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Estimating habitat-specific abundance and behavior of several groundfishes using stationary stereo still cameras in the southern California Bight

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Abstract: The increasing use of underwater cameras to estimate fish abundance often does not account for the behavior of target species. These behaviors can affect detectability of fish and bias density estimates. This study estimated abundance and behavior of several rockfishes (*Sebastes* spp) and lingcod (*Ophiodon elongatus*) at Footprint Bank, a small offshore bank using images from randomly deployed stationary cameras. Deployments collected images at 30-second intervals over ~24 hour periods to examine the behaviors of rockfish that might impact abundance estimates. The results showed that time of day and tidal change had a significant effect on the probability of presence, estimated abundance and species composition of fish, with densities highest for most species during daylight hours. The time elapsed since camera deployment did not have a significant effect on fish density. Fish density was significantly affected by habitat composition, an effect primarily driven by speckled rockfish (*Sebastes ovalis*) which exhibited a 5-fold increase in abundance in bedrock habitats. Speckled rockfish were the most abundant rockfish at depths less than 150 m, with an estimated abundance of 12,994 fish (SE = 6,722) on Footprint Bank. The abundance estimates and coefficients of variation were comparable to surveys conducted in 2011 and 2012 using remotely operated vehicles (ROVs) and manned submersibles. The implications of this study are that habitat and behavior as well as timing of the survey (day/night) are important considerations determining the perceived density of fishes from underwater image surveys.

Keywords: Sebastes; stereo camera; survey design; population estimate; untrawlable habitat; California

Introduction

Underwater cameras have become an increasingly popular approach to estimate fish abundance for fisheries management as an alternative to extractive techniques (Mallet and Pelletier 2014). Underwater camera surveys have advantages over traditional survey methods such as bottom trawls for documenting rare or endangered species with conservation concerns (e.g. Yoklavich et al. 2007) and for high-relief areas that are not easily sampled using trawls or nets (e.g. Cordue 2007, Rooper et al. 2010).

An advantage of traditional survey methods such as bottom trawls is the large volume of research on fish behavior and gear catchability that has previously been conducted and has resulted in better understanding of observed trends. These can include information on gear selectivity of different fish sizes (Huse et al. 2000, Williams et al. 2011, DeRobertis et al. 2017), gear efficiency under varying environmental and fishing conditions (Somerton and Munro 2001, Munro and Somerton 2002, Weinberg 2003, Weinberg and Kotwicki 2008, Kotwicki et al. 2009), and behavioral responses to fishing gear (Bublitz 1996, Bryan et al. 2014). This body of literature is useful to interpret and assess catch rates and the resulting indices of abundance for traditional abundance survey methods, such as trawls, longlines, set nets and traps. Because optical-based surveys will have their own sampling properties and biases a similar line of investigation is needed for those gears (Campbell et al. 2015)

Comparisons of underwater video surveys to other types of gear, such as baited traps have indicated differences in catchability among gear types (Bacheler et al. 2013, Geraldi et al. 2019). These can highlight differences related to behavior, such as size selectivity of some gears (Rooper et al. 2012), differences in spatial patterns of frequency of occurrence (Bacheler et al. 2013), and even differences in detectability among different gears or underwater camera systems

(Bacheler et al. 2014, Kilfoil et al. 2017). Questions about the influence of environmental factors in availability and detectability in camera surveys have not often been addressed and in addition these effects are often strongly influenced by the behavior of targeted fishes. For instance it has been demonstrated that fish behavior influences fish detectability for underwater camera surveys both in response to transiting underwater vehicles (e.g. Laidig et al. 2013, Somerton et al. 2017), response to stimuli from the vehicle, such as lights or sounds (Lorance and Trenkel 2006, Stoner et al. 2008, Rooper et al. 2015) or due to behaviors such as diurnal migrations (Stanley et al. 1999, Rooper et al. 2010) or swimming and schooling behaviors (Bacheler and Shertzer 2015). Fish behaviors can be habitat-specific, such as cryptic or flight response behaviors of some fish in high-relief habitats that influence the ability of detection by cameras (Trenkel et al. 2004, Stone et al. 2015). Therefore, accounting for habitat types in both the abundance estimates and behavior observations is crucial for getting an accurate measure of fish abundance.

The primary objective of this study was to estimate the abundance and variance of seven species of common rockfish (Sebastes spp.) and lingcod (*Ophiodon elongatus*) in untrawlable habitat using stationary cameras. We also examined factors that influence the perceived density from an underwater camera survey using long-term (24 hour) deployments of stationary cameras. Since the cameras were designed to have minimal impact on the behavior of fishes, we examined environmental influences on patterns of density over 24 hour periods. Specifically we looked at tidal and diel cycles, patterns in the initial arrival time of fishes to the camera, variability in density over long-term deployments and the effects of habitat and depth on density estimates. Ultimately, the goal of this study was to make recommendations for future surveys of rockfishes in untrawlable habitats.

Materials and Methods

Study area

All surveys were conducted on Footprint Bank, a rocky seamount in southern California located at the southern end of the Anacapa Passage (between Santa Cruz and Anacapa Islands) in the Channel Islands National Marine Sanctuary at approximately 33° 54.84' N and 119°28.35' W (Figure 1). Footprint Bank is about 10 km^2 in area ranging in depth from 80 to 500 m, and generally trends northwest-southeast. The study site is located inside the State and Federal Footprint Marine Reserves. Footprint Bank consists of high-relief outcrops, sand flats, and cobble fields and hosts a diverse assemblage of groundfishes (Schroeder and Love, 2002; Yoklavich et al., 2013). The area surveyed for this project consisted largely of rocky habitat from 90-150 m depth which reduced the surveyed area to 4.8 km^2 (Figure 1). In total, 50 stations were chosen randomly within this depth range, however due to time constraints (and a single equipment failure), only the first 30 of the randomly selected sites were sampled during the study (Table 1).

Data collection

To estimate overall abundance of rockfish on the Footprint Bank, we used a group of 7 stationary camera systems. The triggered camera (TrigCam) systems are described in Williams et al. (2015, 2018), but were modified for the current project (Figure 2). In brief, the TrigCams are a low-cost, still-image, stereo–camera system optimized for long duration deployments. These cameras are capable of operating in "triggered" mode where images are only captured when motion is detected in the view field. However, during this project, the cameras were configured to collect a stereo-image pair every 30 seconds over the course of ~24 hour deployments.

The TrigCam consists of three housings (Figure 2). The main housing contains two Chameleon3 USB 3 machine vision cameras, an ODroid-XU4-mini-ARM computer, and a custom circuit board for power management and timing control of strobe pulses. The housing was constructed from anodized aluminum with custom manufactured 80 mm radius acrylic partial dome viewports for each camera. A second housing was manufactured from a 51 mm thick acetal plastic plate and contained a neutral white-strobe unit powered by two TaskLED Hyperboost strobe drivers. The system was powered by a 24 V 10 Ah nickel-metal hydride battery pack housed in a cylindrical anodized aluminum housing. The three housings (cameras, strobe, and batteries) were enclosed in a protective aluminum frame.

The TrigCams were deployed and retrieved using an acoustic release system manufactured by DesertStar Systems ARC-1XD. The acoustic-release is attached to a small float and line and was triggered from the surface using a deck box, after which the float rose to the surface allowing retrieval of the unit. Thus, the TrigCams were untethered from the research vessel and maintained a minimal profile during deployment on the seafloor (Figure 2).

Image analysis

Each TrigCam unit was calibrated for stereo-analysis using a standard stereo-calibration routine (Bouguet 2008) modified for marine underwater stereo-camera systems by Williams et al. (2010). Stereo-image analysis was performed using an open-source, stereo-processing package (SEBASTES; Williams et. al, 2016). SEBASTES was used to identify fish to species and estimate fish range and 3D position relative to the camera. Fish locations were estimated by identifying a single corresponding point on each fish seen in both images, such as the fish eye. Fish only partially visible in both image frames were only included when bordering the left and upper sides of the images. In this way, these partial targets were assumed to be 50 % retained for further analysis, reducing the possibility of under- or over-estimates of fish density. Individuals from seven species of common rockfish and lingcod were counted in each frame of each deployment (Table 2). The substrate observed in the underwater camera deployments was classified by a commonly used seafloor substratum classification scheme (Stein et al. 1992; Yoklavich et al. 2000) that consists of a two-letter coding of substratum type denoting a primary substratum with > 50% coverage of the seafloor and a secondary substratum with 20% –49% coverage of the seafloor. There were seven identified substratum types: mud (M), sand (S), gravel-pebble (G, diameter < 6.5 cm), cobble (C, 6.5 < diameter < 25.5 cm), boulder (B, diameter > 25.5 cm), exposed low-relief bedrock (R), and exposed high-relief bedrock (K). Using this classification, a section of seafloor covered primarily in cobble, but with boulders over more than 20% of the surface, would receive the substratum code cobble-boulder (Cb) with the secondary substratum indicated by the lower-case letter. Since the underwater camera deployments were stationary, the substrate classification was constant within each deployment.

To compute fish volumetric density, the volume imaged by both cameras was estimated using a general approximation approach based on a point cloud (Williams et al. 2018). In brief, stereo-image analysis relies on a set of equations that transform pixel coordinates of objects seen by both cameras into real world coordinates using stereo-triangulation. The reverse transformation is termed projection, resulting in the expected position of a real world object on the camera image plane. We use the latter process to estimate the set of points from a generated 3D point cloud that occupy the joint stereo-camera image volume. This process therefore accounts for the intrinsic camera calibration factors (e.g. lens distortion), and extrinsic factors (the inter-camera geometry). To estimate joint image volume, a 3-dimensional grid of points at

10 cm separation was generated extending from the camera origin to a range of 9 m, with the horizontal and vertical extent of the point cloud set to capture the entire view field. The points were then projected back to pixel coordinate space, and only the points that constitute valid pixel coordinates in both left and right camera images were retained (i.e. points that are located below the seafloor are excluded). The grid points were subset into 0.5 m range bins from the camera, and the volume of each range bin was then estimated by scaling the number of points contained in the joint stereo-view and within range intervals by the volume they represent, which in this analysis was 1 L or 0.001 m^3. The volume of each frame that is below the seafloor was also removed from the calculated volume according to the methods of Williams et al. (2018).

