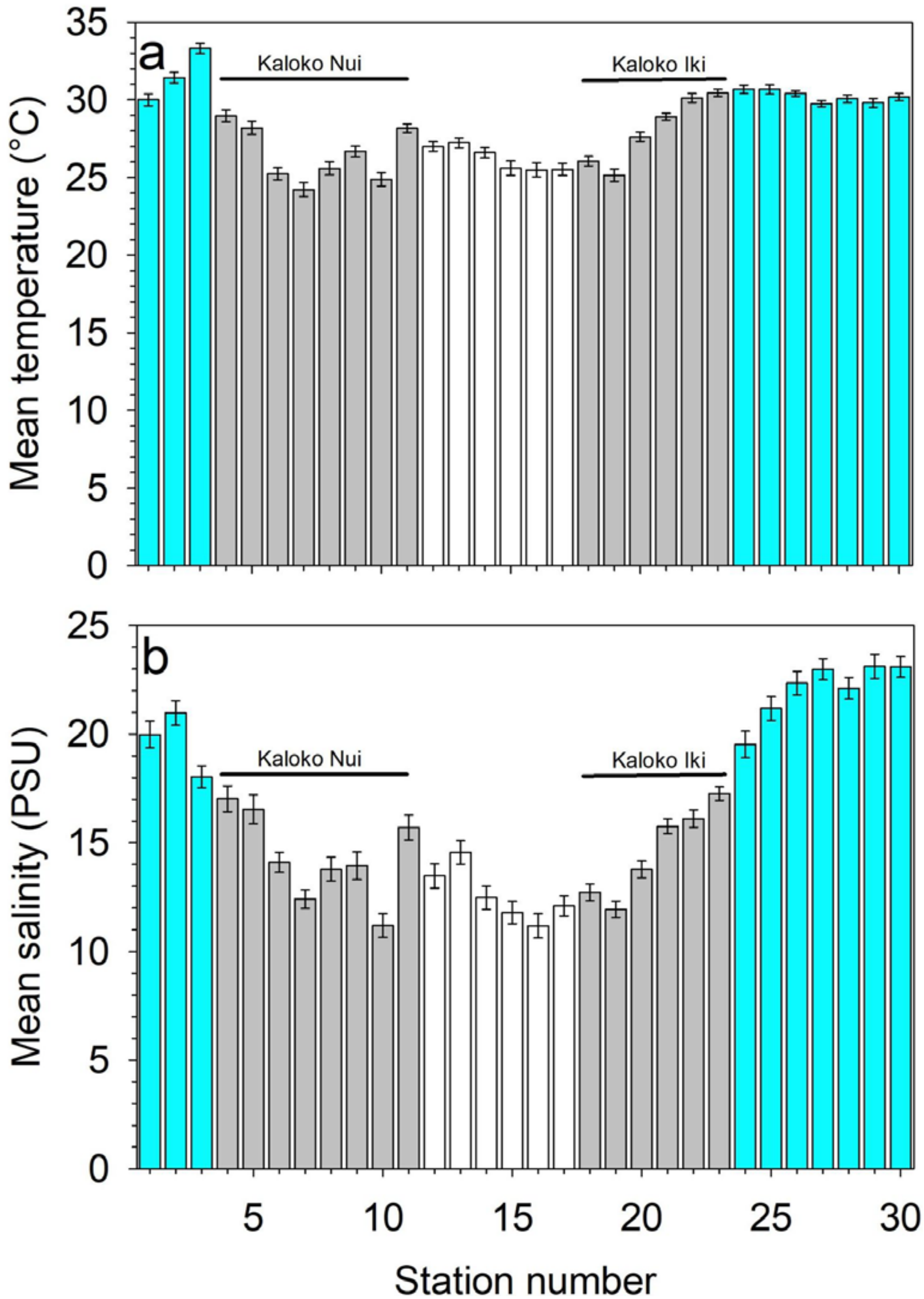

Figure 3. Mean (± 95% confidence intervals) temperature (a) and salinity (b) recorded at stations where shore-based visual surveys of fishes (*n* = 256) were conducted around Kaloko Fishpond at Kaloko Honokōhau National Historic Park, Hawai'i during September-October 2020 and April-September 2022. Blue bars indicate stations that were located closer to the kuapā and mākāhā than to the back edge of the pond while white bars represent stations that were furthest from the ocean. Gray bars indicate stations located in the partially closed coves located on the southeast (Kaloko Nui) and northwest (Kaloko Iki) corners of the pond. Exact locations of sampling stations are shown in Figure 1.

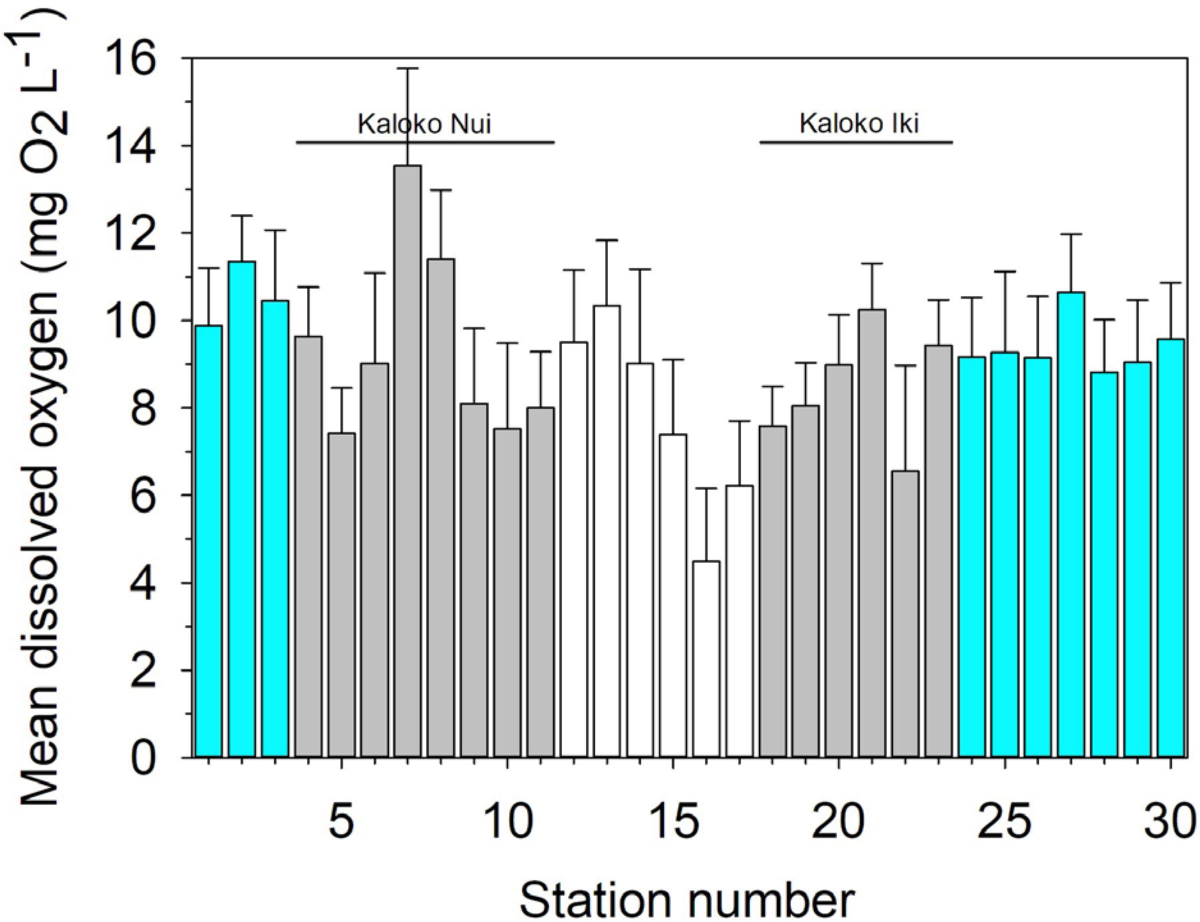

Figure 4. Mean (± 95% confidence intervals) dissolved oxygen (DO) recorded at stations where shore-based visual surveys of fishes (*n* = 256) were conducted around Kaloko Fishpond at Kaloko Honokōhau National Historic Park, Hawai'i during September-October 2020 and April-September 2022. Due to equipment malfunction and supply chain issues, DO was only recorded for a limited number of surveys (*n* = 18). Blue bars indicate stations that were located closer to the kuapā and mākāhā than to the back edge of the pond while white bars represent stations that were furthest from the ocean. Gray bars indicate stations located in the partially closed coves located on the southeast (Kaloko Nui) and northwest (Kaloko Iki) corners of the pond. Exact locations of sampling stations are shown in Figure 1.

Table 3. Species/taxonomic groups of fishes most commonly recorded in shore-based visual surveys (*n* = 256) at stations (*n* =30) around Kaloko Fishpond in Kaloko Honokōhau National Historic Park, Hawai'i during September-October 2020 and April-September 2022. Common and Hawaiian names are taken from Randall (2007).

Family	Common name	Hawaiian name	Scientific name	Proportion of surveys reported	Proportion of stations reported
Mugilidae	mullets[1]	---	---	0.953	1.000
Poeciliidae	Western Mosquitofish	---	*Gambusia affinis*	0.953	1.000
Acanthuridae	Convict Surgeonfish	Manini	*Acanthurus triostegus*	0.949	0.600
Pomacentridae	sergeants	mamo	*Abudefduf* spp.	0.945	0.500
Pomacentridae	Blackspot Sergeant	kupipi	*Abudefduf sordidus*	0.941	0.400
Kuhlidae	flagtails[2]	āholehole	*Kuhlia* spp.	0.848	0.933
Mullidae	goatfishes[3]	---	---	0.750	0.200
Chaetodontidae	Racoon Butterflyfish	kikikapu	*Chaetodon lunula*	0.742	0.200
Tetraodontidae	Guineafowl Puffer	'O'opu Hue	*Arothron melagris*	0.648	0.300
Chaetodontidae	Threadfin Butterflyfish	Kikikapu	*Chaetodon auriga*	0.570	0.200
Labridae	Christmas Wrasse	Awela	*Thalassoma trilobatum*	0.512	0.200
Sphyraenidae	barracudas[4]	---	*Sphyraena* spp.	0.484	0.767
Muraenidae	Snowflake Moray	Puhi Kapa	*Echidna nebulosa*	0.430	0.933
Carangidae	Bluefin Trevally	'Ōmilu	*Caranx melampygus*	0.426	0.433
Lutjanidae	Blacktail Snapper	To'au*	*Lutjanus fulvus*	0.379	0.267
Labridae	Saddle Wrasse	Hinalea Au-wili	*Thalassoma duperrey*	0.336	0.167
Albulidae	bonefishes[5]	'ō'io	*Albula* spp.	0.262	0.400
Muraenidae	moray eels[6]	puhi	*Gymnothorax* spp.	0.246	0.633
Zanclidae	Moorish Idol	Kihikihi	*Zanclus cornutus*	0.199	0.133
Chanidae	Milkfish	Awa	*Chanos chanos*	0.180	0.733
Diodontidae	Porcupinefish	Kokala	*Diodon hystrix*	0.168	0.333
Polynemidae	Sixfeeler Threadfin	Moi	*Polydactlyus sexfilis*	0.141	0.733
Serranidae	Peacock Grouper	Roi*	*Ceaphalopholis argus*	0.086	0.200
Chaetodontidae	Saddle Butterflyfish	Kikikapu	*Chaetodon ephippium*	0.047	0.100
Diodontidae	Spotted Burrfish	---	*Chilomycterus reticulatus*	0.039	0.367
Pomacentridae	Hawaiian Dascyllus	Alo'ilo'i	*Dascyllus albisella*	0.035	0.067
Carangidae	Doublespotted Queenfish	Lai	*Scomberoides lysan*	0.027	0.133
Belonidae	needlefishes[7]	'aha	---	0.020	0.067

Table 3. Continued

Family	Common name	Hawaiian name	Scientific name	Proportion of surveys reported	Proportion of stations reported
Carangidae	Giant Trevally[8]	Ulua Aukea	*Caranx ignobilis*	0.020	0.133
Labridae	Bird Wrasse	Hinalea I'iwi	*Gomphosus varius*	0.020	0.067

[1] Mullets are potentially represented by three species that are visually indistinguishable in surface surveys: Kanda *Osteomugil engeli*, Striped Mullet ('Ama'ama) *Mugil cephalus*, and Sharpnose Mullet (Uouoa) *Neomyxus leucius.*
[2] Flagtails are represented by potentially two species that are visually indistinguishable in surface surveys: *Kuhlia sandvicensis* and *Kuhlia xenura*.
[3] Goatfishes could potentially be represented by 11 species, many of which are visually indistinguishable in surface surveys, but the most likely species to be commonly observed in Hawaiian fishponds, based on Tabandera (2019), is Yellowstripe Goatfish (Weke'a) *Mulloidichthys flavolineatus.*
[4] Bonefishes are represented by potentially two species that are visually indistinguishable in surface surveys: Shortjaw Bonefish ('ō'io) *Albula glossodonta* and Longjaw Bonefish ('ō'io) *Albula virgata.*
[5] There are 42 species of moray eels in Hawaiian waters (Randall 2007), most of which would be visually indistinguishable from one another in a surface-based survey. However, according to Randall (2007), the three most likely to be seen nearshore species are Stout Moray *Gymnothorax eurostus*, Yellowmargin Moray (Puhi Paka) *Gymnothorax flavimarginatus*, and Whitemouth Moray (Puhi 'Ōni'o) *Gymnothorax meleagris.*
[6] Barracudas could potentially be represented by three species that are visually indistinguishable in surface surveys: Great Barracuda (Kaku) *Sphyraena barracuda*, Heller's Barracuda (Kawele'a) *Sphyraena helleri*, and Blacktail Barracuda *Sphyraena qenie.*
[7] Needlefishes could potentially be represented by three species that are visually indistinguishable in surface surveys: Keeltail Needlefish ('aha) *Platybelone argalus*, Agujon ('aha) *Tylosurus acus*, and Houndfish ('aha) *Tylosurus crocodilus.*
[8] While Giant Trevally was the species noted by observers, there are two other trevally species that would be difficult to distinguish in a surface-based survey: Black Trevally (Ulua La'uli) *Caranx lugubris* and Bigeye Trevally (Pake Ulua) *Caranx sexfasciatus*.
*Tahitian common name that has been adopted locally for the species in Hawai'i.