The imaging volume analysis provided estimates of above-seafloor volumes at range intervals for each image frame in the dataset. To estimate fish density, fish counts for targets found within a range interval were divided by the corresponding volume. Densities were then aggregated by species and camera unit. In principle, fish density is expected to decline as the ability to detect and identify fish becomes reduced with increasing target range from the camera. To arrive at an unbiased estimate of density, the expected decline in detectability as a function of range was modeled. A logistic function was used, defined as

$$rd_r = \frac{L}{1+e^{-k(r-x_0)}} \ , \qquad \text{(eq. 1)}$$

where *rd* is the relative density scaled to a maximum of one at range *r* from the camera, and *L*, *k* and x_o are the function parameters. Parameters were estimated by minimizing the negative log-likelihood between the observed density at a site and range interval and the modeled density assuming a normal error distribution. The deviations between observed and predicted density were weighted by the respective volume of each range interval, so that the very small volumes closest to the camera had less influence on the model than larger volume bins farther away. In addition, the x_o parameter, which indicates the midpoint of the function curve, was restricted to be greater than 2 m to prevent outcomes where density occasionally becomes exponentially reduced from the first range interval onward by the presence of a single fish close to the camera. Density for a species, d, for each frame, f, are then calculated as the sum of the species density at each range, r, corrected for the detectability at that range, so that

$$d_f = \sum_{i=1}^{r} \frac{d_{fr}}{rd_r} \quad \text{(eq. 2).}$$

The density of a species for a deployment ($\bar{d}$) was then calculated as the mean of d_f for that deployment. All modeling and statistical analyses were done in R software (R Core Development Team 2018) and R code for estimating the relative density function with documentation can be downloaded as a package at https://github.com/rooperc4/TrigCamDensityEstimation.

Data Analysis

Densities were calculated for each frame of each deployment based on the volume of water observed and the species-specific detection model described above. Densities by frame were used to generate presences or absences for use as replicates for analyses of "within deployment" processes. The mean density for deployments were then used as the replicates in analysis of processes at the "deployment scale" and to estimate the population size for each species of fish. In some analyses, deployments were split into daytime and nighttime segments to facilitate comparisons.

To determine the effect of tidal cycles and diurnal cycles on the presence of fish, we used a generalized additive mixed model (GAMM, Wood 2006) to test for significant linear or non-linear effects of hour-of-the-day and hourly tidal change. This analysis used presence or absences averaged over one hour intervals for each deployment as replicates. Aggregation of data to one hour intervals helped to reduce autocorrelation in the data set. In preliminary analyses the raw frame by frame data and aggregation over five, ten, and fifteen minute intervals were also tested. None of these groupings had an effect on the shape of the relationships between variables and the presence or absence of fish or on the significance of the relationships, but they did affect the overall variance and the temporal aggregation (both increased with decreasing aggregation). The tidal change was calculated from tide station harmonics using the nearest tide gauge (located in Santa Barbara, CA) and was the difference in tidal height from one image frame to the next (every 30 seconds) and averaged over one hour intervals. The tidal heights were estimated using the rtide package in R software (Thorley et al. 2018). The GAMM was implemented with a maximum of k = 5 knots to minimize overfitting and parametric (factor) terms were included for species to account for species -specific differences in density. Deployment was treated as a random effect, so that

$$y = \alpha + s(tidal\ change) + s(hour) + species + deployment + \varepsilon \qquad \text{(eq. 3)}$$

Where *y* is presence or absence of fish, s indicates a thin-plate regression spline smoothing function for the tidal change term and a cyclic cubic spline smoothing function for the hour term (Wood 2006), α is an intercept and ε are binomial distributed errors. An autocorrelation term nested within the deployment at lag = 1 was also included in the model.

Within-deployment variability was examined graphically to determine when the density and variability in density peaked, and specifically if any “settling” period could be detected after the initial TrigCam deployment where fish might have been scared from the area by the approaching gear (data from a pilot study in the same area in 2016 were also used to address this question and are reported in supplemental material).

The effect of substrate type on density was also tested but data for the analysis was limited to imagery captured during daylight hours because of the small sample size of fishes observed during nighttime hours and the results of GAMM modeling which indicated nighttime and daytime data should not be combined for this analysis. An analysis-of-variance was used with the density estimated for each deployment as replicates. Separate tests were conducted for significant effect of primary substrate type and the significant effect of the presence of rocky substrate (high and low relief bedrock or boulders) in either the primary or secondary substrate classes. The effect of depth was also tested, with station depth separated into three depth strata: 90-110 m, 110-130 m and 130-150 m. Fish species was included as an effect in the analysis, along with a primary substrate-species effect or a presence of rocky substrate-species effect, to determine whether some species of fish were more abundant in some substrate types than others. Tukey's post-hoc tests were used to examine significant effects in the analysis and significance of all statistical tests was identified at $p < 0.05$.

Finally, a population abundance (and variance) for each species was calculated for the entirety of Footprint Bank. For this estimate, the area of the bank at depths < 150 m (roughly the area sampled during our study) was calculated as 0.682 km^2 from previous multibeam mapping (Dartnell et al. 2005). This was expanded to 0.852 km^3 using the height of the water column observed by the cameras (1.25 m). This estimate was then used to expand the volumetric densities to a total abundance. Based on the results of the data analyses, three divisions of data and two methods were used to calculate abundances. Non-stratified, random sampling formulae were used to estimate abundances for all the data combined. Separate daytime and nighttime abundances were also estimated. A second method that stratified the data by the substrate using only daytime data was also used. Previous research by Yoklavich et al. (2011) indicated that roughly 22.5% of the upper portion of Footprint Bank (< 200 m) is comprised of primarily bedrock, 7.5% is comprised of primarily high relief boulders, 55% is comprised primarily of cobble habitat and the remaining 15% is comprised of low relief unconsolidated substrates (sand and mud). Thus, based on stratification by these four substrate types, the strata area for rocky substrate was 0.192 km^3, bouder substrate was 0.064 km^3, cobble was 0.469 km^3 and sand was 0.128 km^3. For a stratified estimate of abundance the densities of rockfish from deployments with the corresponding primary substrate type were expanded according to the strata area. For example, all deployments with a primary substrate of sand (n = 17) were expanded over the unconsolidated strata area (0.128 km^3)

Abundance estimates and variances (both stratified and non-stratified) were calculated using the standard formulae of Thompson (1992). For unstratified estimates, the population total in number of fish $\hat{\tau}$ is:

$$\hat{\tau} = A\bar{d} \qquad \text{(eq. 4)}$$

with variance

$$var(\hat{\tau}) = A^2 \frac{s^2}{n} \qquad \text{(eq. 5)}$$

where N is the total study area, $\bar{d}$ is the mean volumetric density, s^2 is the variance of the mean and *n* is the number of deployments. For stratified estimates of the population total, $\hat{\tau}_{st}$, the total population is the sum of the abundance in each strata *h*:

$$\hat{\tau}_{st} = \sum_{h=1}^{L} A_h \, \bar{d}_h \qquad \text{(eq,6)}$$

with variance as the sum of each strata *h* variance is:

$$var(\hat{\tau}_{st}) = \sum_{h=1}^{L} A_h^2 \frac{s_h^2}{n_h} \qquad \text{(eq. 7)}$$

where A_h is the strata area, $\bar{d}_h$ is the mean volumetric density, s_h^2 is the variance of the mean and n_h is the number of deployments in stratum h. Coefficients of variation were calculated as the square-root of the variance divided by the abundance estimate. Since the sample size relative to the total available samples was very small, the finite population correction was ignored.

Results

The detection function for each species indicated that most individuals were identifiable out to about 2-4 m from the camera (Figure 3). Speckled rockfish and greenstriped rockfish (*Sebastes elongatus*) were the exceptions, with speckled rockfish being difficult to identify and count beyond 2.5 m and greenstriped rockfish easily identifiable at a range of over 5 m. The model parameter x_0 for speckled rockfish was estimated at the minimum possible value (2 m). Alternatively, this may indicate that they may have been attracted to the camera and thus occurred within a nearer distance. However, all image analysts noted the difficulty in identifying this species at far distances. The application of the detection function for each species resulted in densities of fish ranging from 0 – 3.5 fish m^{-3} for individual frames. Observations were zero-inflated, with 95.5% of 616,104 frames containing no sightings of the species of interest.

Generalized additive model results show that there was a significant diel effect on the presence of rockfishes and lingcod ($p < 0.0001$). Rockfish probability of presence peaked around mid-day and was lowest during nighttime (Figure 4). The effect of tidal change was also significant ($p = 0.03$) with the probability of fish presence elevated at moderately rising and falling tides (Figure 4). Species was also significant in the GAMM. The patterns of individual species density during day and night hours indicated strong trends towards higher observed densities during daylight hours for most species (Figure 5). The only species that appeared to have higher densities during nighttime hours than daytime hours were bank rockfish (*S. rufus*) and greenstriped rockfish.

The day-night differences in density of fishes had a strong influence on other facets of the data. Since most deployments were started in the evening after dusk (Table 1), the variability in density at a single site was minimal through the first few hours of the deployment (Figure 6). With the onset of daylight, the variability in density at an individual site increased to a peak in mid-afternoon (12:00 – 15:00) and then declined to low levels of variability in the evening. This pattern was linked to changes in average density, as the standard deviation of density increased linearly with increasing density (Figure 6).

It was impossible to determine the amount of time needed for rockfish densities to stabilize after the effect of the deployment of the TrigCams for the 2017 deployments. This was because the time of first arrival for fishes was strongly influenced by the timing of the deployments (Figure 7). The elapsed time between deployment and appearance of the first fish was highly variable across species, but only bocaccio rockfish (*S. paucispinis*) and greenspotted rockfish (*S. chlorostictus*) had median first arrival times prior to dawn. During a pilot study in 2016, it was found that for daytime deployments, the average elapsed time between deployment and the arrival of the first rockfish was 87 minutes (SD = 78, see S1 for details on this analysis).

The same density estimates could be generated from two types of behavior. A single stationary fish observed in 50 consecutive frames of a deployment could generate the same density as 50 fish observed in a single frame during the deployment. For example, lingcod were often seen in consecutive frames (the maximum during one deployment was 24), whereas bocaccio rockfish tended to show greater mobility, with the maximum consecutive frames in which a fish was observed being five during a single deployment. Both of these deployments produced close to the same density estimate(Figure 8). In fact, with the exception of speckled rockfish, the density of fishes was unrelated to the maximum number of frames in which fish were consecutively observed. This indicates that the same range of densities (0 – 0.3 fish * m^{-3}) were being produced by both fish that were moving around and those that were stationary and repeatedly observed.

Primary substrate type also had a significant effect on fish density in the Footprint Bank area (Table 3). Tukey's post-hoc tests indicated that the primary substrate types of bedrock (high and low relief) had significantly higher densities than other types of primary substrates. There were no significant differences found among the other substrates. A species-primary substrate interaction term was highly significant in the analysis as well ($p < 0.0001$), although post-hoc tests revealed that the significant differences were related to high densities to greater densities of speckled rockfish (5x) at sites with bedrock as the primary substrate than all other fish-habitat combinations (Figure 9). There were no significant differences among other species-primary substrate combinations. Site depth was also not significant in the analysis, indicating a minimal effect of depth (at least across the limited range of 90 - 150 m explored here). When the presence of rocky substrate was included as an explanatory variable in the ANOVA in the place of primary substrate type, only species was significant ($p = 0.002$). Depth, the presence of rocky substrate, and the interaction between presence of rocky substrate and species were all insignificant ($p > 0.05$).