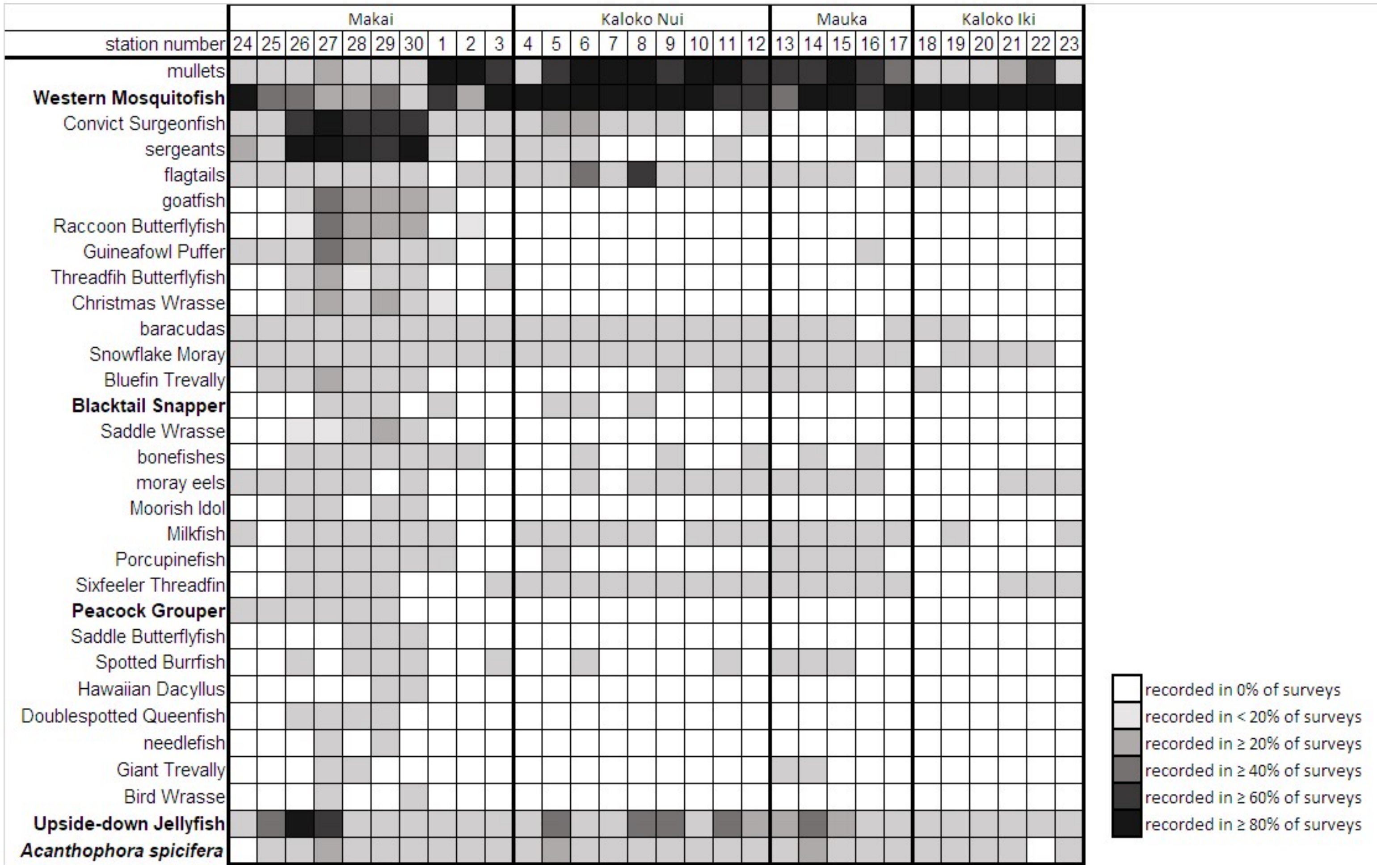

Figure 5. Occurrence of species/taxonomic groups most commonly recorded in shore-based visual surveys (*n* = 256) at stations (*n* =30) around Kaloko Fishpond in Kaloko Honokōhau National Historic Park, Hawai'i during September-October 2020 and April-September 2022. Non-native species are indicated in bold text. Common names are taken from Randall (2007). See Table 3 for scientific and Hawaiian names and description of constituent species for multi-species taxonomic groups. Locations of stations in the Makai, Kaloko Nui, Mauka, and Kaloko Iki sections of Kaloko Fishpond are shown in Figure 1.

Abundance trends of focal taxonomic groups

Of the four target focal species/taxonomic groups, there were sufficient data to model the abundance of mullets, flagtails, and Milkfish with *N*-mixture models. Bonefishes were not observed at enough stations with sufficient frequency to construct workable *N*-mixture models. The estimated abundance (95% confidence interval) of mullets within the surveyable area of Kaloko Fishpond averaged across the five modeled survey intervals was 373 (353 – 392) with an average initial density in Kaloko Fishpond of 0.031 fish/m^2 (95% confidence interval: 0.029 – 0.033 fish/m^2). These estimated abundances were consistent across survey periods (Figure 6). However, the global or null model were among the models receiving the most support in all survey periods except for interval E, encompassing surveys conducted during 9/5/2022-9/27/2022 (Table 4). Models incorporating tidal stage as a covariate of detection were supported in survey interval C (6/30/2022-8/10/2022) and E and in both cases indicated a positive relationship between tidal stage and detection (C: $\beta_{tide} = 0.51 \pm 0.56$; E: $\beta_{tide} = 0.76 \pm 0.52$). The model incorporating salinity as a covariate of detection was also supported in survey interval E and indicated a positive relationship between salinity and detection ($\beta_{salinity} = 0.51 \pm 0.50$). While the global model received the greatest support in survey interval B (4/11/2022-6/29/2022), the model itself failed to converge. In contrast to the estimated initial population density, estimated occupancy (average: 0.171, range: < 0.0001 – 0.599) and detection (average: 0.198, range: 0.001 – 0.599) were highly variable across the five survey intervals.

The estimated population size (95% confidence interval) of flagtails in the surveyable area of Kaloko Fishpond averaged across the five modeled survey intervals was about half that of mullets, 163 (134 – 192) with an average initial population density in Kaloko Fishpond of 0.014 fish/m^2 (95% confidence interval: 0.011 – 0.016 fish/m^2). The resulting estimated population sizes were consistent across survey periods (Figure 6). Similar to the mullets, the null model was the top-performing model in all survey periods for flagtails (Table 5). Models incorporating tidal stage as a covariate of detection were supported in survey intervals B (4/11/2022-6/29/2022) and C (6/30/2022-8/10/2022) and in both cases indicated a positive relationship between tidal stage and detection (B: $\beta_{tide} = 0.50 \pm 0.56$; C: $\beta_{tide} < 0.001 \pm 0.92$). The model incorporating salinity as a covariate of detection was also supported in survey interval E and indicated a positive relationship between salinity and detection ($\beta_{salinity} = 0.49 \pm 0.50$). While the global model received the greatest support in survey interval B (4/11/2022-6/29/2022), the model itself failed to converge. In contrast to the estimated initial population density, estimated occupancy (average: 0.647, range: 0.013 – 0.730) and detection (average: 0.064, range: 0.002 – 0.212) were highly variable across the five survey intervals.

The overall estimated population size (95% confidence interval) of Milkfish in the surveyable area of Kaloko Fishpond averaged across the five modeled survey periods was 233 (189 – 277) (Figure 6) and the estimated initial population density averaged 0.019 fish/m^2 (95% confidence interval: 0.016 – 0.023 fish/m^2). The global or null model were among the models receiving the most support in all survey intervals except for D, where the top supported model incorporated pond region as a covariate for the initial population density (Table 6). Models incorporating turbidity or salinity as a covariate of detection were only supported in interval E and the detection of Milkfish exhibited a positive relationship to turbidity ($\beta_{turbidity}$ = 0.50 ± 0.58) but a negative one to salinity ($\beta_{tsalinity}$ = 0.49 ± 0.50). There was evidence supporting a positive relationship between tidal stage and detection during survey interval B (β_{tide} = 0.67 ± 0.56) and C (β_{tide} = 0.81 ± 0.75). Estimates for the detection of Milkfish among the survey intervals were consistently low (average: 0.033, range: < 0.0001 – 0.088) while occupancy was variable but tended to be considerably higher than that seen for mullets (average: 0.426, range: 0.050 – 0.833).

Table 4. Results of six *a priori* candidate *N*-mixture models run across five survey intervals used to evaluate the abundance of mullets in Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022. λ represents the initial population within each survey area, ψ represents the probability of the species occupying a site, and *p* is the detection probability of the species. AIC = Akaike's Information Criterion, ΔAIC = differences in AIC, w_i = Akaike weights.

Survey interval	Dates	Model	AIC	ΔAIC	w_i
A	9/15/2020-10/11/2020	λ(.), ψ(.), *p*(.)	-4441.2	0.0	1.00
		λ(.), ψ(.), *p*(salinity)	-4429.5	11.8	0.00
		λ(.), ψ(.), *p*(turbidity)	-4406.9	34.3	0.00
		λ(site), ψ(.), *p*(.)	-4309.8	131.4	0.00
		λ(.), ψ(.), *p*(tide)	-4291.7	149.6	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-4082.8	358.4	0.00
B	4/11/2022-6/29/2022	λ(site), ψ(.), *p*(salinity, tide, turbidity)	-21251.9	0.0	1.00
		λ(.), ψ(.), *p*(.)	-17074.4	4177.5	0.00
		λ(.), ψ(.), *p*(salinity)	-17068.5	4183.4	0.00
		λ(.), ψ(.), *p*(tide)	-17050.6	4201.3	0.00
		λ(site), ψ(.), *p*(.)	-17020.6	4231.3	0.00
		λ(.), ψ(.), *p*(turbidity)	-16842.4	4409.4	0.00
C	6/30/2022-8/10/2022	λ(.), ψ(.), *p*(.)	-14962.0	0.0	0.50
		λ(.), ψ(.), *p*(tide)	-14962.0	0.0	0.50
		λ(.), ψ(.), *p*(salinity)	-14952.8	9.2	0.01
		λ(site), ψ(.), p(.)	-14947.5	14.5	0.00
		λ(.), ψ(.), *p*(turbidity)	-14913.6	48.3	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-14906.6	55.3	0.00
D	8/12/2022-9/2/2022	λ(.), ψ(.), *p*(.)	-10783.2	0.0	1.00
		λ(.), ψ(.), *p*(salinity)	-10481.9	301.3	0.00
		λ(.), ψ(.), *p*(tide)	-10477.1	306.1	0.00
		λ(.), ψ(.), *p*(turbidity)	-10468.9	314.3	0.00
		λ(site), ψ(.), *p*(.)	-10326.1	457.1	0.00

Table 4. Continued

Survey interval	Dates	Model	AIC	ΔAIC	w_i
D	8/12/2022-9/2/2022	λ(site), ψ(.), *p*(salinity, tide, turbidity)	-10302.3	480.9	0.00
E	9/5/2022-9/27/2022	λ(.), ψ(.), *p*(turbidity)	-14205.4	0.0	0.71
		λ(.), ψ(.), *p*(salinity)	-14203.6	1.8	0.29
		λ(.), ψ(.), *p*(tide)	-14087.0	118.4	0.00
		λ(site), ψ(.), *p*(.)	-13677.9	527.5	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-13576.6	628.9	0.00
		λ(.), ψ(.), *p*(.)	-13376.9	828.5	0.00

Table 5. Results of six *a priori* candidate *N*-mixture models run across five survey intervals used to evaluate the abundance of flagtails (āholehole) *Kuhlia* spp. in Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022. λ represents the initial population within each survey area, ψ represents the probability of the species occupying a site, and *p* is the detection probability of the species. AIC = Akaike's Information Criterion, ΔAIC = differences in AIC, w_i = Akaike weights.

Survey interval	Dates	Model	AIC	ΔAIC	w_i
A	9/15/2020-10/11/2020	λ(.), ψ(.), *p*(.)	-634.6	0.0	1.00
		λ(.), ψ(.), *p*(salinity)	-600.8	33.7	0.00
		λ(.), ψ(.), *p*(tide)	-583.2	51.4	0.00
		λ(.), ψ(.), *p*(turbidity)	-537.9	96.7	0.00
		λ(site), ψ(.), *p*(.)	-526.9	107.6	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-293.6	341.0	0.00
B	4/11/2022-6/29/2022	λ(.), ψ(.), *p*(.)	-3350.9	0.0	0.48
		λ(.), ψ(.), *p*(tide)	-3350.9	0.0	0.48
		λ(.), ψ(.), *p*(salinity)	-3346.5	4.4	0.05
		λ(.), ψ(.), *p*(turbidity)	-3341.7	9.2	0.00
		λ(site), ψ(.), *p*(.)	-3275.4	75.5	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-3248.7	102.3	0.00
C	6/30/2022-8/10/2022	λ(.), ψ(.), *p*(.)	-1614.9	0.0	0.73
		λ(.), ψ(.), *p*(tide)	-1612.8	2.1	0.26
		λ(.), ψ(.), *p*(salinity)	-1605.0	9.9	0.01
		λ(site), ψ(.), p(.)	-1602.9	12.0	0.00
		λ(.), ψ(.), *p*(turbidity)	-1585.6	29.3	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-1558.6	56.3	0.00
D	8/12/2022-9/2/2022	λ(site), ψ(.), *p*(.)	-4705.6	0.0	1.00
		λ(.), ψ(.), *p*(tide)	-4681.6	24.0	0.00
		λ(.), ψ(.), *p*(salinity)	-4651.6	54.0	0.00
		λ(.), ψ(.), *p*(.)	-4640.1	65.5	0.00
		λ(.), ψ(.), *p*(turbidity)	-4625.2	80.4	0.00

Table 5. Continued

Survey interval	Dates	Model	AIC	ΔAIC	w_i
D	8/12/2022-9/2/2022	λ(site), ψ(.), *p*(salinity, tide, turbidity)	-4331.5	374.1	0.00
E	9/5/2022-9/27/2022	λ(.), ψ(.), *p*(.)	-3041.0	0.0	0.89
		λ(.), ψ(.), *p*(salinity)	-3036.8	4.2	0.11
		λ(.), ψ(.), *p*(tide)	-3022.6	18.4	0.00
		λ(site), ψ(.), *p*(.)	-2982.9	58.0	0.00
		λ(.), ψ(.), *p*(turbidity)	-2886.6	154.4	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-2809.1	231.9	0.00

Table 6. Results of six *a priori* candidate *N*-mixture models run across five survey intervals used to evaluate the abundance of Milkfish (Awa) *Chanos chanos* in Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022. λ represents the initial population within each survey area, ψ represents the probability of the species occupying a site, and *p* is the detection probability of the species. AIC = Akaike's Information Criterion, ΔAIC = differences in AIC, w_i = Akaike weights.

Survey interval	Dates	Model	AIC	ΔAIC	w_i
A	9/15/2020-10/11/2020	λ(.), ψ(.), *p*(.)	-4441.2	0.0	1.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-4082.8	358.4	0.00
		λ(.), ψ(.), *p*(salinity)	-4429.5	11.8	0.00
		λ(.), ψ(.), *p*(turbidity)	-4406.9	34.3	0.00
		λ(.), ψ(.), *p*(tide)	-4291.7	149.6	0.00
		λ(site), ψ(.), *p*(.)	-4309.8	131.4	0.00
B	4/11/2022-6/29/2022	λ(.), ψ(.), *p*(.)	-1638.4	0.0	0.89
		λ(.), ψ(.), *p*(tide)	-1634.1	4.2	0.11
		λ(site), ψ(.), *p*(.)	-1577.4	61.0	0.00
		λ(.), ψ(.), *p*(turbidity)	-1574.2	64.2	0.00
		λ(.), ψ(.), *p*(salinity)	-1515.2	123.2	0.00
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-1407.8	230.6	0.00
C	6/30/2022-8/10/2022	λ(.), ψ(.), *p*(.)	-14962.0	0.0	0.50
		λ(.), ψ(.), *p*(tide)	-14962.0	0.0	0.50
		λ(.), ψ(.), *p*(salinity)	-14952.8	9.2	0.01
		λ(site), ψ(.), *p*(.)	-14947.5	14.5	0.00
		λ(.), ψ(.), *p*(turbidity)	-14913.6	48.3	0.00
		λ(site), ψ(.), p(salinity, tide, turbidity)	-14906.6	55.3	0.00
D	8/12/2022-9/2/2022	λ(site), ψ(.), *p*(.)	-1197.0	0.0	1.00
		λ(.), ψ(.), *p*(.)	-1185.6	11.4	0.00
		λ(.), ψ(.), *p*(turbidity)	-1066.5	130.5	0.00
		λ(.), ψ(.), *p*(tide)	-1023.7	173.3	0.00
		λ(.), ψ(.), *p*(salinity)	-841.1	356.0	0.00

Table 6. Continued

Survey interval	Dates	Model	AIC	ΔAIC	w_i
D	8/12/2022-9/2/2022	λ(site), ψ(.), *p*(salinity, tide, turbidity)	-739.0	458.0	0.00
E	9/5/2022-9/27/2022	λ(.), ψ(.), *p*(.)	-424.1	0.0	0.44
		λ(.), ψ(.), *p*(turbidity)	-424.1	0.0	0.44
		λ(.), ψ(.), *p*(salinity)	-420.6	3.5	0.08
		λ(.), ψ(.), *p*(tide)	-418.1	6.0	0.02
		λ(site), ψ(.), *p*(.)	-417.0	7.1	0.01
		λ(site), ψ(.), *p*(salinity, tide, turbidity)	-401.9	22.2	0.00