Based on these results, abundance estimates were computed for each species using the TrigCam deployments as replicates for 1) all data combined, 2) daytime only, 3) nighttime only and 4) daytime only and stratified by primary substrate type. The resulting estimates were highly variable both within and across species (Figure 10). Stratified estimates of the daytime data tended to give the highest estimates of abundance for all species with the lowest average coefficient of variation (CV = 0.57). The CV for these stratified estimates ranged from 0.23 for bocaccio rockfish to 0.96 for lingcod. Using only nighttime data resulted in the lowest abundance estimates for all species (except bank rockfish) and the highest average coefficient of variation (CV = 0.81), ranging from 0.43 for greenspotted rockfish to 1.00 for flag rockfish (*S. rubrivinctus*) and cowcod. (*S. levis*). Using unstratified daytime-only data and using all the data from both day and night gave estimates of the average coefficient of variation of 0.59 and 0.63 across all species respectively. For individual species the average values of CV ranged from 0.23 (greenspotted rockfish) to 0.96 (lingcod) for daytime estimates and ranged from 0.22 for (greenspotted rockfish) to 0.96 (lingcod) for all data. The most abundant species was speckled rockfish with a population of 12,994 individuals (SE = 6,722) within the surveyed area of Footprint Bank (stratified estimate). Greenstriped rockfish were estimated to be the least abundant with an estimate of only 82 individuals (SE = 50) within the surveyed area of Footprint Bank.

Discussion

Population estimates of rockfish that included a habitat stratification showed a marginal improvement in precision (i.e. CV) for bocaccio rockfish, cowcod, bank rockfish and speckled rockfish compared to a random survey design. This was not surprising given the known affinity of rockfish for highly rugose habitats (Love et al. 1991, Jones et al. 2012, Yoklavich 2013). However, the improvement of CV with stratification for these species was relatively small

(~7%). There was an increase in the estimate of abundance for all species when stratification by primary substrate type was used. Sand was the primary substrate at 17 of the 30 deployment sites (Table 1). Although the abundance from the 13 deployments in the rocky strata was higher than for the sand strata, the increased in variability with increased density negated most of the improvement in precision that could be gained by stratification. A more efficient sample allocation scheme could have improved the results and given more precise estimates of abundance by placing a higher number of samples within the high density-high variability rocky strata for some species. In the current study, more samples (17) were allocated to sand habitat stratum where density was lower than the rocky habitat strata (bedrock = 4, boulder = 5 and cobble = 4). To maximize the precision of estimates of rockfish a Neyman allocation (Thompson 1992) incorporating the observed strata variances (averaged across species) from this study would allocate 70.0% of stations into the bedrock stratum, 5.2% of stations into the boulder stratum, 19.3% of stations into the cobble stratum and 5.5% of stations into the sand strata. For individual species this allocation scheme varied depending on their variances among strata. Bocaccio rockfish for example, which had a relatively low CV for the stratified population estimate (23%), were relatively close to the optimal station allocation.

The results of this study showed that environmental factors can significantly influence the measured density and encounter rates of rockfishes. Diurnal cycles in particular had a large influence on the probability of presence and perceived density of rockfish during the study, whereas tidal cycles while significant did not appear to affect rockfish as much. Substrate type was also an important factor in determining density of rockfish and this effect varied among species, highlighting the likely importance of stratification in producing abundance estimates. The overall goal of this study was to produce population (and variance) estimates for Footprint

Bank using stationary cameras as an alternative sampling method. There are some important differences in terms of the area surveyed between these stationary cameras and more traditional survey methods for rockfish such as bottom trawls and more recently developed mobile camera systems (remote-operated vehicles, manned submersibles and autonomous underwater vehicles). The average field-of-view (FOV) for the stationary cameras during each deployment was 27.8 m^3 (SE = 0.45), while bottom trawl surveys typically cover > 1 ha (10,000 m^2) of seafloor and mobile camera surveys typically cover 500 - 1000 m^2 of seafloor in each deployment (Yoklavich et al. 2007, Tolimieri et al. 2008, Clarke et al. 2009, Rooper et al. 2016, Stierhoff et al. 2016). Despite the large differences in spatial coverage obtained between methods, the abundance estimates from the stationary camera survey of Footprint Bank were comparable to previous studies conducted in 2011 and 2009 using manned submersibles and remotely operated vehicles (Stierhoff et al. 2013, Yoklavich et al. 2013). The TrigCam estimates of abundance tended to be lower than the other two surveys for Footprint Bank (Figure 11), with the exception of speckled rockfish and greenspotted rockfish (the two most common species in the TrigCam survey). The deployment depths (Table 1) and total area sampled by the TrigCam survey was slightly less than for the other two surveys which may partially explain the observed differences. The coefficients of variation of the estimates of abundance were similar across three studies, although both the ROV and TrigCam surveys showed a wider range of CV's across the shared species than the manned submersible.

One of the major implications for assessing rockfishes from this study is that the time of day during which the survey is conducted is important to perceived densities of fishes. Fish abundance at stationary cameras was higher during daylight hours when fish were more likely to be active and moving throughout the area. However, this effect was species-specific, with bank rockfish and greenstriped rockfish more likely to be observed during nighttime hours. This is consistent with other research that has found diel behaviors are important for rockfishes (Stanley et al. 1999, Stanley et al. 2000, Ressler et al. 2009, Rooper et al. 2010). In a study of rocky habitat in the eastern Bering Sea, northern rockfish (*S. polyspinis*) were observed to rise into the water column to feed during daylight hours and settle to the seafloor at night; whereas juvenile Pacific ocean perch (*S. alutus*) were more likely to be observed in higher densities near the seafloor during daylight hours (Rooper et al. 2010). Stanley et al. (2000, 2007) and Ressler et al. (2009) both observed schooling rockfishes in the water column during nighttime hours. This behavior has been linked to feeding patterns, which is also consistent with the information available for greenstriped rockfish which tend to feed on fishes, shrimps and squids which may be more available near the seafloor at night, in addition to zooplankton (Love et al. 2002). Identifying the diel behavior of the species to be assessed is important in interpreting perceived abundance, especially where survey gear can only observe a limited part of the animal's habitat, such only near the seafloor for benthic camera systems or only in the water column for acoustic systems(Rooper et al. 2010). In addition this has major implications for survey design and execution regardless of using an optical or more traditional fisheries gear, such as a bottom trawl.

One objective of this study was to identify the length of time fish needed to acclimate to the presence of the TrigCam. However, we found no detectible difference in times of arrival to the stationary cameras that would indicate fish left the area during deployment and returned. This may indicate that there was no acclimation time necessary after the deployment of the camera, however, there are a number of other potential explanations. The lack of observed effect may have been the result of the interval length (30 seconds) between captured images being long enough that fish reactions occurred prior to capturing the initial image. The lack of effect was more likely a result of the relative paucity of rockfish observed during nighttime hours when most cameras were deployed. During the night, most species were either less active or less abundant in the study area, so unless the camera was deployed near a fish, it was likely that no reaction would have been observable. There was no indication from the data that there was a difference in fish behavior in response to the camera deployment between night and day. For example, we did not observe any marked orientation behavior to the camera, and fish were observed both arriving and departing from the FOV. The relative unobtrusiveness of the TrigCam compared to other survey gears, especially mobile gears (e.g. manned submersibles or remote operated vehicles), may have contributed to the absence of a perceived response to deployment of the cameras.

Conclusion

This study showed the importance of considering the behavior of target species and its interaction with perceived density when designing a survey to estimate fish abundance. Underwater camera surveys have parallel issues to traditional survey methods such as bottom trawls and longlines in terms of fish availability by habitat and fish detectability by the gear. For camera surveys, these issues are often related to the behavior of the fishes. Thus, it is important to continue to study and estimate the effects of survey equipment on fish behavior and perceived abundance. In this study, stratification of the survey area by habitat type had an effect on the estimates of population size and a limited impact on the variance estimate. This indicates that optimizing the allocation of samples and simulation of optimal allocation schemes is likely to point to directions that can further improve abundance estimation for rockfishes in untrawlable habitats.

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The findings and conclusions in the paper are those of the authors and do not necessarily represent the views of the National Marine Fishery Service, NOAA. Reference to trade names does not imply endorsement by the National Marine Fisheries Service, NOAA.

References

Bacheler, N.M., Schobernd, C.M., Schobernd, Z.H., Mitchell, W.A., Berrane, D.J., Kellison, G.T., and Reichert, M.J.M. 2013. Comparison of trap and underwater video gears for indexing reef fish presence and abundance in the southeast United States. Fish. Res. 143:81-88.

Bacheler, N.M., Berrane, D.J., Mitchell, W.A., Schobernd, C.M., Schobernd, Z.H., Teer, B.Z., and Ballenger, J.C. 2014. Environmental conditions and habitat characteristics influence trap and video de-tection probabilities for reef fish species. Marine Ecology Progress Series, 517:1–14. https://doi.org/10.3354/meps11094

Bacheler, N.M., and Shertzer, K.W. 2015. Estimating relative abundance and species richness from video surveys of reef fishes. Fish. Bull. 113:15-26.

Bouguet, J.Y. 2008. Camera Calibration Toolbox for Matlab [online]. Available from vision.caltech.edu/bouguetj/calib_doc/index.html [accessed 20 September 2008].

Bryan, D.R., Bosley, K.L., Hicks, A.C., Haltuch, M.A. and Wakefield, W.W. 2014. Quantitative video analysis of flatfish herding behavior and impact on effective area swept of a survey trawl. Fish. Res. 154: 120-126.

Bublitz, C.G. 1996. Quantitative evaluation of fish behaviour during capture by trawl gear. Fish. Res. 25: 293–304.

Campbell, M.D., Pollack, A.G., Gledhill, C.T., Switzer, T.S., and DeVries, D.A. 2015. Comparison of relative abundance indices calculated from two methods of generating video count data. Fish. Res. 170:125-133.

Clarke, M.E., Tolimieri, N., and Singh, H. 2009. Using the seabed AUV to assess populations of groundfish in untrawlable areas, p. 357-372.. In: Beamish R.J., Rothschild B.J. (eds), The Future of Fisheries Science in North America. Fish & Fisheries Series, vol 31. Springer, Dordrecht

Cordue, P. 2007. A note on non-random error structure in trawl survey abundance indices. ICES J. Mar. Sci. 64:1333-1337.

Dartnell, P., Cochrane, G., and Dunaway, M.E. 2005. Multibeam bathymetry and backscatter data: Northeastern Channel Islands region, Southern California, U.S. Geological Survey Open-File Report 05-1153, http://pubs.usgs.gov/of/2005/1153/.

DeRobertis, A., Taylor, K., Williams, K., and Wilson, C.D. 2017. Species and size selectivity of two midwater trawls used in acoustic survey of the Alaska arctic. Deep-Sea Res. II. 135:40-50.

Geraldi, N.R., Bacheler, N.M, and Kellison, G.T. 2019. Method-dependent influence of environmental variables on reef fish assemblages when comparing trap and video surveys. Mar. Ecol. 40:e12538. https://doi.org/10.1111/maec.12538

Huse, I., Lokkeborg, S., and Soldal, A.V. 2000. Relative selectivity in trawl, longline, and gillnet fisheries for cod and haddock. ICES J. Mar. Sci. 57:1271-1282.

Jones, D.T., Wilson, C.D., De Robertis, A., Rooper, C.N., Weber, T.C., and Butler, J.L. 2012. Evaluation of rockfish abundance in untrawlable habitat: combining acoustic and complementary sampling tools. Fish. Bull. U,S, 110:332-343.

Kilfoil, J.P. Wirsing, A.J., Campbell, M.D., Kiszka, J.J., Gastrich, K.R., Heithaus, M.R., Zhang, Y., and Bond, M.E. 2017. Baited remote underwater video surveys undercount sharks at high densities: insights from full-spherical camera technologies. Mar. Ecol. Prog. Ser. 585:113-121.

Kotwicki, S., De Robertis, A., von Szalay, P., and Towler, R. 2009. The effect of light intensity on the availability of walleye pollock (*Theragra chalcogramma*) to bottom trawl and acoustic surveys. Can. J. Fish. Aquat. Sci. 66:983-994.

Laidig, T.E., Krigsman, L.M., and Yoklavich, M.M. 2013. Reactions of fishes to two underwater survey tools, a manned submersible and a remotely operated vehicle. Fish. Bull., U.S. 111(1): 54-67.

Lorance, P. and Trenkel, V.M. 2006. Variability in natural behavior, and observed reactions to an ROV, by mid-slope fish species. J. Exp. Marine Biol. Ecol. 332:106-119.

Love M.S., Yoklavich, M., and Thorsteinson, L. 2002. The Rockfishes of the Northeast Pacific. University of California Press, Berkeley and Los Angeles California.

Love, M.S., Carr, M.H., and Haldorson, L.J. 1991. The ecology of substrate-associated juveniles of the genus Sebastes. Environ. Biol. Fish. 30: 225–243. http://dx.doi.org/10.1007/BF02296891

Mallet, D. and Pelletier, D. 2014. Underwater video techniques for observing coastal marine biodiversity: A review of sixty years of publications (1952-2012). Fish. Res. 154:44-62.

Munro, P.T. and Somerton, D.A.. 2002. Estimating net efficiency of a survey trawl for flatfishes. Fish. Res. 55:267-279.

R Core Development team. 2018 R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Ressler, P.H., Fleischer, G.W., Wespestad, V.G, and Harms, J. 2009. Developing a commercial-vessel-based stock assessment survey methodology for monitoring the U.S. West Coast widow rockfish (*Sebastes entomelas*) stock. Fish. Res. 99:63-73.

Rooper C.N., Sigler, M., Goddard, P., Malecha, P.W., Towler, R., Williams, K., Wilborn, R., and Zimmermann, M. 2016. Validation and improvement of species distribution models for structure forming invertebrates in the eastern Bering Sea with an independent survey. Mar. Ecol. Prog. Ser. 551:117-130.

Rooper, C.N., Hoff, G.R., and De Robertis, A. 2010. Assessing habitat utilization and rockfish (*Sebastes* sp.) biomass in an isolated rocky ridge using acoustics and stereo image analysis. Can. J. Fish. Aquat. Sci. 67:1658-1670.

Rooper, C.N., Martin, M.H., Butler, J.L., Jones, D.T., and Zimmermann, M. 2012. Estimating species and size composition of rockfishes to verify targets in acoustic surveys of untrawlable areas. Fish. Bull. 110:317-331.

Rooper, C.N., Williams, K., De Robertis, A., and Tuttle, V. 2015. Effect of underwater lighting on observations of density and behavior of rockfish during camera transects. Fish. Res. 172:157-167.

Somerton, D.A., and Munro, P. 2001. Bridle efficiency of a survey trawl for flatfish. Fish. Bull., U.S. 99:641–652.

Somerton, D.A., Williams, K., and Campbell, M.D. 2017. Quantifying the behavior of fish in response to moving camera vehicle by using benthic stereo cameras and target tracking. Fish. Bull., U.S. 115:343-354.

Stanley, R.D., Kieser, R., Leaman, B.M., and Cooke, K.D. 1999. Diel vertical migration by yellowtail rockfish, *Sebastes flavidus*, and its impact on acoustic biomass estimation. Fish. Bull., U.S. 97:320-331.

Stanley, R.D., Kieser, R., Cooke, K., Surry, A.M., and Mose, B. 2000. Estimation of a widow rockfish (*Sebastes entomelas*) shoal off British Columbia, Canada as a joint exercise between stock assessment staff and the fishing industry. ICES J. Mar. Sci. 57:1035-1049.

Stein, D.L., Tissot, B.N., Hixon, M.A., and Barss, W. 1992. Fish-habitat associations on a deep reef at the edge of the Oregon continental shelf. Fish. Bull., U.S. 90: 540-551.

Stierhoff, K.L., Murfin, D.W., Demer, D.A., Mau, S.A., and Pinkard-Meier, D.R. 2016. Improving the estimations of transect length and width for underwater visual surveys of targets on or near the seabed. ICES J. Mar. Sci. 73:2729-2736.

Stierhoff, K.L., Butler, J.L., Mau, S.A., and Murfin, D.W. 2013. Abundance and biomass estimates of demersal fishes at the Footprint and Piggy Bank from optical surveys using a remotely operated vehicle (ROV). NOAA-TM-NMFS-SWFSC-521. US Department of Commerce, Technical Memorandum, Southwest Fisheries Science Center, La Jolla, CA.

Stone, R.P., Masuda, M.M., and Karinen, J.F. 2015. Assessing the ecological importance of red tree coral thickets in the eastern Gulf of Alaska. ICES J. Mar. Sci. 72:900-915.

Schroeder, D.M. and Love, M.S. 2002. Recreational fishing and marine fish populations in California. CalCOFI Rep 43:182-190

Stoner, A.W., Ryer, C.H., Parker, S.J., Auster, P.J., and Wakefield, W.W. 2008. Evaluating the role of fish behavior in surveys conducted with underwater vehicles. Can. J. Fish. Aquat. Sci. 65:1230-1243.

Thompson, S.K. 1992. Sampling. John Wiley, New York, New York. 343 pp.

Thorley, J., Miller, L., and Fleishman, A. 2018. rtide: Tide Heights. R package version 0.0.5. https://github.com/poissonconsulting/rtide

Tolimieri, N, Clarke, E.M., Singh, H., and Goldfinger, C. 2008. Evaluating the SeaBED AUV for Monitoring Groundfish in Untrawlable Habitat, p. 99-107. In J.R. Reynolds and H.G. Greene (editors), Marine Habitat Mapping Technology for Alaska. Alaska Sea Grant College Program Rep. No. AK-SG-08-03, University of Alaska, Fairbanks.

Trenkel V.M., Lorance, P., and Mahévas, S. 2004. Do visual transects provide true population density estimates for deepwater fish? ICES J. Mar. Sci. 61(7):1050-1056.

Trenkel V.M., Francis, R.I.C.C., Lorance, P., Mahévas, S., Rochet, M.J., and Tracey, D.M. 2004b. Availability of deep-water fish to trawling and visual observation from a remotely operated vehicle (ROV). Mar. Ecol. Prog. Ser. 284:293-303.Weinberg, K. L. 2003.

Change in the performance of a Bering Sea survey trawl due to varied trawl speed. Alaska Fish. Res. Bull. 10:42-49.

Weinberg, K.L. and Kotwicki, S. 2008. Factors influencing net width and sea floor contact of a survey bottom trawl. Fish. Res. 93:265-279.

Williams, K., Punt, A.E., Wilson, C.D., and Horne, J.K. 2011. Length-selective retention of walleye pollock, *Theragra chalcogramma*, by midwater trawls. ICES J. Mar. Sci. 68:119–129.

Williams, K., Horne, J.K., and Punt, A.E. 2015. Examining influences of environmental, trawl gear, and fish population factors on midwater trawl performance using acoustic methods. Fish. Res. 164:94–101.

Williams, K., De Robertis, A.W., Berkowitz, Z., Rooper, C.N., and Towler, R. 2015. An underwater stereo-camera trap. Methods Oceangr. 11:1-12.

Williams, K., Rooper, C.N., and Towler, R. 2010. Use of stereo camera systems for assessment of rockfish abundance in untrawlable areas and for recording pollock behavior during midwater trawls. Fish. Bull., U.S. 108:352-362.

Williams, K., Rooper, C.N., De Robertis, A., Levine, M., and Towler, R.H. 2018. A method for computing volumetric fish density using stereo cameras. J Exp. Mar. Biol. Ecol. 508:21-26.

Williams, K., Towler, R., Goddard, P., Wilborn, R., and Rooper, C. 2016. *Sebastes* stereo image analysis software. AFSC Processed Rep. 2016-03, 42 p. Alaska Fish. Sci. Cent., NOAA, Natl. Mar. Fish. Serv., 7600 Sand Point Way NE, Seattle WA 98115.

Wood, S.N. 2006. Generalized Additive Models: An Introduction with R. Chapman & Hall/CRC Press, Boca Raton, FL.

Yoklavich, M., Laidig, T., Watters, D. and Love, M. 2013. Understanding the capabilities of new technologies and methods to survey west coast groundfishes: Results from a visual survey conducted in 2011 using the Dual Deepworker manned submersible at Footprint and Piggy banks off southern California. Research Report available online at https://swfsc.noaa.gov/publications/CR/2013/2013Yoklavich.pdf

Yoklavich, M.M., Greene, H.G., Cailliet, G.M., Sullivan, D.E., Lea, R.N., and Love, M.S. 2000. Habitat associations of deep-water rockfishes in a submarine canyon: an example of a natural refuge. Fish. Bull., U.S. 98:625-641.

Yoklavich, M.M., Love, M.S., and Forney, K.A., 2007. A fishery-independent assessment of an overfished rockfish stock, cowcod (*Sebastes levis*), using direct observations from an occupied submersible. Can. J. Fish. Aquat. Sci. 64:1795-1804.

Tables

Table 1. Characteristics of each TrigCam deployment on Footprint Bank in the southern California Bight.

Deployment	Time of deployment	Depth of deployment	Primary substrate
1	10/12/17 20:12	101	Sand
2	10/12/17 19:47	105	Boulder
3	10/12/17 19:23	97	High Bedrock
4	10/12/17 18:58	141	Low Bedrock
5	10/13/17 19:08	133	Cobble
6	10/13/17 18:48	134	Cobble
7	10/13/17 20:15	100	Cobble
8	10/14/17 18:57	134	Boulder
9	10/14/17 20:22	134	Sand
10	10/14/17 19:58	117	Sand
11	10/16/17 4:44	141	Sand
12	10/16/17 4:16	116	Boulder
13	10/16/17 19:07	100	Sand
14	10/17/17 4:06	98	Boulder
15	10/17/17 4:42	117	Sand
16	10/17/17 5:04	121	Sand
17	10/18/17 4:02	113	Boulder
18	10/18/17 4:25	117	Sand
19	10/18/17 4:59	111	High Bedrock
20	10/19/17 4:05	101	Sand
21	10/19/17 4:24	120	Sand
22	10/19/17 4:49	121	Sand
23	10/21/17 17:38	105	Boulder
24	10/21/17 18:16	122	Sand
25	10/21/17 17:51	105	Sand
26	10/22/17 4:33	121	Sand
27	10/22/17 4:26	123	Cobble
28	10/23/17 4:04	112	Sand
29	10/23/17 4:34	115	Sand
30	10/23/17 4:48	105	Sand

Table 2. Species used in the analyses of rockfish abundance and density on 30 deployments from Footprint Bank in the southern California Bight.