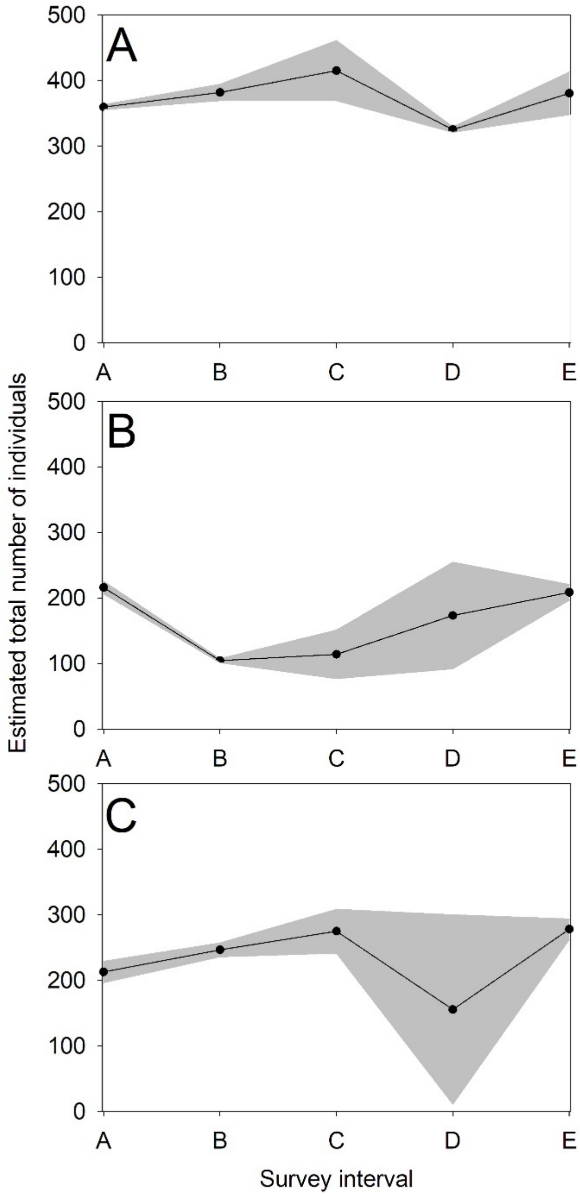

Figure 6. Estimated total abundance of mullets (A), flagtails (B) and Milkfish (awa) *Chanos chanos* (C) in the surveyable nearshore area of Kaloko Fishpond in Kailua-Kona, Hawaiʻi based on *N*-mixture modeling of shore-based visual survey data collected during September-October 2020 and April-September 2022. Shaded area indicates the 95% confidence interval around the estimated abundance. Survey intervals include an approximately equal number of surveys conducted during 9/15/2020-10/11/2020 (A), 4/11/2022-6/29/2022 (B), 6/30/2022-8/10/2022 (C), 8/12/2022-9/2/2022 (D), and 9/5/2022-9/27/2022 (E).

Occupancy patterns of invasive species

The invasive algae, *A. spicifera*, was widely distributed throughout the pond and consistently observed for the duration of the study. However, the mean salinity or temperature at a survey site, nor the distance of the survey site from ˈauwai, were good predictors of *A. spicifera* occupancy. Instead, the occupancy model that grouped sites according to the different regions of the pond, i.e., the sites designated as being within the makai region, Kaloko Nui, the mauka region, and Kalko Iki, and allowed detection (*p*) to vary by survey events had overwhelming support (Table 7). Within this top model, sites within a region shared occupancy (ψ), colonization (γ), and extinction (ε) probabilities, with sites in Kaloko Iki having lower occupancy and colonization rates and higher extinction rates than sites in the other three regions (Figure 6). When present, the mean (±SD) survey-specific detection probability for *A. spicifera* was 0.34 ± 0.25; however, detection exhibited considerable variation between surveys (Figure 7) and ranged from 0.05 – 1.00.

Similar to *A. spicifera*. Upside-down Jellyfish were also widely distributed throughout Kaloko Fishpond. The model receiving the most support was also the same as that for *A. spicifera* (Table 7). Upside-down Jellyfish occupancy and colonization rates were best described by grouping sites according to the different regions of the pond, while detection probability was best described by being survey-specific. Models incorporating salinity, temperature, and distance from ʻauwai did not receive any support (Table 8). Kaloko Iki had the lowest occupancy and colonization rates of Upside-down Jellyfish and occupied sites within that region experienced a high rate of extinction between survey events (Figure 8). The differences in occupancy, colonization, and extinction rates between the other three regions were relatively minor (Figure 7). Upside-down Jellyfish detection tended to be higher than that of *A. spicifera*, with a mean (±SD) of 0.42 ± 0.22 (range: 0.10 – 1.00). However, Upside-down Jellyfish detection exhibited a consistent increase from April to September despite removal events conducted by Hui Kaloko-Honokōhau occurring on a regular basis throughout the survey period (Figure 9).

Table 7. Model selection table for the six *a priori* candidate multi-season occupancy models used to evaluate the occurrence of *Acanthophora spicifera*, an invasive alga species in Kaloko Fishpond, Kailua-Kona, Hawaiʻi, based on shore-based visual surveys conducted during April-September 2022. ψ represents the probability of the species occupying a site, γ represents the probability of the species colonizing a previously unoccupied site between survey events, ε represents the probability of a species going extinct at a previously occupied site between survey events, and *p* is the detection probability of the species. AIC = Akaike's Information Criterion, ΔAIC = differences in AIC, w_i = Akaike weights.

Model	AIC	ΔAIC	w_i
ψ(area), γ(area), *p*(survey)	3062.90	0.00	1.00
ψ(mean_salinity, mean_temperature, distance), γ(area), *p*(survey)	3121.53	58.63	0.00
ψ(distance), γ(area), *p*(season)	3181.99	119.09	0.00
ψ(area), γ(area), *p*(.)	3204.92	142.02	0.00
ψ(.), γ(.), ε(.), *p*(.)	3214.78	151.88	0.00
ψ(area, mean_salinity, mean_temperature, distance), γ(area, survey), *p*(survey)	4124.31	1061.41	0.00

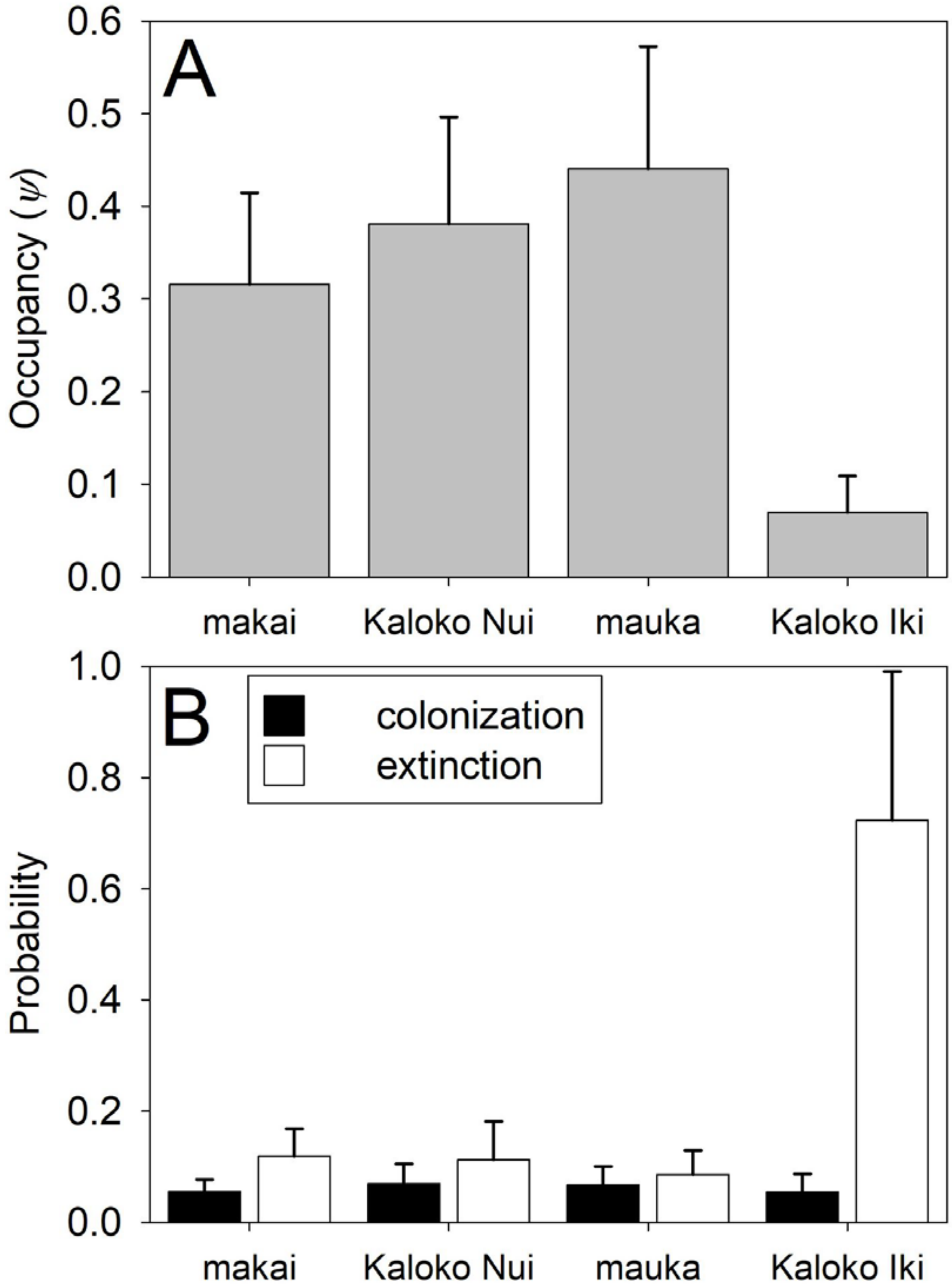

Figure 6. Estimated occupancy (ψ) probability (A), and colonization (γ) and extinction (ε) probabilities (B) of the invasive algae, *Acanthophora spicifera*, in four regions of Kaloko Fishpond in Kailua-Kona, Hawai'i based on shore-based visual surveys conducted during April-September 2022. Error bars represent 95% confidence intervals.

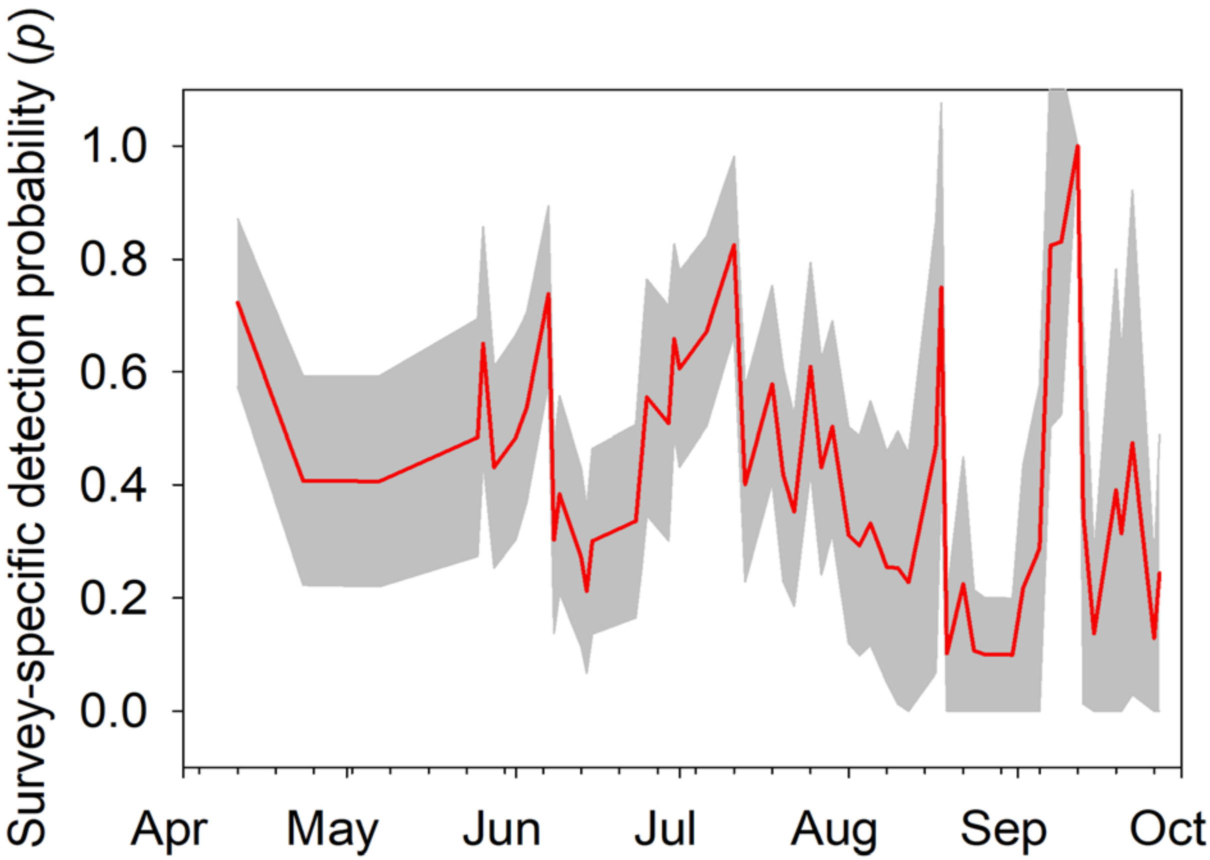

Figure 7. Estimated survey-specific detection probabilities (*p*; red line) of the invasive algae, *Acanthophora spicifera*, in Kaloko Fishpond in Kailua-Kona, Hawai'i based on shore-based visual surveys conducted during April-September 2022. The gray area indicates the 95% confidence interval around the estimated detection probability.

Table 8. Results of six *a priori* candidate multi-season occupancy models used to evaluate the occurrence of Upside-down Jellyfish *Cassiopea andromeda* in Kaloko Fishpond in Kailua-Kona, Hawai'i during April-September 2022. ψ represents the probability of the species occupying a site, γ represents the probability of the species colonizing a previously unoccupied site between survey events, ε represents the probability of a species going extinct at a previously occupied site between survey events, and *p* is the detection probability of the species. AIC = Akaike's Information Criterion, ΔAIC = differences in AIC, w_i = Akaike weights.