Common name	Species name	Number observed	Frequency of occurrence
Bank rockfish	*Sebastes rufus*	148	5
Cowcod	*S. levis*	90	9
Flag rockfish	*S. rubrivinctus*	54	7
Speckled rockfish	*S. ovalis*	660	20
Bocaccio	*S. paucispinnis*	302	22
Greenspotted rockfish	*S. chlorostictus*	2337	26
Greenstriped rockfish	*S. elongatus*	253	4
Lingcod	*Ophiodon elongatus*	178	3

Table 3. Analysis of variance table testing for differences in density among primary substrate types, species and depth bins.

Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Primary substrate type	4	0.001714	0.000429	4.302	0.0023
Species	7	0.002840	0.000406	4.073	0.0003
Depth	2	0.000135	0.000068	0.680	0.5078
Primary substrate*Species	28	0.007233	0.000258	2.594	0.0001
Residuals	206	0.020516	0.000100		

Figures

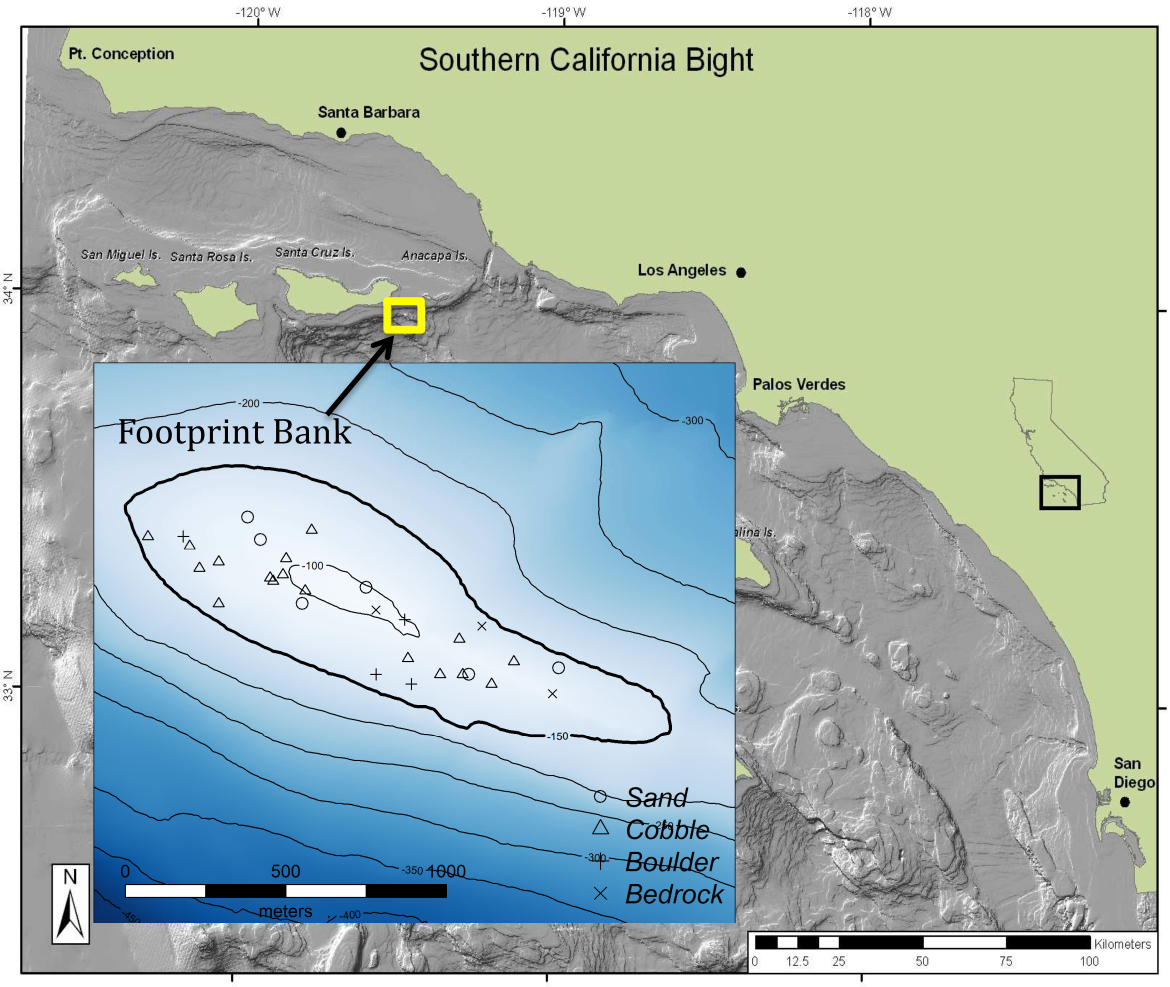


Figure 1. A map of Footprint Bank located in southern California south of Santa Cruz and Anacapa Islands. Dots indicate location of the 30 Trigcam deployments color coded by primary substrate type. The heavy contour line is the 150 m depth contour demarking the area of the study.

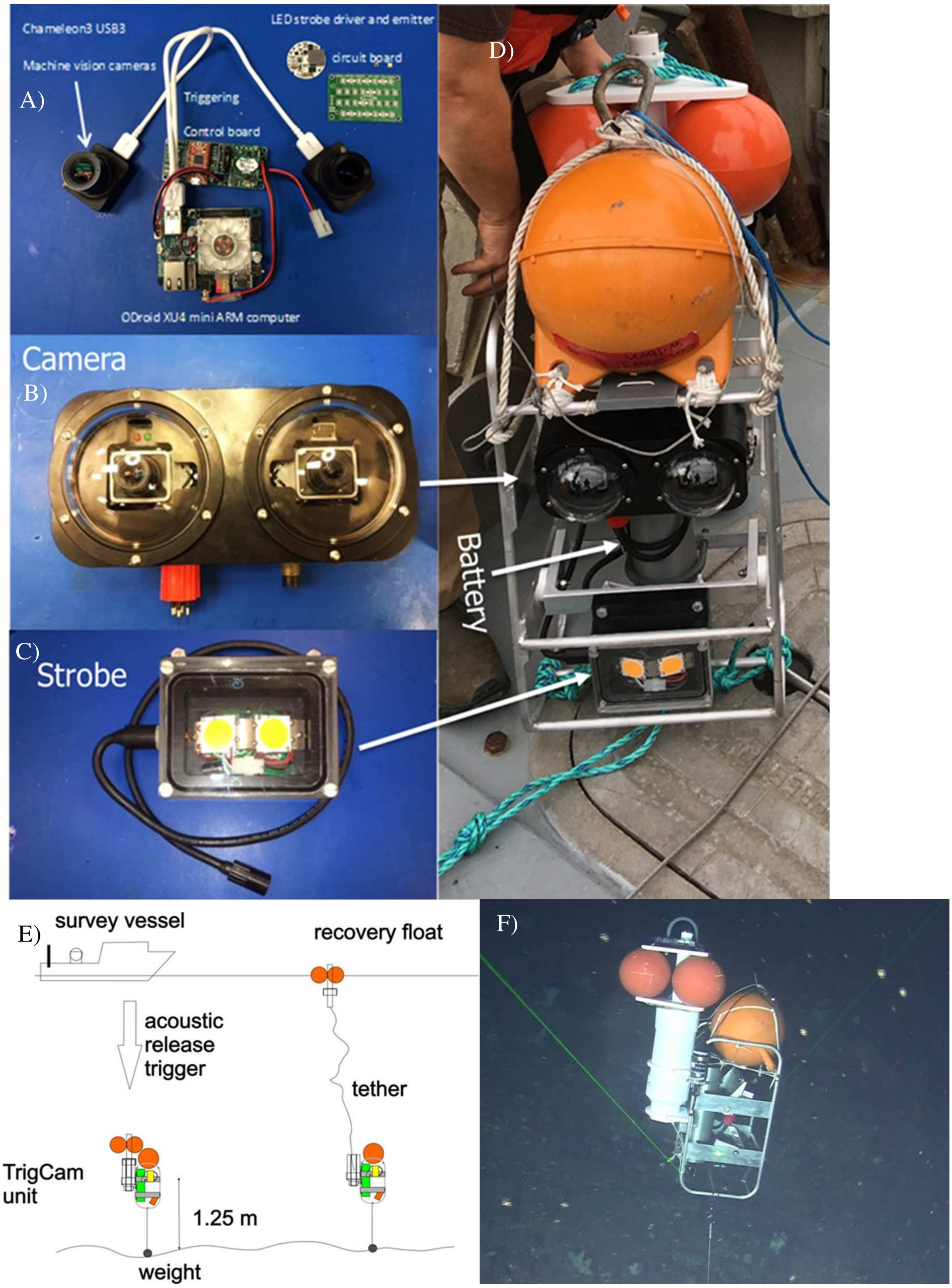


Figure 2. Image of TrigCam components (A-C), fully assembled TrigCam inside an aluminum frame (D), illustration of the deployment and recovery system (E), and deployed TrigCam (photo from manned submersible, F).

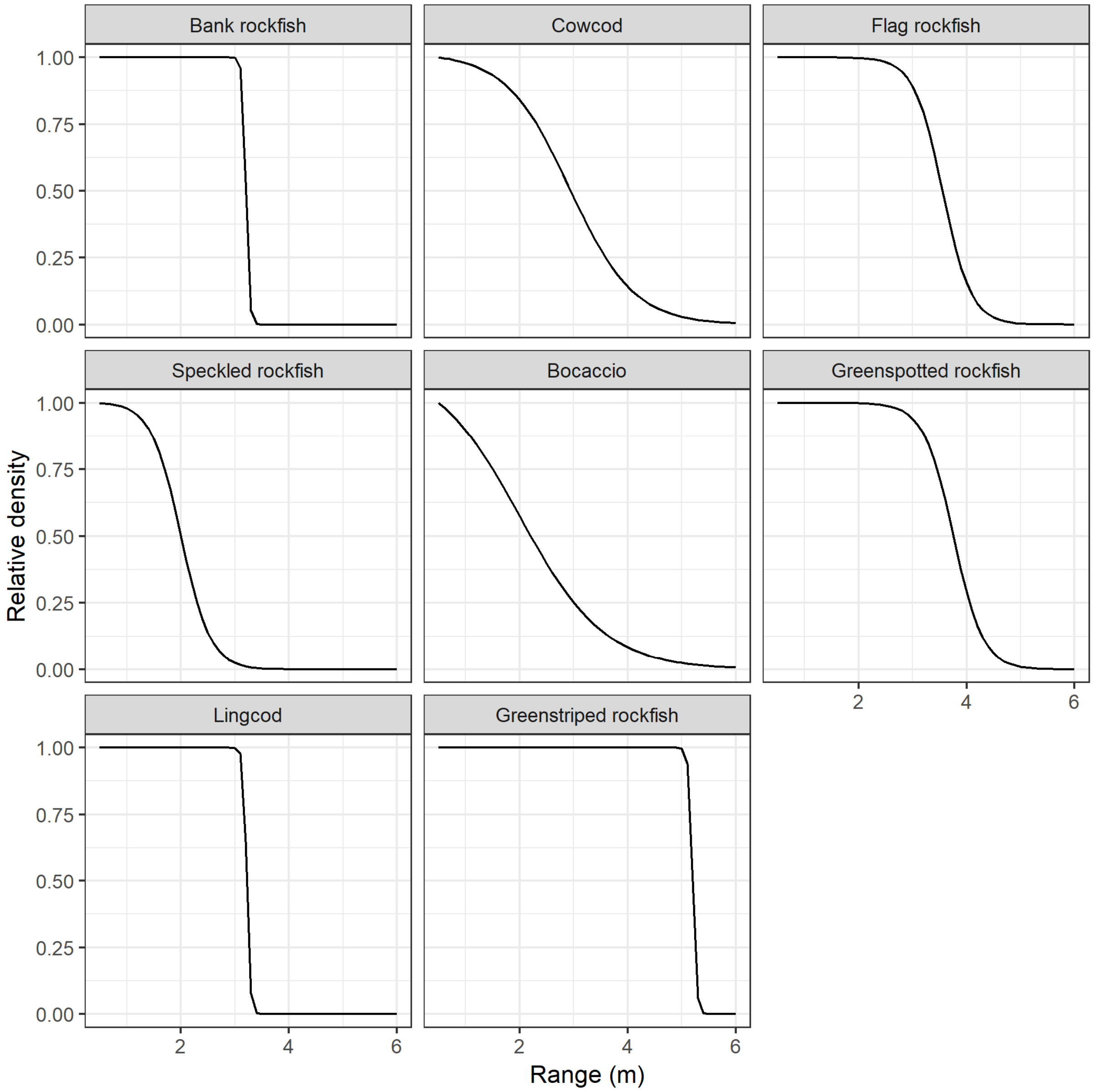


Figure 3. Detection function for rockfish species portraying the relative density of each species (scaled to 1) as a function of distance (range) from the stationary camera platform (m).

A)

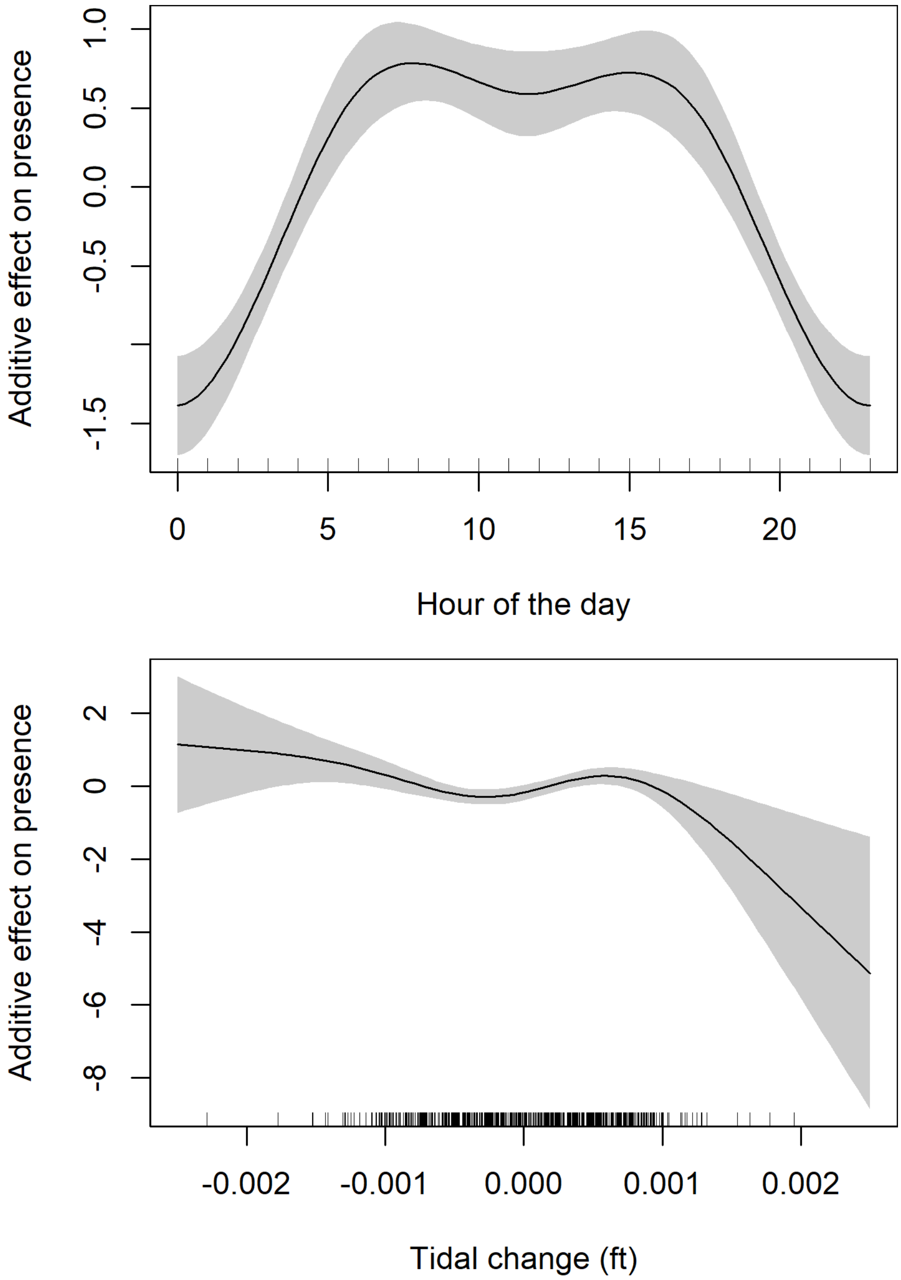


Fig. 4. Relationships from a generalized additive model of the effect of the hour of the day (A) and tidal change (B) and on fish presence or absence measured at 30 deployments in the southern California Bight over 24 hour periods.

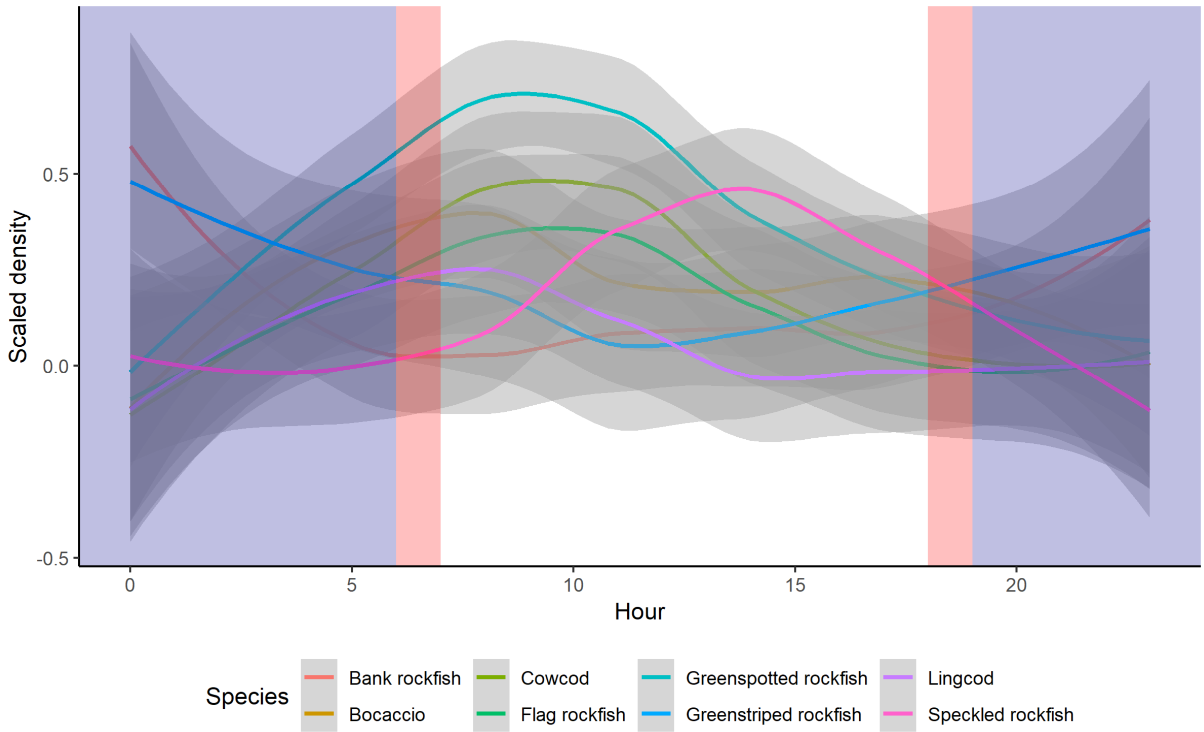


Figure 5. Density of rockfishes and lingcod recorded by time of day during 30 stationary camera deployments in the southern California Bight. Data are smoothed using a Loess smoother (standard errors of the smooth are represented by grey shading for each line). Purple shaded areas indicate local hours of nighttime and pink shaded areas indicate the hour surrounding dawn and dusk. Densities are scaled to 1 for each species to facilitate graphical representation.