Model	AIC	ΔAIC	w_i
ψ(area), γ(area), *p*(survey)	3863.15	0.00	1.00
ψ(mean_salinity, mean_temperature, distance), γ(area), *p*(survey)	3911.71	48.56	0.00
ψ(distance), γ(area), *p*(season)	3940.48	77.33	0.00
ψ(area), γ(area), *p*(.)	3943.03	79.88	0.00
ψ(.), γ(.), ε(.), *p*(.)	3943.03	79.88	0.00
ψ(area, mean_salinity, mean_temperature, distance), γ(area, survey), *p*(survey)	5277.30	1414.15	0.00

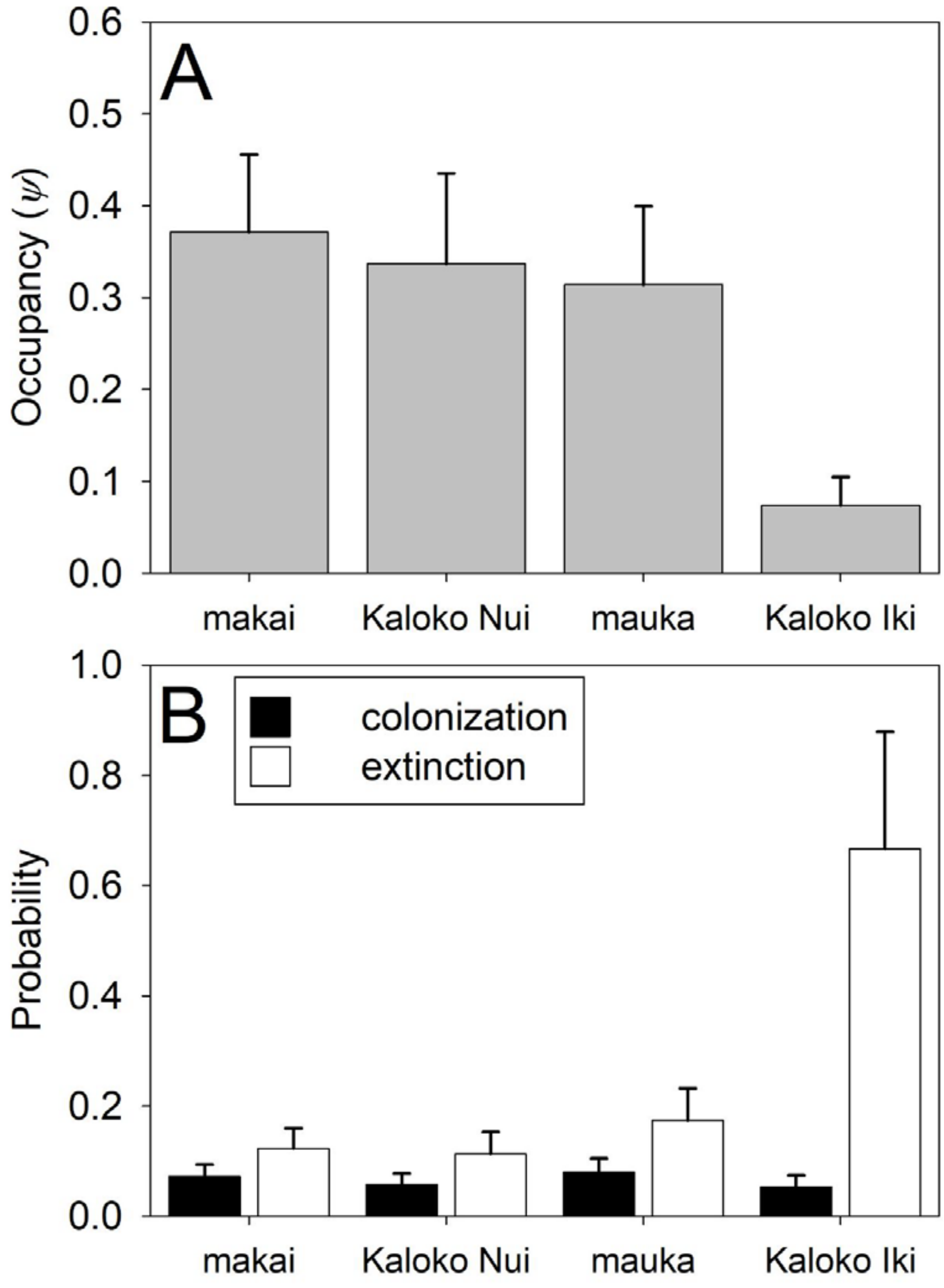

Figure 8. Estimated occupancy (ψ) probability (A) and colonization (γ) and extinction (ε) probabilities (B) of Upside-down Jellyfish *Cassiopea andromeda* in four regions of Kaloko Fishpond in Kailua-Kona, Hawai'i based on shore-based visual surveys conducted during April-September 2022. Error bars represent 95% confidence intervals.

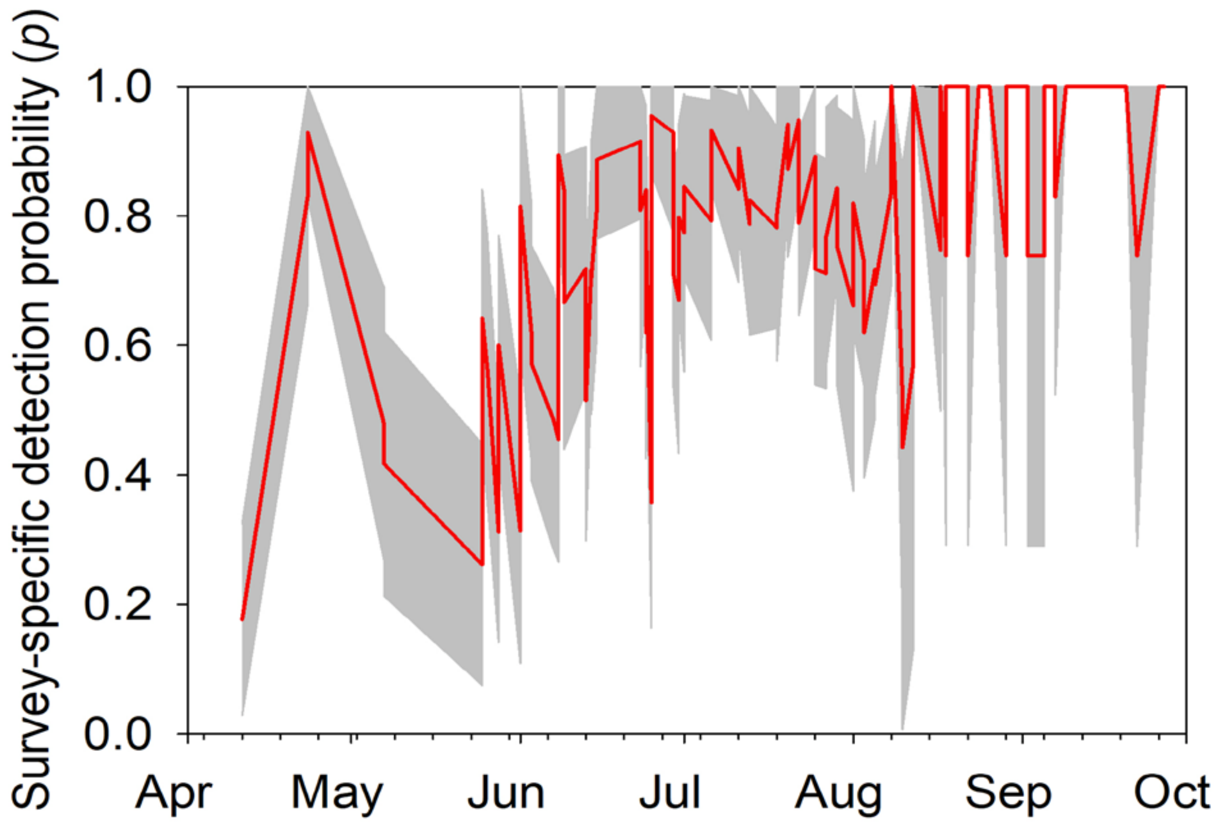

Figure 9. Estimated survey-specific detection probabilities (*p*; red line) of Upside-down Jellyfish *Cassiopea andromeda* in Kaloko Fishpond in Kailua-Kona, Hawai'i based on shore-based visual surveys conducted during April-September 2022. The gray area indicates the 95% confidence interval around the estimated detection probability.

Discussion

The diversity and distribution of fishes observed in Kaloko Fishpond through shore-based visual surveys were comparable to that noted in more intensive surveys of other Hawaiian fishponds. For example, Tabandera (2019) captured 53 species from a complex of three fishponds along the Keaukaha shoreline of Hilo Bay on the east side of Hawai'i Island over a comparable time scale to the present study. While the ponds in Keaukaha were considerably smaller than Kaloko Fishpond, species diversity exhibited a similar gradient, with the largest number of species being captured from sites near the kuapā where salinities and temperatures tended to be higher. In general, the fish assemblage at sites in the makai region of the pond were dominated by reef fishes that were associated with the kuapā and the rocky substrate adjacent to it. Reef fishes were sighted less frequently with increased distance from the kuapā. This decline in the occurrence of reef fishes was the primary driver for a more general decline in species diversity associated with increasing distance from the kuapā. Furthermore, the contribution of invasive species to the fish assemblage tended to increase with increasing distance from the kuapā. This pattern was observed both within and between fishponds in Keaukaha (Tabandera 2019). The invasive species observed in Hawaiian fishponds, especially poeciliids such as Western Mosquitofish, tend to be tolerant of wide temperature and salinity ranges (Moyle and Marchetti 2006) whereas the reef fishes observed in the fishponds are presumed to have narrower tolerances, though this is not well documented in the literature. Furthermore, invasive species seem to utilize the mud and silt that are the predominant substrates in the portions of fishponds away from the kuapā. In contrast, the more euryhaline and eurythermic native species, such as Striped Mullet, have decreased apparent survival, i.e., lower survival and/or higher emigration rates, at sites with a higher area of mud and silt substrate (Tabandera 2019) and tend to actively avoid depositional habitats when feeding (Fraiola and Carlson 2017), which is congruent with lower rates of occupancy or smaller numbers of individuals at those sites as observed in this study.

While the species richness and general distribution of fishes in Kaloko Fishpond is similar to that described for other fishponds, the degree to which the structure of the fish assemblage in Kaloko Fishpond differs from that reported from other ponds is difficult to determine due to the different biases inherent to the survey methods used. For example, mullets were the most commonly recorded taxonomic group in Kaloko Fishpond, but were considerably less commonly encountered, even when pooling all mullet species together, during sampling events in the Keaukaha ponds (Tabandera 2019). Yellowstripe Goatfish (Weke'a'a) *Mulloidichthys flavolineatus*, which was the most commonly captured species in the Keaukaha ponds (Tabandera 2019), were relatively rarely sighted in Kaloko Fishpond. There were far more invasive species (n = 7) captured from Keaukaha ponds (Tabandera 2019) than observed at Kaloko Fishpond (n = 3), though it is likely Kanda was observed and is represented in the mullet category. It is important to note that the differences in the sampling methods used between these sites makes direct comparisons complicated. For example, predatory fishes, such as Giant

Trevally, barracudas, and moray eels, were observed in Kaloko Fishpond at a much higher rate than they were captured during surveys of fishponds in Keaukaha, likely due to their ability to avoid the sampling gear (Tabandera 2019).

Population densities and population size estimates of mullets, flagtails, and Milkfish from our *N*-mixture models were consistent across the survey intervals with a relatively high degree of certainty. However, the covariates measured in the surveys did not offer particularly meaningful explanatory power for variations in mullet, flagtail, and Milkfish counts across sites. Further, the estimated population size of mullets, flagtail and Milkfish in Kaloko seem to be relatively small given the size of the fishpond and historical accounts of Hawaiian fishpond productivity (Kikuchi 1976; Costa-Pierce 1987). However, *N*-mixture models are typically applied to survey data conducted over broader spatial scales and thus, it may require reconsideration of what the parameters estimated from the models correspond to at the more limited spatial scale that was encompassed by the present study. In the present survey design, there is a high risk of violating the underlying assumption of independence and closure of sample sites. Individual fish not only can move in and out of a survey site during a survey event, but that movement could also occur between survey sites. Violation of this assumption would tend to overestimate the population size (Fogarty and Fleishman 2021). While information on the typical population size or density of fishes in Hawaiian fishponds is limited, the densities estimated by the models suggest that mullets and Milkfish populations in Kaloko are considerably lower than what is seen in semi-intensively managed fishponds on other Pacific islands (Nelson and Marygrace 2009) and lower than those seen in smaller, more intensively managed fishponds on the east side of Hawai'i Island (Tabandera 2019). Further, surveyors did not note the consistent movement of individuals along the shoreline in a manner that would suggest that the fish were moving between sites during a survey. Movement of fishes during the survey was more typically from the shallower water of the surveyed site to deeper water towards the center of the pond. Once out of view of the surveyors, the fishes could then return to the survey site to be inadvertently counted again or relocate to another survey site. However, the low population estimates generated from the models suggest that this was not the case. Instead, this movement likely contributed to the disagreement in the counts of mullets and Milkfish between the two surveyors at a site, leading to the observed low and inconsistent detection probabilities across survey intervals. The tendency of both mullets and Milkfish to form schools as they forage within the pond also likely contributed to the disagreement in counts between observers just due to the challenge of accurately counting a large number of moving animals. Further, this schooling behavior resulted in the clumping of individuals into a few large schools within the pond and led to only a relatively few sites during any given survey event having mullets or Milkfish recorded as present, contributing to the low estimated occupancy rates. In contrast, flagtails tended to be more sedentary and more likely to have movements restricted to within the survey areas which may in part explain the more consistent estimates of occupancy for this group compared to mullets and Milkfish. Given all these caveats, the interpretation of the estimated initial population density, λ, is that it is a reasonable metric of the number of individuals within the surveyable area around the edge of Kaloko Fishpond and thus, could serve as a proxy to monitor total abundance in Kaloko.

Invasive fishes have been observed to dominate fish assemblages at stations characterized by lower salinities and lower temperatures (Tabandera 2019); however, in Kaloko, the invasive algae, *A. spicifera*, and Upside-down Jellyfish were both associated with regions of higher salinity and temperature. Both invasive species were less likely to occupy or colonize areas farther from the kuapā than areas closer to it. The invasive species occupying sites in Kaloko Iki were also more likely to experience extinction between survey events. This is consistent with laboratory studies indicating that the growth and survival of *A. spicifera* are inhibited at salinities < 25 PSU (Pereira et al. 2017). We could not find similar studies that examined the growth and survival of Upside-down Jellyfish, but the species is frequently described as being tolerant to a broad range of salinities (0-40 PSU; Aljbour et al. 2017, Morandini et al. 2017) and it is possible that the species is more limited by the temperature and salinity tolerances of the *Symbiodinium* spp. hosted in their tissues (Moffat 2021). However, the strong support for regional effects but lack of a clear relationship between occupancy or colonization to the mean salinity, temperature, or distance to the kuapā in the multi-season occupancy models suggests that either some interaction of these factors and/or factors not measured in this study were driving *A. spicifera* and Upside-down Jellyfish occupancy and colonization in Kaloko. The relatively low detection rates of both invasive species were also surprising. However, both species exhibit coloration that does not contrast with the substrate they are found on, rendering them difficult to discern, particularly in areas of higher turbidity and muddy substrate, such as areas with invasive Pickleweed *Batis maritima* growing along the shoreline. Kaloko Iki is an area characterized by high turbidity, muddy substrate, and extensive growths of Pickleweed. While the detection probability of *A. spicifera* and Upside-down Jellyfish at Kaloko Iki sites did not differ from that in other parts of the pond, it is possible that these species could be present and recorded as absent by both observers under the conditions at Kaloko Iki. The occupancy model would treat these cases as a true absence which would tend to lead to underestimated occupancy rates and overestimated turnover in cases of low detection probability (Cruickshank et al. 2019). While the status of invasive *A. spicifera* and Upside-down Jellyfish at Kaloko Iki warrants additional investigation, the relatively low detection probabilities of these species highlight the need to ensure that surveyors are adequately trained prior to participation to minimize the likelihood of false positives and false negatives in the monitoring data.

The visual survey method developed for the present study offers several clear advantages to capture-based surveys, such as requiring minimal pre-survey planning, logistical support, and training of personnel; being less disruptive to the pond habitat; and being more compatible with traditional kilo practices. Depending on the research or monitoring objectives, the uncertainty surrounding species identification in several key taxonomic groups, e.g., mullets, goatfishes, etc., and the difficulty in comparing results to other studies employing capture-based methods may limit the utility of the shore-based visual survey method developed for the present study.

Furthermore, the results of the present study suggest that shore-based visual surveys conducted on a bi-monthly basis are likely sufficient to both estimate the abundance of focal taxonomic groups, such as mullets and Milkfish, as well as track changes in the occupancy patterns of invasive species. The lack of any significant influence of the environmental covariates, e.g., salinity, temperature, tidal stage, and turbidity, on detection, occupancy, or abundance in either modeling approach suggests that these parameters are not influencing the ability of the surveyors to accurately count the focal species or strongly influencing the distribution of organisms within Kaloko Fishpond. Better characterization of in-pond habitat, such as substrate composition and productivity, may provide better predictors of variability in abundance and occupancy. Further refinement of the survey methods could include relying on temperature and salinity data collected from data loggers deployed within each region. This would provide temperature and salinity data from the periods between survey events to examine their effect on colonization and extinction rates. Additional training and validation of observer counts may also serve to improve data collection. Better incorporating kilo observations into the models may also serve to better explain the variability in counts. Finally, a better understanding of how mullet and Milkfish use the deeper areas in the center of the pond would provide greater confidence for interpreting λ as a proxy for their total abundance in the pond rather than only an estimate of the number of individuals in the surveyable areas.

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Appendix 1. Informational materials and datasheet provided to observers conducting shore-based visual surveys of Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022.

Identification guide
Species likely to occur in Kaloko fishpond

Focal species

- Focal species: these need to be identified carefully and counted accurately in the first 5-minute visual survey. These care placed in to 5 Categories Mullet(3 sp), Flagtail (2 sp), Threadfin (1 sp.), Milkfish(1 sp.), Bonefish(2 sp).

- Mullet
- Flagtail
- Threadfin
- Milkfish
- Bonefish

Non-native

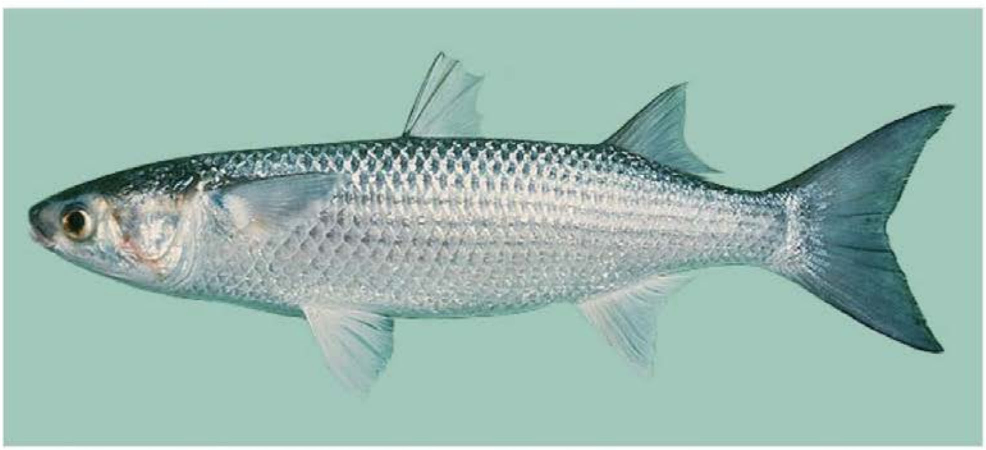
- Non-native species are denoted and should be identified as part of the 3-minute presence/absence recording.

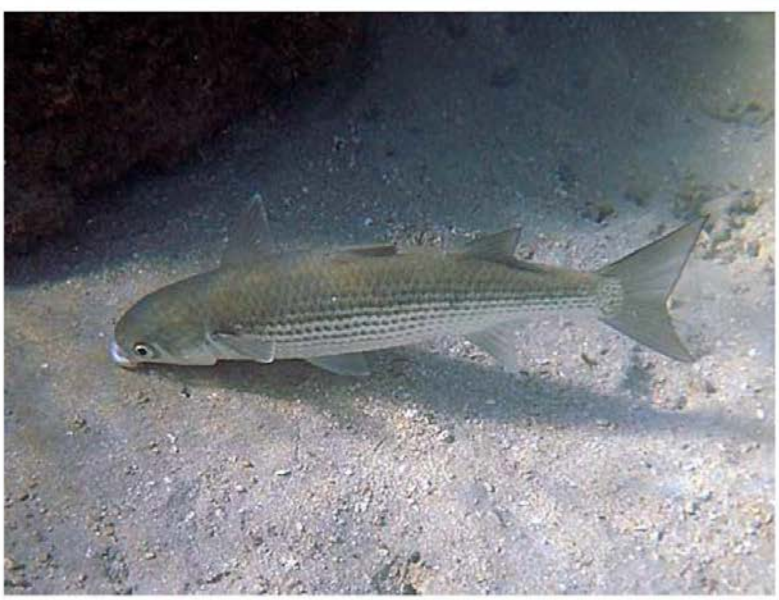
- Predators: identified as part of the 3-minute presence/absence recording.

Striped Mullet | ‘Ama'ama

(*Mugil cephalus)*

Medium bodied reef fish ~50 cm up to 90 cm long. Associated with Low salinities from estuaries through to full freshwaters. Often found schooling with similar sized individuals. When feeding these fish will nose down and roll from side to side flashing silver. Beyond their larger maximum size identifiable from Kanda mullet by dark stripes and blue spot on base of pectoral fins





Sharpnose Mullet | Uouoa

(Neomyxus leuciscus)

Small bodied reef fish ~40 cm up to 60 cm long. Associated with High salinities from estuaries through to full strength ocean conditions. Often found schooling with similar sized individuals. When feeding these fish will nose down and roll from side to side flashing silver. Beyond their larger maximum size identifiable from Kanda mullet by lack of striped and yellow spot on base of pectoral fins

Non-native

Kanda

(Osteomugil engeli)

Small bodied reef fish ~30 cm up to 50 cm long. Broad salinity tolerances from estuaries through to full freshwaters. Often found schooling with similar sized individuals. When feeding these fish will nose down and roll from side to side flashing silver. Identifiable from Striped mullet by lack of stripes and no coloration on base of pectoral fins.

Milkfish | Awa

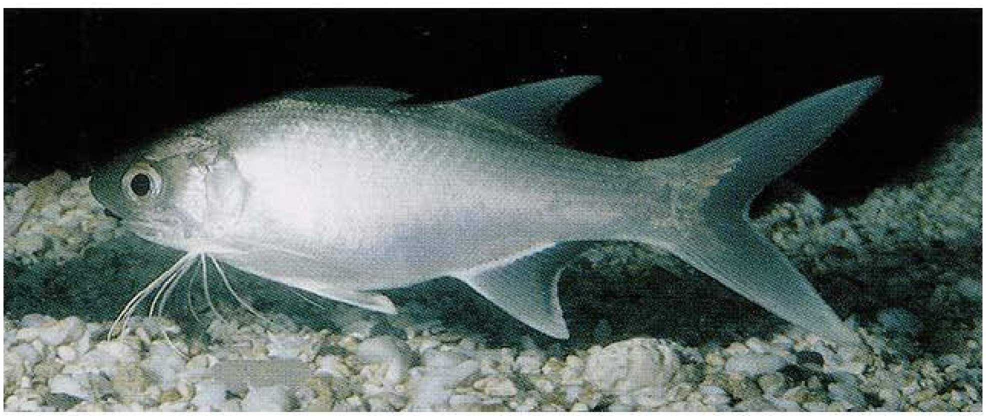
(Chanos chanos)

Large bodied reef fish ~50 cm up to 130 cm long. Associated with higher salinity portions of estuaries although can tolerate freshwater for short periods. Often found solitary or in small schools <5 individuals. Fast swimmers that are easily spooked. Distinguished from other silver fish by their long tail fin with its deep V shape

Pacific Threadfin | Moi

(Polydactylus sexfilis)

Medium bodied reef fish up to 60 cm long. Associated with higher salinity portions of estuaries although can tolerate freshwater for short periods. Associated with sandy areas with significant white water. Found in small schools. When feeding, threadlike appendages extend and search through the sediment. Slower swimming individuals with blunt nose in comparison to milkfish that share a deep tailfin.



Presence/absence of organisms of interest

- 3 Minute period to make observations of any species you can positively ID. Anything you are unsure of leave out.
- Additionally, noting the presence/absence of these specific groups is also done at this time : predators, turtles, invasive species.

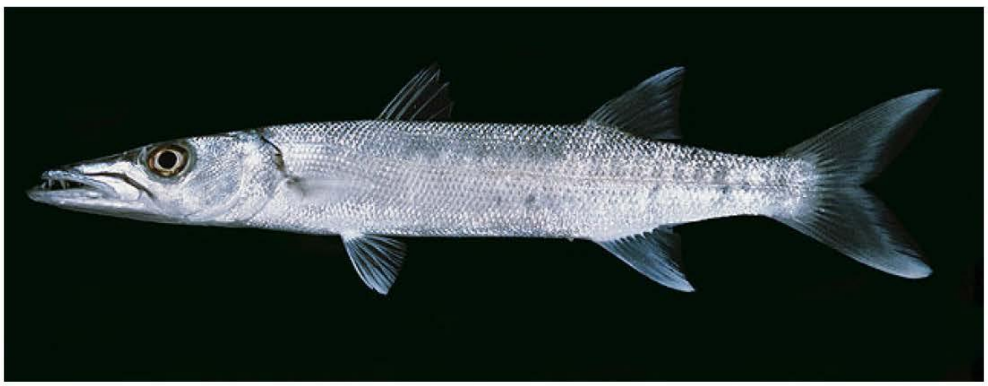
Non-native

Western Mosquitofish (*Gambusia affinis*) and Guppy (*Poecilia reticulata*)

Associated with shallow, fresh water, but can occupy salinities up to 25ppt. Schooling fish found around muddy bottoms individuals 5-60 mm. Often mistaken for newly recruited mullet but differ in their behavior with guppies generally swimming slower and remaining within a relatively small area. Distinguishing factor from mullet are schools of guppies vary in individual size within a school, lack the silver shine, and are deeper and wider in the body than mullets

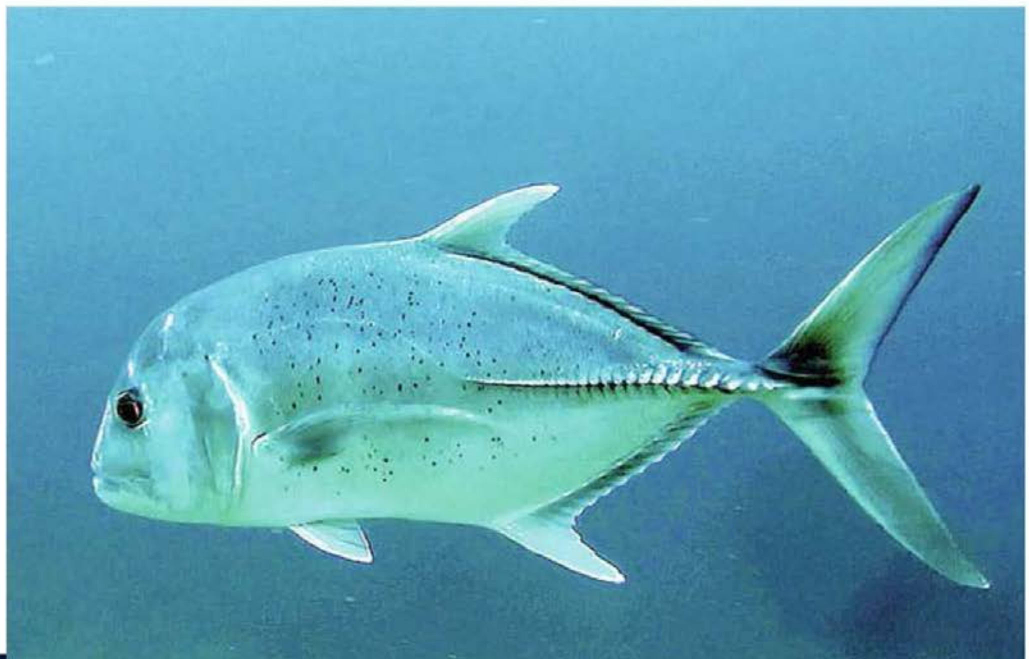
Great Barracuda | Kaku (Sphyraena barracuda) and Heller's Barracuda | Kawele'a (*Sphyraena helleri*)

Large predatory reef fishes up to 1m long. Associated with higher salinities but can occupy relatively fresh conditions down to ~15 ppt. Often found floating still within this pond when not feeding. When feeding these fish will quickly dart through schooling fish to capture prey. Silvery in profile but can range in top coloration from silver to dark brown.



Jacks | Ulua/Papio (*Caranx spp.*) and Bluefin Trevally | 'Omilu (*Caranx melampygus*)

Large predatory reef fishes up to 130 cm long. Associated with higher salinities but can occupy relatively fresh conditions down to ~15 ppt. Often found aggressively perusing schools of fish. Often found solo, but will school into small hunting parties of <5 individuals. Multiple species range in color (white, black, and some blue) but this family has a distinctive body profile.



Non-native

Upside-down Jellyfish

(*Cassiopea spp.)*

Small jellyfish yellow-brown with white or pale spots and streaks that sit bell side down on the substrate (up to 20 cm in diameter). Usually on sand but may occasionally be on flat rock. Has the ability to sting causing irritation and rash.

Green Sea Turtle | Honu

(*Chelonia mydas*)

Large up to 150 cm sea turtle with four flippers, a large carapace and often covered in algae. Often found surfacing for air or hauled out on the bank sunning.