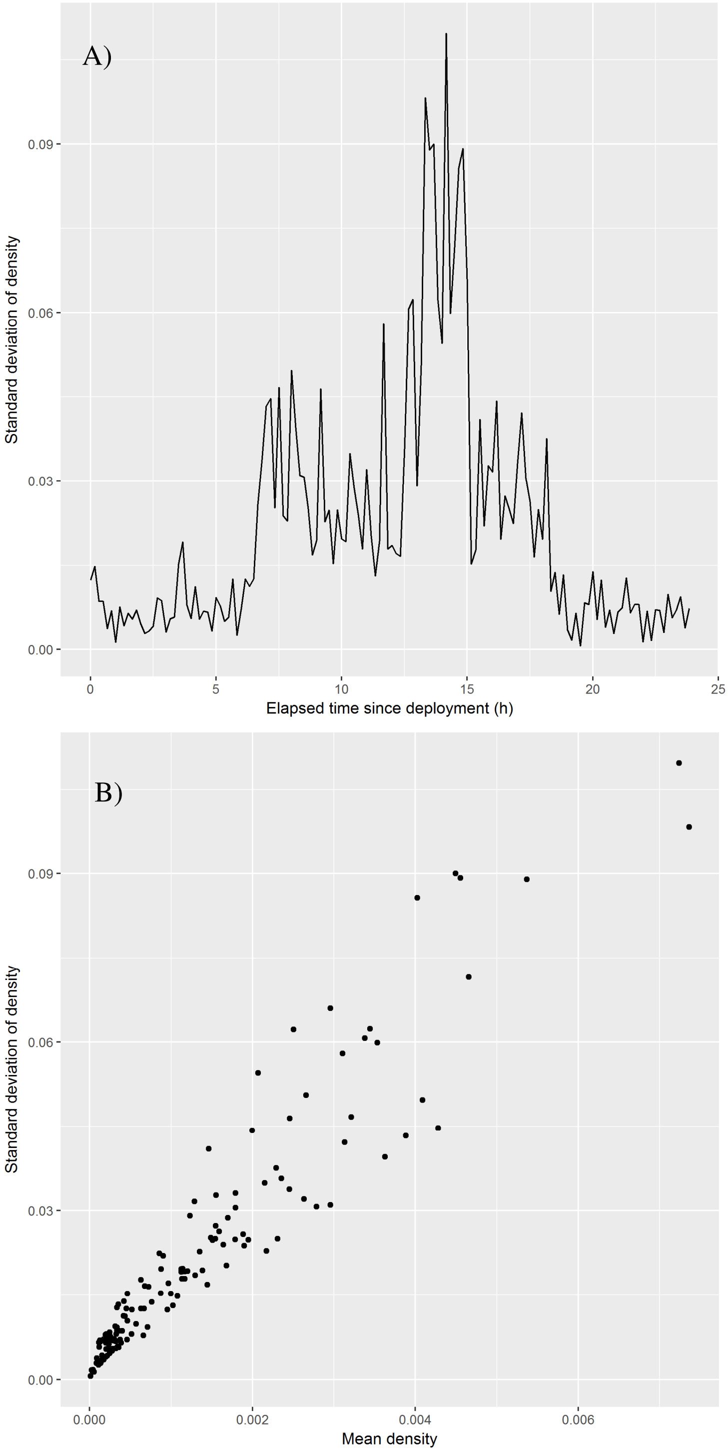


Figure 6. Variability of fish in same deployment over time since the deployment in 10-minute intervals (A) and the relationship between mean density and the standard deviation of the mean for those same intervals since deployment (B).

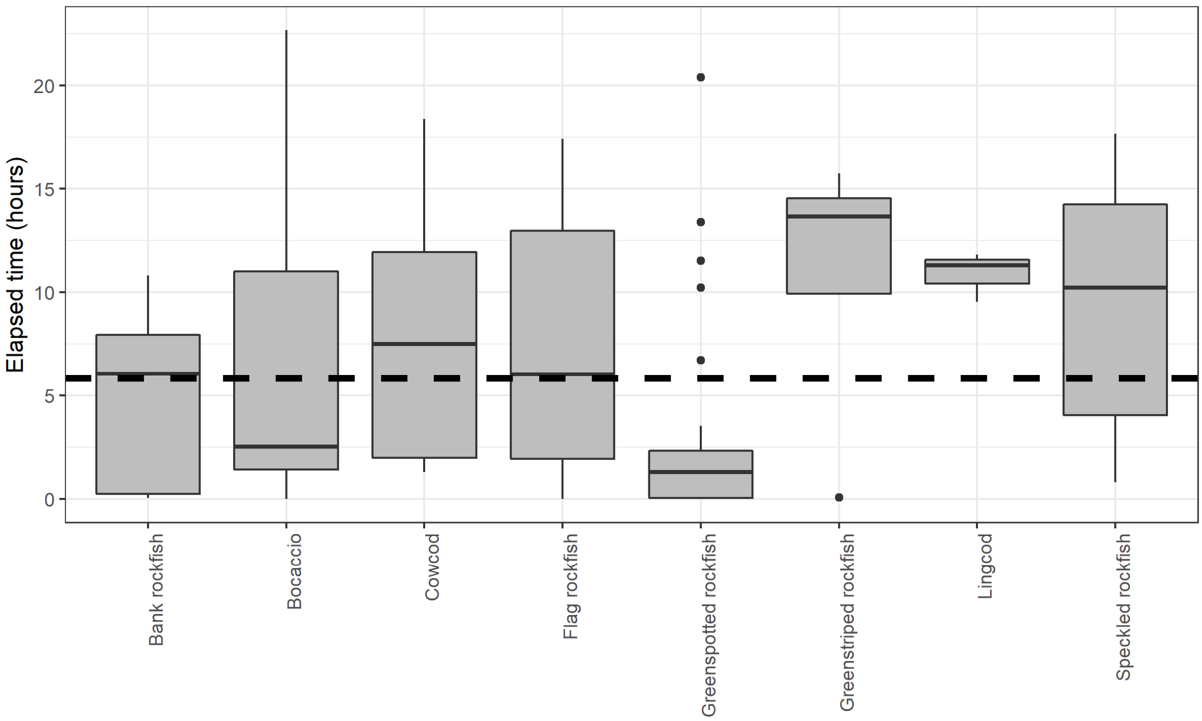


Figure 7. Elapsed time between deployment and first arrival of fish (by species) across 30 deployments of stationary cameras in the southern California Bight. The orange dashed line indicates the average elapsed time until daylight (1/2 hour after sunrise). Lines inside the colored boxes indicate median values and the height of the box corresponds to the 1st and 3rd quartiles of the data. Outliers are shown as individual points.

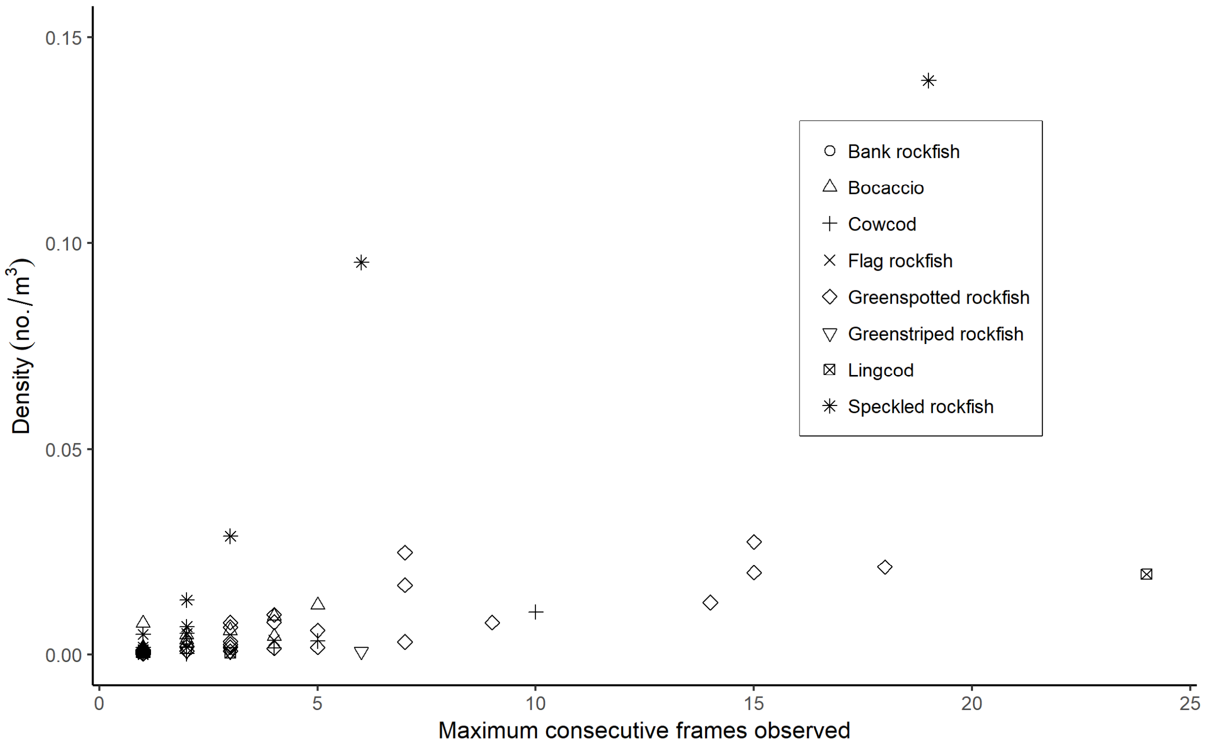


Fig. 8. Density of fish for TrigCam deployments versus the maximum number of consecutive frames in which fish of that species were observed. Data are from 30 deployments of TrigCams on the Footprint Bank in 2017 during daylight hours.

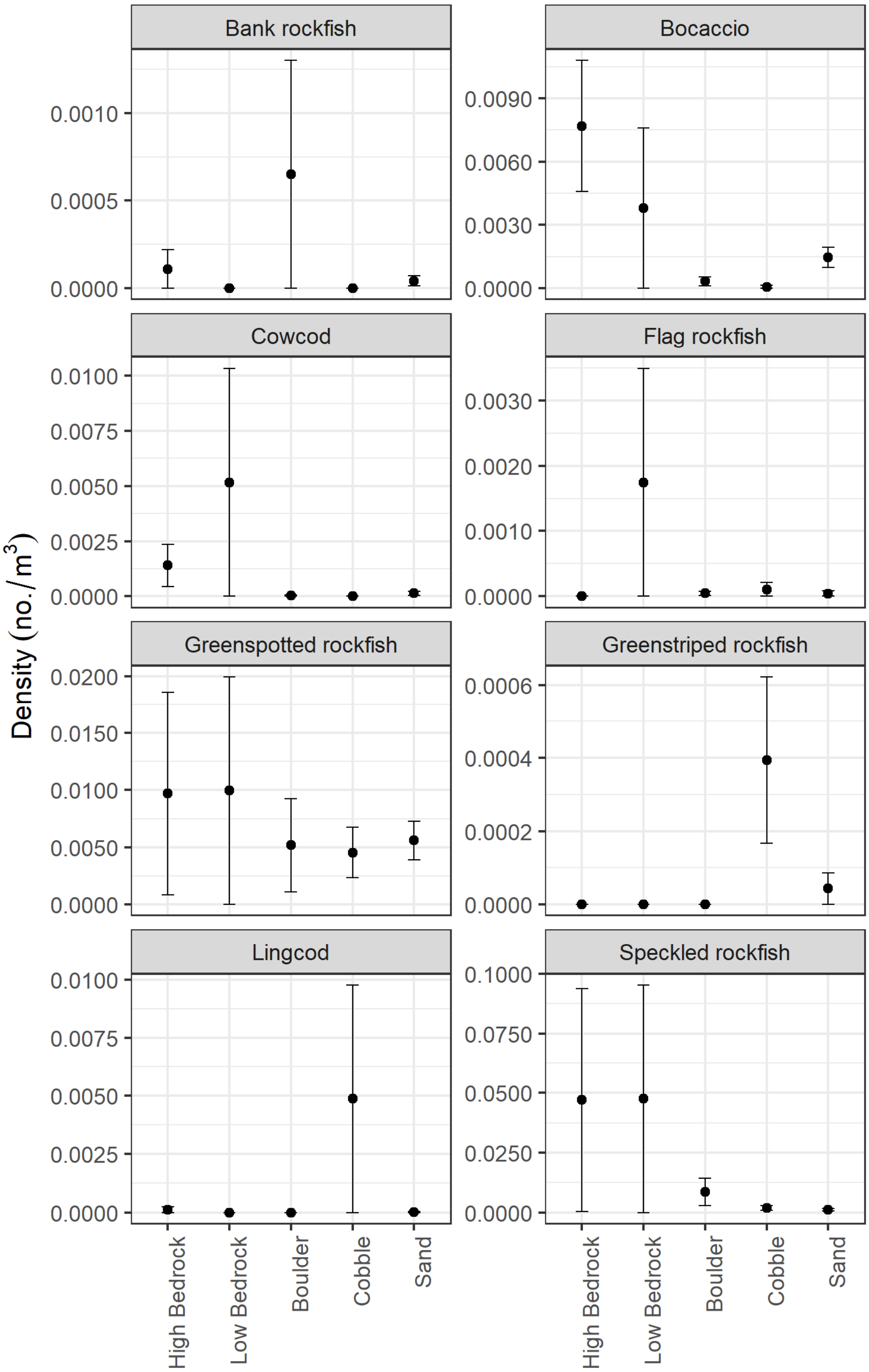


Fig. 9. Density of fish by primary substrate type and standard error bars for TrigCam deployments on the Footprint Bank in 2017.