Appendix 2. R code used to test six *a priori* candidate *N*-mixture models run across five survey intervals used to evaluate the abundance of mullets in Kaloko Fishpond in Kailua-Kona, Hawai'i during September-October 2020 and April-September 2022. The code specifically related to running the models is highlighted as bold text.

```
# install.packages("unmarked")
# install.packages("tidyverse")
#load packages required
library("unmarked")
library("tidyverse")
getwd()#find the directory/folder that R is using to store and call files from
#can use setwd() to change the directory
#all data files should be located in this directory
list.files()#use to get the name of csv
kaloko<-read.csv("nmix_w_tide 20220929.csv")#strings as factors codes repeated character
vectors as levels in a factor
#replace all blank cells with a zero as these are act
kaloko[is.na(kaloko)]<-0
#use this to check if the data is loaded correctly
#used to convert other data types to factor
kaloko<-kaloko %>% mutate(across(c("Observer","Station.x","Survey.number","date"),
as.factor))
head(kaloko)
#check to see if the data is in the right structure
#names of people should be factors, mesurments should be int or num
str(kaloko)
#simplify the tide height col into tide
kaloko$Tide<-kaloko$TideHeight
#deleting unneeded col
kaloko<-select(kaloko, -c(Station.y, TideHeight,Turbidity..bricks.,X ))
kaloko$Station.x<-as.factor(kaloko$Station.x)#forcing station to be a factor
kaloko$Salinity..ppt.<-as.numeric(kaloko$Salinity..ppt.)
#################################################################################
#############
#dealing with data issues from raw file
# obs.list<-unique(kaloko$Observer)
#Ashlynn Ashylnn and any levels with extra spaces
kaloko<- kaloko %>% mutate(Observer= recode(Observer, "Ashlynn "="Ashlynn" , "Ashylnn"=
"Ashlynn" ))
###################
```

```
#we need to have the sites as rows and visits as columns
#subset the master dataset and add the new numbers to each specific count or covariate matrix
#reorder the df to be consistently ascending order
kaloko<-kaloko %>% arrange(Survey.number, Station.x)
#rename station to remove x
kaloko<-kaloko %>% dplyr::rename(Station=Station.x)
####################################
#plot and visualize the data to check for errors/inconsistencies
kaloko %>% ggplot()+
  geom_histogram(aes(x=Mullet),fill="#FF6666")+
  xlab("Mullet point counts")+
  theme_minimal()+
  ggtitle("Frequency of point count of Mullet")
sal.plot<-kaloko %>% ggplot()+
  geom_histogram(aes(x=Salinity..ppt.),fill="blue")+
  xlab("Salinity (ppt)")+
  theme_minimal()+
  ggtitle("Salinity")
temp.plot<-kaloko %>% ggplot()+
  geom_histogram(aes(x=Temperature..C.),fill="green")+
  xlab("Temperature (C)")+
  theme_minimal()+
  ggtitle("Temperature")
turb.plot<-kaloko %>% ggplot()+
  geom_histogram(aes(x=Visible.Distance..m.),fill="brown")+
  xlab("Turbidity(# of bricks visable)")+
  theme_minimal()+
  ggtitle("Turbidity(# of bricks visable)")
tide.plot<-kaloko %>% ggplot()+
  geom_histogram(aes(x=Tide),fill="orange")+
  xlab("Tide height(m)")+
  theme_minimal()+
  ggtitle("Tide height ")
ggpubr::ggarrange(sal.plot,temp.plot,turb.plot,tide.plot)
################################
#load the site covariates
kaloko.site.factor<-read.csv("site_key.csv")
unique(kaloko$Survey.number)
kaloko %>% distinct(date, Survey.number)
#A
```

```
20200915 20200917 20201009 20201011
block_a<-kaloko %>% filter(date %in% c(20200915, 20200917, 20201009, 20201011))
9/02
#B
block_b<-kaloko %>% filter(date %in% c(20220411, 20220423, 20220507, 20220525,
20220526, 20220528, 20220601, 20220603, 20220607, 20220608, 20220609, 20220613,
20220614, 20220615, 20220623, 20220624, 20220625, 20220629))
#C
block_c<-kaloko %>% filter(date %in% c(20220630, 20220701, 20220706, 20220711,
20220713, 20220718, 20220720, 20220722, 20220725, 20220727,20220729, 20220801,
20220803, 20220805, 20220808,20220810))
#D
block_d<-kaloko %>% filter(date %in% c(20220812, 20220817, 20220818, 20220819,
20220822, 20220824, 20220826, 20220829, 20220831, 20220902))
#E
block_e<-kaloko %>% filter(date %in% c(20220905, 20220907,20220909, 20220912,
20220913, 20220915, 20220919, 20220920, 20220922, 20220926, 20220927))
#subset based on mullet and milkfish
block_a_mullet.sub<- block_a %>% dplyr::select(Station, Survey.number,Mullet)
block_b_mullet.sub<- block_b %>% dplyr::select(Station, Survey.number,Mullet)
block_c_mullet.sub<- block_c %>% dplyr::select(Station, Survey.number,Mullet)
block_d_mullet.sub<- block_d %>% dplyr::select(Station, Survey.number,Mullet)
block_e_mullet.sub<- block_e %>% dplyr::select(Station, Survey.number,Mullet)
block_a_milkfish.sub<- block_a %>% dplyr::select(Station, Survey.number,Milkfish)
block_b_milkfish.sub<- block_b %>% dplyr::select(Station, Survey.number,Milkfish)
block_c_milkfish.sub<- block_c %>% dplyr::select(Station, Survey.number,Milkfish)
block_d_milkfish.sub<- block_d %>% dplyr::select(Station, Survey.number,Milkfish)
block_e_milkfish.sub<- block_e %>% dplyr::select(Station, Survey.number,Milkfish)
###### convert from long format to wide for milkfish and mullet
block_a_mullet.wide<- block_a_mullet.sub %>% pivot_wider(names_from = Survey.number,
values_from=c(Mullet))
block_b_mullet.wide<- block_b_mullet.sub %>% pivot_wider(names_from = Survey.number,
values_from=c(Mullet))
block_c_mullet.wide<- block_c_mullet.sub %>% pivot_wider(names_from = Survey.number,
values_from=c(Mullet))
block_d_mullet.wide<- block_d_mullet.sub %>% pivot_wider(names_from = Survey.number,
values_from=c(Mullet))
block_e_mullet.wide<- block_e_mullet.sub %>% pivot_wider(names_from = Survey.number,
values_from=c(Mullet))
```

```
block_a_milkfish.wide<- block_a_milkfish.sub %>% pivot_wider(names_from =
Survey.number, values_from=c(Milkfish))
block_b_milkfish.wide<- block_b_milkfish.sub %>% pivot_wider(names_from =
Survey.number, values_from=c(Milkfish))
block_c_milkfish.wide<- block_c_milkfish.sub %>% pivot_wider(names_from =
Survey.number, values_from=c(Milkfish))
block_d_milkfish.wide<- block_d_milkfish.sub %>% pivot_wider(names_from =
Survey.number, values_from=c(Milkfish))
block_e_milkfish.wide<- block_e_milkfish.sub %>% pivot_wider(names_from =
Survey.number, values_from=c(Milkfish))
######### extract long form enviromental variables
block_a_env.sal<-block_a %>% select(5,6,8)
block_a_env.tide<-block_a %>% select(5,6,13)
block_a_env.Turb<-block_a %>% select(5,6,14)
block_b_env.sal<-block_b %>% select(5,6,8)
block_b_env.tide<-block_b %>% select(5,6,13)
block_b_env.Turb<-block_b %>% select(5,6,14)
block_c_env.sal<-block_c %>% select(5,6,8)
block_c_env.tide<-block_c %>% select(5,6,13)
block_c_env.Turb<-block_c %>% select(5,6,14)
block_d_env.sal<-block_d %>% select(5,6,8)
block_d_env.tide<-block_d %>% select(5,6,13)
block_d_env.Turb<-block_d %>% select(5,6,14)
block_e_env.sal<-block_e %>% select(5,6,8)
block_e_env.tide<-block_e %>% select(5,6,13)
block_e_env.Turb<-block_e %>% select(5,6,14)
############ convert environmental variables from long to wide format
block_a_wide.sal<-block_a_env.sal %>% pivot_wider(names_from = Survey.number,
values_from=c(Salinity..ppt.))
block_a_wide.tide<-block_a_env.tide %>% pivot_wider(names_from = Survey.number,
values_from=c( Tide))
block_a_wide.turb<-block_a_env.Turb %>% pivot_wider(names_from = Survey.number,
values_from=c( Visible.Distance..m.))
block_b_wide.sal<-block_b_env.sal %>% pivot_wider(names_from = Survey.number,
values_from=c(Salinity..ppt.))
block_b_wide.tide<-block_b_env.tide %>% pivot_wider(names_from = Survey.number,
values_from=c( Tide))
block_b_wide.turb<-block_b_env.Turb %>% pivot_wider(names_from = Survey.number,
values_from=c( Visible.Distance..m.))
```

```
block_c_wide.sal<-block_c_env.sal %>% pivot_wider(names_from = Survey.number,
values_from=c(Salinity..ppt.))
block_c_wide.tide<-block_c_env.tide %>% pivot_wider(names_from = Survey.number,
values_from=c( Tide))
block_c_wide.turb<-block_c_env.Turb %>% pivot_wider(names_from = Survey.number,
values_from=c( Visible.Distance..m.))
block_d_wide.sal<-block_d_env.sal %>% pivot_wider(names_from = Survey.number,
values_from=c(Salinity..ppt.))
block_d_wide.tide<-block_d_env.tide %>% pivot_wider(names_from = Survey.number,
values_from=c( Tide))
block_d_wide.turb<-block_d_env.Turb %>% pivot_wider(names_from = Survey.number,
values_from=c( Visible.Distance..m.))
block_e_wide.sal<-block_e_env.sal %>% pivot_wider(names_from = Survey.number,
values_from=c(Salinity..ppt.))
block_e_wide.tide<-block_e_env.tide %>% pivot_wider(names_from = Survey.number,
values_from=c( Tide))
block_e_wide.turb<-block_e_env.Turb %>% pivot_wider(names_from = Survey.number,
values_from=c( Visible.Distance..m.))
#format each blocks enviornmental covs into obs covariate matrix
block_a_obs.covs<-list(sal=as.matrix((block_a_wide.sal[,2:length(block_a_wide.sal)])),
tide=as.matrix(block_a_wide.tide[,2:length(block_a_wide.sal)], nrow = 30, ncol =
length(block_a_wide.sal)), turb=as.matrix(block_a_wide.turb[,2:length(block_a_wide.sal)],
nrow = 30, ncol = length(block_a_wide.sal)))
block_b_obs.covs<-list(sal=as.matrix((block_b_wide.sal[,2:length(block_b_wide.sal)])),
tide=as.matrix(block_b_wide.tide[,2:length(block_b_wide.sal)], nrow = 30, ncol =
length(block_b_wide.sal)), turb=as.matrix(block_b_wide.turb[,2:length(block_b_wide.sal)],
nrow = 30, ncol = length(block_b_wide.sal)))
block_c_obs.covs<-list(sal=as.matrix((block_c_wide.sal[,2:length(block_c_wide.sal)])),
tide=as.matrix(block_c_wide.tide[,2:length(block_c_wide.sal)], nrow = 30, ncol =
length(block_c_wide.sal)), turb=as.matrix(block_c_wide.turb[,2:length(block_c_wide.sal)],
nrow = 30, ncol = length(block_c_wide.sal)))
block_d_obs.covs<-list(sal=as.matrix((block_d_wide.sal[,2:length(block_d_wide.sal)])),
tide=as.matrix(block_d_wide.tide[,2:length(block_d_wide.sal)], nrow = 30, ncol =
length(block_d_wide.sal)), turb=as.matrix(block_d_wide.turb[,2:length(block_d_wide.sal)],
nrow = 30, ncol = length(block_d_wide.sal)))
block_e_obs.covs<-list(sal=as.matrix((block_e_wide.sal[,2:length(block_e_wide.sal)])),
tide=as.matrix(block_e_wide.tide[,2:length(block_e_wide.sal)], nrow = 30, ncol =
length(block_e_wide.sal)),turb=as.matrix(block_e_wide.turb[,2:length(block_e_wide.sal)], nrow
= 30, ncol = length(block_e_wide.sal)))
kaloko.site.factor<-read.csv("site_key.csv", stringsAsFactors = TRUE)
```

```
# format data into unmarked object
block_a_mullet.un<-
unmarkedFramePCount(y=block_a_mullet.wide[,2:length(block_a_mullet.wide)], obsCovs
=block_a_obs.covs, siteCovs = kaloko.site.factor )
block_a_milkfish.un<-
unmarkedFramePCount(y=block_a_milkfish.wide[,2:length(block_a_milkfish.wide)], obsCovs
=block_a_obs.covs, siteCovs = kaloko.site.factor )
block_b_mullet.un<-
unmarkedFramePCount(y=block_b_mullet.wide[,2:length(block_b_mullet.wide)], obsCovs
=block_b_obs.covs, siteCovs = kaloko.site.factor )
block_b_milkfish.un<-
unmarkedFramePCount(y=block_b_milkfish.wide[,2:length(block_b_milkfish.wide)], obsCovs
=block_b_obs.covs, siteCovs = kaloko.site.factor )
block_c_mullet.un<-
unmarkedFramePCount(y=block_c_mullet.wide[,2:length(block_c_mullet.wide)], obsCovs
=block_c_obs.covs, siteCovs = kaloko.site.factor )
block_c_milkfish.un<-
unmarkedFramePCount(y=block_c_milkfish.wide[,2:length(block_c_milkfish.wide)], obsCovs
=block_c_obs.covs, siteCovs = kaloko.site.factor )
block_d_mullet.un<-
unmarkedFramePCount(y=block_d_mullet.wide[,2:length(block_d_mullet.wide)], obsCovs
=block_d_obs.covs, siteCovs = kaloko.site.factor )
block_d_milkfish.un<-
unmarkedFramePCount(y=block_d_milkfish.wide[,2:length(block_d_milkfish.wide)], obsCovs
=block_d_obs.covs, siteCovs = kaloko.site.factor )
block_e_mullet.un<-
unmarkedFramePCount(y=block_e_mullet.wide[,2:length(block_e_mullet.wide)], obsCovs
=block_e_obs.covs, siteCovs = kaloko.site.factor )
block_e_milkfish.un<-
unmarkedFramePCount(y=block_e_milkfish.wide[,2:length(block_e_milkfish.wide)], obsCovs
=block_e_obs.covs, siteCovs = kaloko.site.factor )

#use this to find max observation to set K to value bigger than observed
summary(block_a_mullet.un)
summary(block_a_milkfish.un)
block_a_mullet.null <- pcount(~1 ~1, # P THEN LAMBDA
                    data=block_a_mullet.un, mixture =  "ZIP",
                    K=250, )
block_a_milkfish.null <- pcount(~1 ~1, # P THEN LAMBDA
                              data=block_a_milkfish.un, mixture =  "ZIP",
```

```
                       K=30, engine = "C" )
block_a_mullet.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                       block_a_mullet.un,  mixture =  "ZIP" ,
                       K=250, engine = "C")
block_a_milkfish.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                       block_a_milkfish.un,  mixture =  "ZIP" ,
                       K=30, engine = "C")
block_a_mullet.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                       block_a_mullet.un,  mixture =  "ZIP" ,
                       K=250, engine = "C")
block_a_milkfish.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                       block_a_milkfish.un,  mixture =  "ZIP" ,
                       K=30, engine = "C")
block_a_mullet.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                       block_a_mullet.un,  mixture =  "ZIP" ,
                       K=250, engine = "C")
block_a_milkfish.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                       block_a_milkfish.un,  mixture =  "ZIP" ,
                       K=30, engine = "C")
block_a_mullet.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                       block_a_mullet.un,  mixture =  "ZIP" ,
                       K=250, engine = "C")
block_a_milkfish.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                       block_a_milkfish.un,  mixture =  "ZIP" ,
                       K=30, engine = "C")
block_a_mullet.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                       block_a_mullet.un,  mixture =  "ZIP" ,
                       K=250, engine = "C")
block_a_milkfish.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                       block_a_milkfish.un,  mixture =  "ZIP" ,
                       K=30, engine = "C")
###########################
summary(block_b_mullet.un)
summary(block_b_milkfish.un)
block_b_mullet.null <- pcount(~1 ~1, # P THEN LAMBDA
                       data=block_b_mullet.un, mixture =  "ZIP",
                       K=190,engine = "C" )
block_b_milkfish.null <- pcount(~1 ~1, # P THEN LAMBDA
                       data=block_b_milkfish.un, mixture =  "ZIP",
                       K=50 )
```

```
block_b_mullet.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                        block_b_mullet.un,  mixture =  "ZIP" ,
                        K=250, starts = c(1,1,1,1,-3,-4,-4,-4,-5), engine = "C")
block_b_milkfish.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                        block_b_milkfish.un,  mixture =  "ZIP" ,
                        K=50)
block_b_mullet.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                        block_b_mullet.un,  mixture =  "ZIP" ,
                        K=250)
block_b_milkfish.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                        block_b_milkfish.un,  mixture =  "ZIP" ,
                        K=50)
block_b_mullet.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                        block_b_mullet.un,  mixture =  "ZIP" ,
                        K=250, engine = "C")
block_b_milkfish.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                        block_b_milkfish.un,  mixture =  "ZIP" ,
                        K=50, engine = "C")
block_b_mullet.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                        block_b_mullet.un,  mixture =  "ZIP" ,
                        K=250, engine = "C")
block_b_milkfish.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                        block_b_milkfish.un,  mixture =  "ZIP" ,
                        K=50, engine = "C")
block_b_mullet.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                        block_b_mullet.un,  mixture =  "ZIP" ,
                        K=250, engine = "C")
block_b_milkfish.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                        block_b_milkfish.un,  mixture =  "ZIP" ,
                        K=50, engine = "C")
########################
summary(block_c_mullet.un)
summary(block_c_milkfish.un)
block_c_mullet.null <- pcount(~1 ~1, # P THEN LAMBDA
                        data=block_c_mullet.un, mixture =  "ZIP",
                        K=700 )
block_c_milkfish.null <- pcount(~1 ~1, # P THEN LAMBDA
                        data=block_c_milkfish.un, mixture =  "ZIP",
                        K=50 )
block_c_mullet.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
```

```
                        block_c_mullet.un,  mixture =  "ZIP" ,
                        K=700)
block_c_milkfish.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                        block_c_milkfish.un,  mixture =  "ZIP" ,
                        K=50)
block_c_mullet.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                        block_c_mullet.un,  mixture =  "ZIP" ,
                        K=700)
block_c_milkfish.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                        block_c_milkfish.un,  mixture =  "ZIP" ,
                        K=50)
block_c_mullet.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                        block_c_mullet.un,  mixture =  "ZIP" ,
                        K=700, engine = "C")
block_c_milkfish.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                        block_c_milkfish.un,  mixture =  "ZIP" ,
                        K=50, engine = "C")
block_c_mullet.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                        block_c_mullet.un,  mixture =  "ZIP" ,
                        K=700, engine = "C")
block_c_milkfish.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                        block_c_milkfish.un,  mixture =  "ZIP" ,
                        K=50, engine = "C")
block_c_mullet.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                        block_c_mullet.un,  mixture =  "ZIP" ,
                        K=700, engine = "C")
block_c_milkfish.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                        block_c_milkfish.un,  mixture =  "ZIP" ,
                        K=50, engine = "C")
####################
summary(block_d_mullet.un)
summary(block_d_milkfish.un)
block_d_mullet.null <- pcount(~1 ~1, # P THEN LAMBDA
                        data=block_d_mullet.un, mixture =  "ZIP",
                        K=180 )
block_d_milkfish.null <- pcount(~1 ~1, # P THEN LAMBDA
                        data=block_d_milkfish.un, mixture =  "NB",
                        K=75 )
block_d_mullet.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                        block_d_mullet.un,  mixture =  "ZIP" ,
```

```
                    K=250)
block_d_milkfish.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                    block_d_milkfish.un,  mixture =  "ZIP" ,
                    K=75)
block_d_mullet.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                    block_d_mullet.un,  mixture =  "ZIP" ,
                    K=250)
block_d_milkfish.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                    block_d_milkfish.un,  mixture =  "ZIP" ,
                    K=75)
block_d_mullet.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                    block_d_mullet.un,  mixture =  "ZIP" ,
                    K=250, engine = "C")
block_d_milkfish.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                    block_d_milkfish.un,  mixture =  "ZIP" ,
                    K=75, engine = "C")
block_d_mullet.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                    block_d_mullet.un,  mixture =  "ZIP" ,
                    K=250, engine = "C")
block_d_milkfish.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                    block_d_milkfish.un,  mixture =  "ZIP" ,
                    K=75, engine = "C")
block_d_mullet.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                    block_d_mullet.un,  mixture =  "ZIP" ,
                    K=250, engine = "C")
block_d_milkfish.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                    block_d_milkfish.un,  mixture =  "ZIP" ,
                    K=75, engine = "C")
########################
summary(block_e_mullet.un)
summary(block_e_milkfish.un)
block_e_mullet.null <- pcount(~1 ~1, # P THEN LAMBDA
                    data=block_e_mullet.un, mixture =  "NB",
                    K=400 )
block_e_milkfish.null <- pcount(~1 ~1, # P THEN LAMBDA
                    data=block_e_milkfish.un, mixture =  "ZIP",
                    K=50 )
block_e_mullet.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                    block_e_mullet.un,  mixture =  "ZIP" ,
                    K=400)
```

```
block_e_milkfish.global <- pcount(~sal+turb+tide ~site_key , # P THEN LAMBDA
                              block_e_milkfish.un,  mixture =  "ZIP" ,
                              K=50)
block_e_mullet.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                              block_e_mullet.un,  mixture =  "ZIP" ,
                              K=400)
block_e_milkfish.sal <- pcount(~sal ~1 , # P THEN LAMBDA
                              block_e_milkfish.un,  mixture =  "ZIP" ,
                              K=50)
block_e_mullet.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                              block_e_mullet.un,  mixture =  "ZIP" ,
                              K=400, engine = "C")
block_e_milkfish.turb <- pcount(~turb ~1 , # P THEN LAMBDA
                              block_e_milkfish.un,  mixture =  "ZIP" ,
                              K=50, engine = "C")
block_e_mullet.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                              block_e_mullet.un,  mixture =  "ZIP" ,
                              K=400, engine = "C")
block_e_milkfish.tide <- pcount(~tide ~1 , # P THEN LAMBDA
                              block_e_milkfish.un,  mixture =  "ZIP" ,
                              K=50, engine = "C")
block_e_mullet.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                              block_e_mullet.un,  mixture =  "ZIP" ,
                              K=400, engine = "C")
block_e_milkfish.key <- pcount(~1 ~site_key , # P THEN LAMBDA
                              block_e_milkfish.un,  mixture =  "ZIP" ,
                              K=50, engine = "C")
# unmarked::parboot(block_e_mullet.null)
################## extract values into table
block_a_model.names<-
c("block_a_mullet.null","block_a_mullet.global","block_a_mullet.sal","block_a_mullet.turb","bl
ock_a_mullet.tide","block_a_mullet.key")
block_b_model.names<-
c("block_b_mullet.null","block_b_mullet.global","block_b_mullet.sal","block_b_mullet.turb","b
lock_b_mullet.tide","block_b_mullet.key")
block_c_model.names<-c("block_c_mullet.null","block_c_mullet.global","block_c_mullet.sal",
"block_c_mullet.turb","block_c_mullet.tide","block_c_mullet.key")
block_d_model.names<-
c("block_d_mullet.null","block_d_mullet.global","block_d_mullet.sal","block_d_mullet.turb","b
lock_d_mullet.tide","block_d_mullet.key")
```

```
block_e_model.names<-c("block_e_mullet.null","block_e_mullet.global","block_e_mullet.sal",
"block_e_mullet.turb","block_e_mullet.tide","block_e_mullet.key")
block_a_model.AIC<-
c(AICcmodavg::extractLL(block_a_mullet.null),AICcmodavg::extractLL(block_a_mullet.global
),AICcmodavg::extractLL(block_a_mullet.sal),
AICcmodavg::extractLL(block_a_mullet.turb),AICcmodavg::extractLL(block_a_mullet.tide),AI
Ccmodavg::extractLL(block_a_mullet.key))
block_b_model.AIC<-
c(AICcmodavg::extractLL(block_b_mullet.null),AICcmodavg::extractLL(block_b_mullet.global
),AICcmodavg::extractLL(block_b_mullet.sal),
AICcmodavg::extractLL(block_b_mullet.turb),AICcmodavg::extractLL(block_b_mullet.tide),AI
Ccmodavg::extractLL(block_b_mullet.key))
block_c_model.AIC<-
c(AICcmodavg::extractLL(block_c_mullet.null),AICcmodavg::extractLL(block_c_mullet.global
),AICcmodavg::extractLL(block_c_mullet.sal),
AICcmodavg::extractLL(block_c_mullet.turb),AICcmodavg::extractLL(block_c_mullet.tide),AI
Ccmodavg::extractLL(block_c_mullet.key))
block_d_model.AIC<-
c(AICcmodavg::extractLL(block_d_mullet.null),AICcmodavg::extractLL(block_d_mullet.global
),AICcmodavg::extractLL(block_d_mullet.sal),
AICcmodavg::extractLL(block_d_mullet.turb),AICcmodavg::extractLL(block_d_mullet.tide),AI
Ccmodavg::extractLL(block_d_mullet.key))
block_e_model.AIC<-
c(AICcmodavg::extractLL(block_e_mullet.null),AICcmodavg::extractLL(block_e_mullet.global
),AICcmodavg::extractLL(block_e_mullet.sal),
AICcmodavg::extractLL(block_e_mullet.turb),AICcmodavg::extractLL(block_e_mullet.tide),AI
Ccmodavg::extractLL(block_e_mullet.key))
mullet_total.model.names<-
cbind(block_a_model.names,block_b_model.names,block_c_model.names,block_d_model.name
s,block_e_model.names)
total.model.aic<-
cbind(block_a_model.AIC,block_b_model.AIC,block_c_model.AIC,block_d_model.AIC,block_
e_model.AIC)
total.aic.table<-cbind(mullet_total.model.names,total.model.aic)
write.csv(total.aic.table,file = "mullet_total_aic_table_20230126.csv")
###################################
block_a_model.names<-
c("block_a_milkfish.null","block_a_milkfish.global","block_a_milkfish.sal","block_a_milkfish.t
urb","block_a_milkfish.tide","block_a_milkfish.key")
```

```
block_b_model.names<-
c("block_b_milkfish.null","block_b_milkfish.global","block_b_milkfish.sal","block_b_milkfish.
turb","block_b_milkfish.tide","block_b_milkfish.key")
block_c_model.names<-
c("block_c_milkfish.null","block_c_milkfish.global","block_c_milkfish.sal",
"block_c_milkfish.turb","block_c_milkfish.tide","block_c_milkfish.key")
block_d_model.names<-
c("block_d_milkfish.null","block_d_milkfish.global","block_d_milkfish.sal",
"block_d_milkfish.turb","block_d_milkfish.tide","block_d_milkfish.key")
block_e_model.names<-
c("block_e_milkfish.null","block_e_milkfish.global","block_e_milkfish.sal",
"block_e_milkfish.turb", "block_e_milkfish.tide","block_e_milkfish.key")
block_a_model.AIC<-
c(AICcmodavg::extractLL(block_a_milkfish.null),AICcmodavg::extractLL(block_a_milkfish.gl
obal),AICcmodavg::extractLL(block_a_milkfish.sal),
        AICcmodavg::extractLL(block_a_milkfish.turb),AICcmodavg::extractLL(block_a_milkfi
sh.tide),AICcmodavg::extractLL(block_a_milkfish.key))
block_b_model.AIC<-
c(AICcmodavg::extractLL(block_b_milkfish.null),AICcmodavg::extractLL(block_b_milkfish.gl
obal),AICcmodavg::extractLL(block_b_milkfish.sal),
        AICcmodavg::extractLL(block_b_milkfish.turb),AICcmodavg::extractLL(block_b_milkf
ish.tide),AICcmodavg::extractLL(block_b_milkfish.key))
block_c_model.AIC<-
c(AICcmodavg::extractLL(block_c_milkfish.null),AICcmodavg::extractLL(block_c_milkfish.gl
obal),AICcmodavg::extractLL(block_c_milkfish.sal),
AICcmodavg::extractLL(block_c_milkfish.turb),AICcmodavg::extractLL(block_c_milkfish.tide)
,AICcmodavg::extractLL(block_c_milkfish.key))
block_d_model.AIC<-
c(AICcmodavg::extractLL(block_d_milkfish.null),AICcmodavg::extractLL(block_d_milkfish.gl
obal),AICcmodavg::extractLL(block_d_milkfish.sal),
        AICcmodavg::extractLL(block_d_milkfish.turb),AICcmodavg::extractLL(block_d_milkf
ish.tide),AICcmodavg::extractLL(block_d_milkfish.key))
block_e_model.AIC<-
c(AICcmodavg::extractLL(block_e_milkfish.null),AICcmodavg::extractLL(block_e_milkfish.gl
obal),AICcmodavg::extractLL(block_e_milkfish.sal),

AICcmodavg::extractLL(block_e_milkfish.turb),AICcmodavg::extractLL(block_e_milkfish.tide)
,AICcmodavg::extractLL(block_e_milkfish.key))
```

```
milkfish_total.model.names<-
cbind(block_a_model.names,block_b_model.names,block_c_model.names,block_d_model.name
s,block_e_model.names)
total.model.aic<-
cbind(block_a_model.AIC,block_b_model.AIC,block_c_model.AIC,block_d_model.AIC,block_
e_model.AIC)
total.aic.table<-cbind(milkfish_total.model.names,total.model.aic)
write.csv(total.aic.table,file = "milkfish_total_aic_table_20230126.csv")
#use these to extract beta values
block_a_mullet.null.coef<-coef(block_a_mullet.null)  %>% stack  %>%
mutate(model="block_a_null")
block_a_mullet.null.se<-SE(block_a_mullet.null)  %>% stack        %>% rename( SE=values)
block_a_mullet.all=cbind(block_a_mullet.null.coef,block_a_mullet.null.se)
block_a_mullet.global.coef<<-coef(block_a_mullet.global) %>% stack  %>%
mutate(model="block_a_mullet_global")
block_a_mullet.global.se<-SE(block_a_mullet.global)  %>% stack            %>% rename(
SE=values)
block_a_mullet.g.all=cbind(block_a_mullet.global.coef,block_a_mullet.global.se)
block_a_mullet.sal.coef<-coef(block_a_mullet.sal) %>% stack  %>%
mutate(model="block_a_mullet_sal")
block_a_mullet.sal.se<-SE(block_a_mullet.sal) %>% stack            %>% rename( SE=values)
block_a_mullet.s.all=cbind(block_a_mullet.sal.coef,block_a_mullet.sal.se)
block_a_mullet.turb.coef<-coef(mullet.turb)  %>% stack  %>%
mutate(model="block_a_mullet_turb")
block_a_mullet.turb.se<-SE(block_a_mullet.turb)  %>% stack       %>% rename( SE=values)
block_a_mullet.tu.all=cbind(block_a_mullet.turb.coef,block_a_mullet.turb.se)
block_a_mullet.tide.coef<-coef(block_a_mullet.tide)   %>% stack  %>%
mutate(model="block_a_mullet_tide")
block_a_mullet.tide.se<-SE(block_a_mullet.tide)  %>% stack        %>% rename( SE=values)
block_a_mullet.ti.all=cbind(block_a_mullet.tide.coef,block_a_mullet.tide.se)
block_a_mullet.model.output.coef<-
rbind(block_a_mullet.all,block_a_mullet.g.all,block_a_mullet.s.all,block_a_mullet.tu.all,block_a
_mullet.ti.all)
write.csv(block_a_mullet.model.output.coef,
file="block_a_mullet_model_output_coef_20230126.csv")
##########################################
block_b_mullet.null.coef<-coef(block_b_mullet.null)  %>% stack  %>%
mutate(model="block_b_null")
block_b_mullet.null.se<-SE(block_b_mullet.null)  %>% stack       %>% rename( SE=values)
block_b_mullet.all=cbind(block_b_mullet.null.coef,block_b_mullet.null.se)