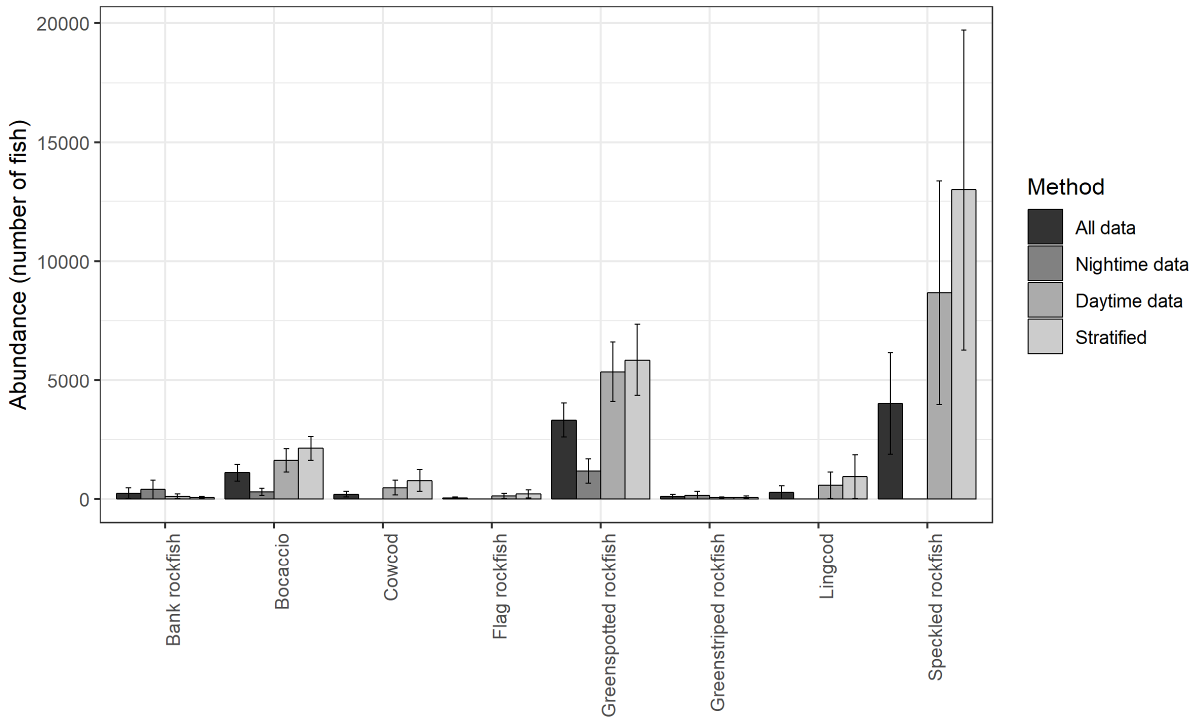
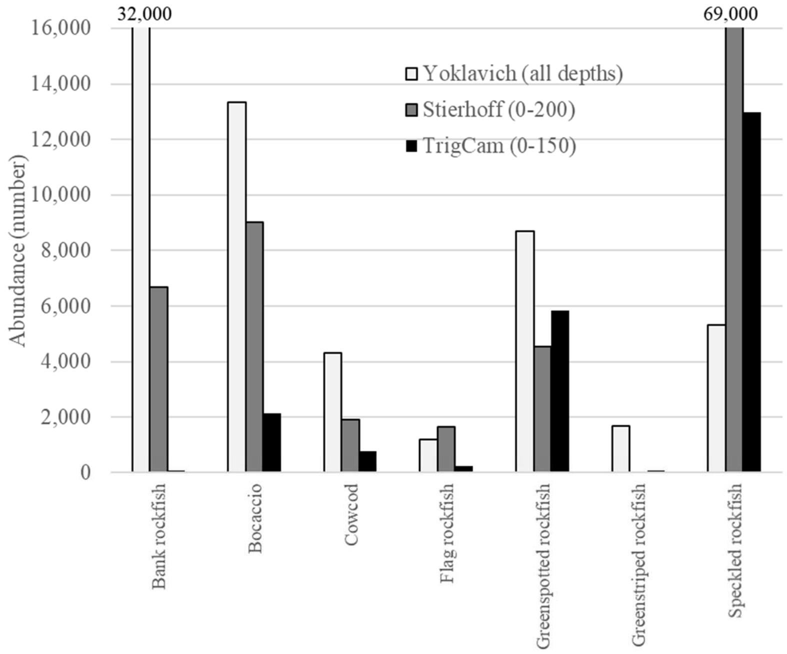


Fig. 10. Estimated abundance and standard error bars of rockfishes from Footprint Bank from TrigCam data in 2017 with four methods to calculate the abundance; 1) all data combined, 2) nighttime only, 3) daytime only, and 4) daytime only and stratified by primary substrate type.

A)



B)

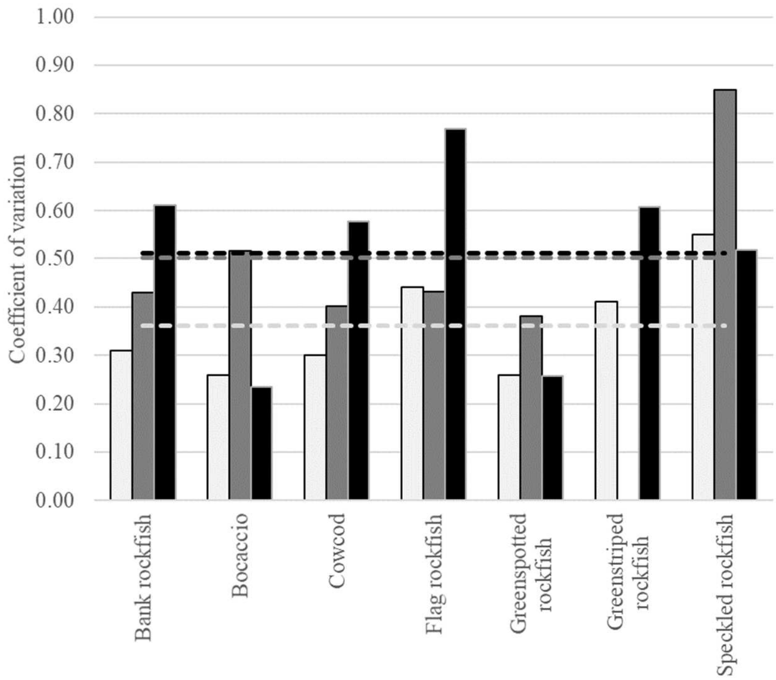


Figure 11. Abundance estimates (A) and coefficients of variation (B) of rockfishes from this study (TrigCam) at depths to 150 m, the Stierhoff et al. 2012 study of Footprint Bank (from transects to depths of 200 m) and the Yoklavich et al. 2013 study (at depths to 400 m) at Footprint Bank. The bars are abundance estimates for the Footprint Bank (in numbers of fish) and the lines are coefficients of variation for those estimates of abundance. The dashed lines are the corresponding average CV across rockfish species. Two abundance estimates were truncated in (A) above, with the estimate shown as numbers at the top of the bar.

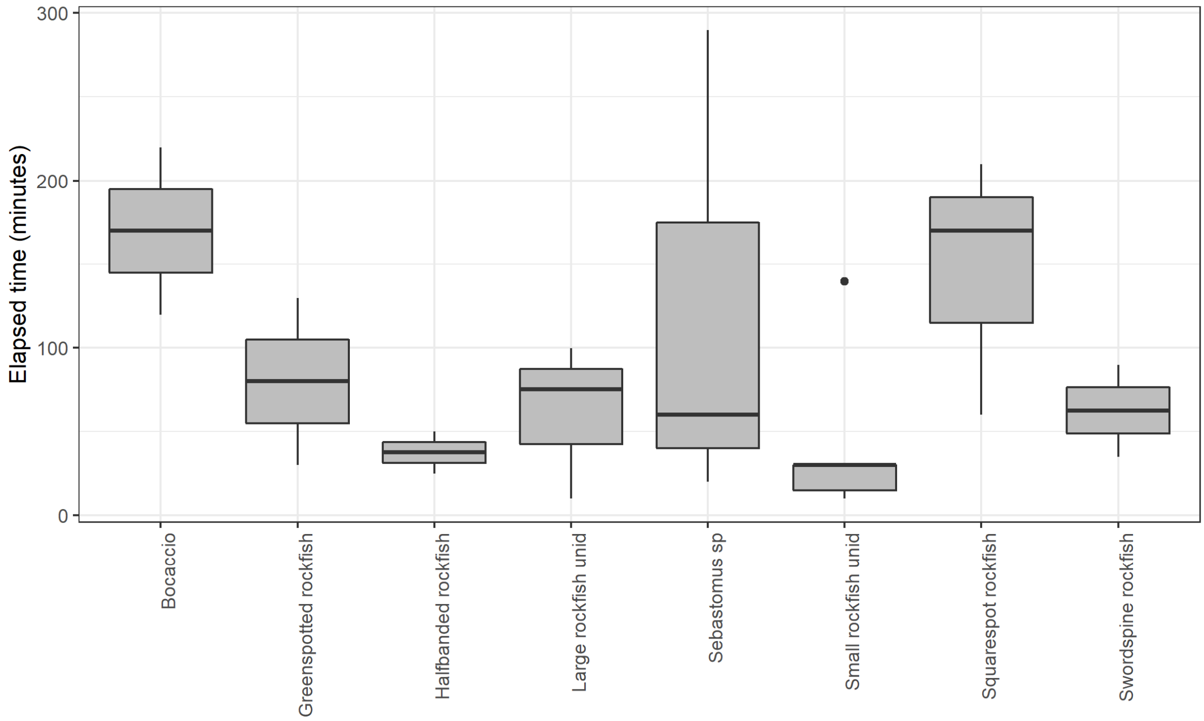


Figure S1. Elapsed time between first contact with the seafloor and first observation of rockfish by species or species group. The data are averages for 5 deployments conducted in 2016 where the TrigCam was shooting images when it reached the seafloor and the deployment was made prior to 13:00. The average elapsed time across all species was 87 minutes (sd = 78). Species was not significant ($p = 0.41$) and when species were combined into large and small species, there were no differences observed.