```

```
block_b_mullet.global.coef<<-coef(block_b_mullet.global) %>% stack  %>%
mutate(model="block_b_mullet_global")
block_b_mullet.global.se<-data.frame(SE=c("DNC","DNC","DNC")) %>%
mutate(ind="block_b_mullet_global")
block_b_mullet.g.all=cbind(block_b_mullet.global.coef,block_b_mullet.global.se)
block_b_mullet.sal.coef<-coef(block_b_mullet.sal) %>% stack  %>%
mutate(model="block_b_mullet_sal")
block_b_mullet.sal.se<-SE(block_b_mullet.sal) %>% stack            %>% rename( SE=values)
block_b_mullet.s.all=cbind(block_b_mullet.sal.coef,block_b_mullet.sal.se)
block_b_mullet.turb.coef<-coef(mullet.turb)  %>% stack  %>%
mutate(model="block_b_mullet_turb")
block_b_mullet.turb.se<-SE(block_b_mullet.turb)  %>% stack       %>% rename( SE=values)
block_b_mullet.tu.all=cbind(block_b_mullet.turb.coef,block_b_mullet.turb.se)
block_b_mullet.tide.coef<-coef(block_b_mullet.tide)   %>% stack  %>%
mutate(model="block_b_mullet_tide")
block_b_mullet.tide.se<-SE(block_b_mullet.tide)  %>% stack        %>% rename( SE=values)
block_b_mullet.ti.all=cbind(block_b_mullet.tide.coef,block_b_mullet.tide.se)
block_b_mullet.model.output.coef<-
rbind(block_b_mullet.all,block_b_mullet.g.all,block_b_mullet.s.all,block_b_mullet.tu.all,block_
b_mullet.ti.all)
write.csv(block_b_mullet.model.output.coef,
file="block_b_mullet_model_output_coef_20230126.csv")
####################################
block_c_mullet.null.coef<-coef(block_c_mullet.null)  %>% stack  %>%
mutate(model="block_c_null")
block_c_mullet.null.se<-SE(block_c_mullet.null)  %>% stack        %>% rename( SE=values)
block_c_mullet.all=cbind(block_c_mullet.null.coef,block_c_mullet.null.se)
block_c_mullet.global.coef<<-coef(block_c_mullet.global)>% stack%>%
mutate(model="block_c_mullet_global")
block_c_mullet.global.se<-SE(block_c_mullet.global)  %>% stack%>% rename( SE=values)
block_c_mullet.g.all=cbind(block_c_mullet.global.coef,block_c_mullet.global.se)
block_c_mullet.sal.coef<-coef(block_c_mullet.sal) %>% stack%>%
mutate(model="block_c_mullet_sal")
block_c_mullet.sal.se<-SE(block_c_mullet.sal) %>% stack%>% rename( SE=values)
block_c_mullet.s.all=cbind(block_c_mullet.sal.coef,block_c_mullet.sal.se)
block_c_mullet.turb.coef<-coef(mullet.turb)  %>% stack%>%
mutate(model="block_c_mullet_turb")
block_c_mullet.turb.se<-SE(block_c_mullet.turb)  %>% stack%>% rename( SE=values)
block_c_mullet.tu.all=cbind(block_c_mullet.turb.coef,block_c_mullet.turb.se)
```

```
block_c_mullet.tide.coef<-coef(block_c_mullet.tide)   %>% stack  %>%
mutate(model="block_c_mullet_tide")
block_c_mullet.tide.se<-SE(block_c_mullet.tide)  %>% stack         %>% rename( SE=values)
block_c_mullet.ti.all=cbind(block_c_mullet.tide.coef,block_c_mullet.tide.se)
block_c_mullet.model.output.coef<-
rbind(block_c_mullet.all,block_c_mullet.g.all,block_c_mullet.s.all,block_c_mullet.tu.all,block_c
_mullet.ti.all)
write.csv(block_c_mullet.model.output.coef,
file="block_c_mullet_model_output_coef_20230126.csv")
####################################
block_d_mullet.null.coef<-coef(block_d_mullet.null)  %>% stack  %>%
mutate(model="block_d_null")
block_d_mullet.null.se<-SE(block_d_mullet.null)  %>% stack        %>% rename( SE=values)
block_d_mullet.all=cbind(block_d_mullet.null.coef,block_d_mullet.null.se)
block_d_mullet.global.coef<<-coef(block_d_mullet.global) %>% stack  %>%
mutate(model="block_d_mullet_global")
block_d_mullet.global.se<-SE(block_d_mullet.global)  %>% stack            %>% rename(
SE=values)
block_d_mullet.g.all=cbind(block_d_mullet.global.coef,block_d_mullet.global.se)
block_d_mullet.sal.coef<-coef(block_d_mullet.sal) %>% stack  %>%
mutate(model="block_d_mullet_sal")
block_d_mullet.sal.se<-SE(block_d_mullet.sal) %>% stack            %>% rename( SE=values)
block_d_mullet.s.all=cbind(block_d_mullet.sal.coef,block_d_mullet.sal.se)
block_d_mullet.turb.coef<-coef(mullet.turb)  %>% stack  %>%
mutate(model="block_d_mullet_turb")
block_d_mullet.turb.se<-SE(block_d_mullet.turb)  %>% stack        %>% rename( SE=values)
block_d_mullet.tu.all=cbind(block_d_mullet.turb.coef,block_d_mullet.turb.se)
block_d_mullet.tide.coef<-coef(block_d_mullet.tide)   %>% stack  %>%
mutate(model="block_d_mullet_tide")
block_d_mullet.tide.se<-SE(block_d_mullet.tide)  %>% stack        %>% rename( SE=values)
block_d_mullet.ti.all=cbind(block_d_mullet.tide.coef,block_d_mullet.tide.se)
block_d_mullet.model.output.coef<-
rbind(block_d_mullet.all,block_d_mullet.g.all,block_d_mullet.s.all,block_d_mullet.tu.all,block_
d_mullet.ti.all)
write.csv(block_d_mullet.model.output.coef,
file="block_d_mullet_model_output_coef_20230126.csv")
##################################
block_e_mullet.null.coef<-coef(block_e_mullet.null)  %>% stack  %>%
mutate(model="block_e_null")
block_e_mullet.null.se<-SE(block_e_mullet.null)  %>% stack        %>% rename( SE=values)
```

```
block_e_mullet.all=cbind(block_e_mullet.null.coef,block_e_mullet.null.se)
block_e_mullet.global.coef<<-coef(block_e_mullet.global) %>% stack  %>%
mutate(model="block_e_mullet_global")
block_e_mullet.global.se<-SE(block_e_mullet.global)  %>% stack            %>% rename(
SE=values)
block_e_mullet.g.all=cbind(block_e_mullet.global.coef,block_e_mullet.global.se)
block_e_mullet.sal.coef<-coef(block_e_mullet.sal) %>% stack  %>%
mutate(model="block_e_mullet_sal")
block_e_mullet.sal.se<-SE(block_e_mullet.sal) %>% stack            %>% rename( SE=values)
block_e_mullet.s.all=cbind(block_e_mullet.sal.coef,block_e_mullet.sal.se)
block_e_mullet.turb.coef<-coef(block_e_mullet.turb)  %>% stack  %>%
mutate(model="block_e_mullet_turb")
block_e_mullet.turb.se<-SE(block_e_mullet.turb)  %>% stack        %>% rename( SE=values)
block_e_mullet.tu.all=cbind(block_e_mullet.turb.coef,block_e_mullet.turb.se)
block_e_mullet.tide.coef<-coef(block_e_mullet.tide)   %>% stack  %>%
mutate(model="block_e_mullet_tide")
block_e_mullet.tide.se<-SE(block_e_mullet.tide)  %>% stack        %>% rename( SE=values)
block_e_mullet.ti.all=cbind(block_e_mullet.tide.coef,block_e_mullet.tide.se)
block_e_mullet.model.output.coef<-
rbind(block_e_mullet.all,block_e_mullet.g.all,block_e_mullet.s.all,block_e_mullet.tu.all,block_e
_mullet.ti.all)
write.csv(block_e_mullet.model.output.coef,
file="block_e_mullet_model_output_coef_20230126.csv")
#####################################################
##milkfish
block_a_milkfish.null.coef<-coef(block_a_milkfish.null)  %>% stack  %>%
mutate(model="block_a_null")
block_a_milkfish.null.se<-SE(block_a_milkfish.null)  %>% stack  %>% rename( SE=values)
block_a_milkfish.all=cbind(block_a_milkfish.null.coef,block_a_milkfish.null.se)
block_a_milkfish.global.coef<<-coef(block_a_milkfish.global)       %>% stack  %>%
mutate(model="block_a_milkfish_global")
block_a_milkfish.global.se<-SE(block_a_milkfish.global)  %>% stack       %>% rename(
SE=values)
block_a_milkfish.g.all=cbind(block_a_milkfish.global.coef,block_a_milkfish.global.se)
block_a_milkfish.sal.coef<-coef(block_a_milkfish.sal) %>% stack  %>%
mutate(model="block_a_milkfish_sal")
block_a_milkfish.sal.se<-SE(block_a_milkfish.sal) %>% stack  %>% rename( SE=values)
block_a_milkfish.s.all=cbind(block_a_milkfish.sal.coef,block_a_milkfish.sal.se)
block_a_milkfish.turb.coef<-coef(block_a_milkfish.turb)  %>% stack  %>%
mutate(model="block_a_milkfish_turb")
```

```
block_a_milkfish.turb.se<-SE(block_a_milkfish.turb)  %>% stack  %>% rename( SE=values)
block_a_milkfish.tu.all=cbind(block_a_milkfish.turb.coef,block_a_milkfish.turb.se)
block_a_milkfish.tide.coef<-coef(block_a_milkfish.tide)   %>% stack  %>%
mutate(model="block_a_milkfish_tide")
block_a_milkfish.tide.se<-SE(block_a_milkfish.tide)  %>% stack   %>% rename( SE=values)
block_a_milkfish.ti.all=cbind(block_a_milkfish.tide.coef,block_a_milkfish.tide.se)
block_a_milkfish.model.output.coef<-
rbind(block_a_milkfish.all,block_a_milkfish.g.all,block_a_milkfish.s.all,block_a_milkfish.tu.all,
block_a_milkfish.ti.all)
write.csv(block_a_milkfish.model.output.coef,
file="block_a_milkfish_model_output_coef_20230126.csv")
##########################################
block_b_milkfish.null.coef<-coef(block_b_milkfish.null)  %>% stack  %>%
mutate(model="block_b_null")
block_b_milkfish.null.se<-SE(block_b_milkfish.null)  %>% stack            %>% rename(
SE=values)
block_b_milkfish.all=cbind(block_b_milkfish.null.coef,block_b_milkfish.null.se)
# does not converge on reasonable values, replace  SE with DNC to maintain formating of tables
block_b_milkfish.global.coef<<-coef(block_b_milkfish.global)      %>% stack  %>%
mutate(model="block_b_milkfish_global")
block_b_milkfish.global.se<-data.frame(SE=c("DNC","DNC","DNC")) %>%
mutate(ind="block_b_milkfish_global")
block_b_milkfish.g.all=cbind(block_b_milkfish.global.coef,block_b_milkfish.global.se)
block_b_milkfish.sal.coef<-coef(block_b_milkfish.sal) %>% stack  %>%
mutate(model="block_b_milkfish_sal")
block_b_milkfish.sal.se<-SE(block_b_milkfish.sal) %>% stack      %>% rename( SE=values)
block_b_milkfish.s.all=cbind(block_b_milkfish.sal.coef,block_b_milkfish.sal.se)
block_b_milkfish.turb.coef<-coef(block_b_milkfish.turb)  %>% stack  %>%
mutate(model="block_b_milkfish_turb")
block_b_milkfish.turb.se<-SE(block_b_milkfish.turb)  %>% stack           %>% rename(
SE=values)
block_b_milkfish.tu.all=cbind(block_b_milkfish.turb.coef,block_b_milkfish.turb.se)
block_b_milkfish.tide.coef<-coef(block_b_milkfish.tide)   %>% stack  %>%
mutate(model="block_b_milkfish_tide")
block_b_milkfish.tide.se<-SE(block_b_milkfish.tide)  %>% stack  %>% rename( SE=values)
block_b_milkfish.ti.all=cbind(block_b_milkfish.tide.coef,block_b_milkfish.tide.se)
block_b_milkfish.model.output.coef<-
rbind(block_b_milkfish.all,block_b_milkfish.g.all,block_b_milkfish.s.all,block_b_milkfish.tu.all
,block_b_milkfish.ti.all)
```

```
write.csv(block_b_milkfish.model.output.coef,
file="block_b_milkfish_model_output_coef_20230126.csv")
#####################################
block_c_milkfish.null.coef<-coef(block_c_milkfish.null)  %>% stack  %>%
mutate(model="block_c_null")
block_c_milkfish.null.se<-SE(block_c_milkfish.null)  %>% stack   %>% rename( SE=values)
block_c_milkfish.all=cbind(block_c_milkfish.null.coef,block_c_milkfish.null.se)
block_c_milkfish.global.coef<<-coef(block_c_milkfish.global)      %>% stack  %>%
mutate(model="block_c_milkfish_global")
block_c_milkfish.global.se<-SE(block_c_milkfish.global)  %>% stack       %>% rename(
SE=values)
block_c_milkfish.g.all=cbind(block_c_milkfish.global.coef,block_c_milkfish.global.se)
block_c_milkfish.sal.coef<-coef(block_c_milkfish.sal) %>% stack  %>%
mutate(model="block_c_milkfish_sal")
block_c_milkfish.sal.se<-SE(block_c_milkfish.sal) %>% stack       %>% rename( SE=values)
block_c_milkfish.s.all=cbind(block_c_milkfish.sal.coef,block_c_milkfish.sal.se)
block_c_milkfish.turb.coef<-coef(block_c_milkfish.turb)  %>% stack  %>%
mutate(model="block_c_milkfish_turb")
block_c_milkfish.turb.se<-SE(block_c_milkfish.turb)  %>% stack             %>% rename(
SE=values)
block_c_milkfish.tu.all=cbind(block_c_milkfish.turb.coef,block_c_milkfish.turb.se)
block_c_milkfish.tide.coef<-coef(block_c_milkfish.tide)   %>% stack  %>%
mutate(model="block_c_milkfish_tide")
block_c_milkfish.tide.se<-SE(block_c_milkfish.tide)  %>% stack   %>% rename( SE=values)
block_c_milkfish.ti.all=cbind(block_c_milkfish.tide.coef,block_c_milkfish.tide.se)
block_c_milkfish.model.output.coef<-
rbind(block_c_milkfish.all,block_c_milkfish.g.all,block_c_milkfish.s.all,block_c_milkfish.tu.all,
block_c_milkfish.ti.all)
write.csv(block_c_milkfish.model.output.coef,
file="block_c_milkfish_model_output_coef_20230126.csv")
######################################
block_d_milkfish.null.coef<-coef(block_d_milkfish.null)  %>% stack  %>%
mutate(model="block_d_null")
block_d_milkfish.null.se<-SE(block_d_milkfish.null)  %>% stack             %>% rename(
SE=values)
block_d_milkfish.all=cbind(block_d_milkfish.null.coef,block_d_milkfish.null.se)
block_d_milkfish.global.coef<<-coef(block_d_milkfish.global)      %>% stack  %>%
mutate(model="block_d_milkfish_global")
block_d_milkfish.global.se<-SE(block_d_milkfish.global)  %>% stack      %>% rename(
SE=values)
```

```
block_d_milkfish.g.all=cbind(block_d_milkfish.global.coef,block_d_milkfish.global.se)
block_d_milkfish.sal.coef<-coef(block_d_milkfish.sal) %>% stack  %>%
mutate(model="block_d_milkfish_sal")
block_d_milkfish.sal.se<-SE(block_d_milkfish.sal) %>% stack      %>% rename( SE=values)
block_d_milkfish.s.all=cbind(block_d_milkfish.sal.coef,block_d_milkfish.sal.se)
block_d_milkfish.turb.coef<-coef(block_d_milkfish.turb)  %>% stack  %>%
mutate(model="block_d_milkfish_turb")
block_d_milkfish.turb.se<-SE(block_d_milkfish.turb)  %>% stack            %>% rename(
SE=values)
block_d_milkfish.tu.all=cbind(block_d_milkfish.turb.coef,block_d_milkfish.turb.se)
block_d_milkfish.tide.coef<-coef(block_d_milkfish.tide)   %>% stack  %>%
mutate(model="block_d_milkfish_tide")
block_d_milkfish.tide.se<-SE(block_d_milkfish.tide)  %>% stack  %>% rename( SE=values)
block_d_milkfish.ti.all=cbind(block_d_milkfish.tide.coef,block_d_milkfish.tide.se)
block_d_milkfish.model.output.coef<-
rbind(block_d_milkfish.all,block_d_milkfish.g.all,block_d_milkfish.s.all,block_d_milkfish.tu.all
,block_d_milkfish.ti.all)
write.csv(block_d_milkfish.model.output.coef,
file="block_d_milkfish_model_output_coef_20230126.csv")
####################################
block_e_milkfish.null.coef<-coef(block_e_milkfish.null)  %>% stack  %>%
mutate(model="block_e_null")
block_e_milkfish.null.se<-SE(block_e_milkfish.null)  %>% stack  %>% rename( SE=values)
block_e_milkfish.all=cbind(block_e_milkfish.null.coef,block_e_milkfish.null.se)
block_e_milkfish.global.coef<<-coef(block_e_milkfish.global)      %>% stack  %>%
mutate(model="block_e_milkfish_global")
block_e_milkfish.global.se<-SE(block_e_milkfish.global)  %>% stack      %>% rename(
SE=values)
block_e_milkfish.g.all=cbind(block_e_milkfish.global.coef,block_e_milkfish.global.se)
block_e_milkfish.sal.coef<-coef(block_e_milkfish.sal) %>% stack  %>%
mutate(model="block_e_milkfish_sal")
block_e_milkfish.sal.se<-SE(block_e_milkfish.sal) %>% stack      %>% rename( SE=values)
block_e_milkfish.s.all=cbind(block_e_milkfish.sal.coef,block_e_milkfish.sal.se)
block_e_milkfish.turb.coef<-coef(block_e_milkfish.turb)  %>% stack  %>%
mutate(model="block_e_milkfish_turb")
block_e_milkfish.turb.se<-SE(block_e_milkfish.turb)  %>% stack            %>% rename(
SE=values)
block_e_milkfish.tu.all=cbind(block_e_milkfish.turb.coef,block_e_milkfish.turb.se)
block_e_milkfish.tide.coef<-coef(block_e_milkfish.tide)   %>% stack  %>%
mutate(model="block_e_milkfish_tide")
```

```
block_e_milkfish.tide.se<-SE(block_e_milkfish.tide)  %>% stack   %>% rename( SE=values)
block_e_milkfish.ti.all=cbind(block_e_milkfish.tide.coef,block_e_milkfish.tide.se)
block_e_milkfish.model.output.coef<-
rbind(block_e_milkfish.all,block_e_milkfish.g.all,block_e_milkfish.s.all,block_e_milkfish.tu.all,
block_e_milkfish.ti.all)
write.csv(block_e_milkfish.model.output.coef,
file="block_e_milkfish_model_output_coef_20230126.csv")
```