Estimating detection probabilities for reef fishes on baited underwater video

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ABSTRACT:

Using video to survey fish populations has become widespread due to technological advances of cameras, and it is often assumed that detection of species is constant (or 100%) in video surveys. We tested these assumptions by analyzing paired video and chevron trap data (n = 11,091) from a region-wide survey along the southeast United States Atlantic coast (2015–2023). Using nonlinear logistic regression, we related the presence or absence of eight reef-associated fish species on video (when they were confirmed to be present based on trap catch) to predictor variables including water clarity and current direction relative to the camera view after standardizing for variable site abundance. Empirical video detection estimates ranged from 0.49 for bank sea bass *Centropristis ocyurus*, a relatively small, plainly colored, demersal species, to 0.91 for red porgy *Pagrus pagrus*, a larger, distinct species that tends to circle the baited trap-video array. Regression models only explained 9–28% of the variation in video detection for the eight species, suggesting video detection was variable and difficult to predict. After accounting for variable site abundance, the effects of water clarity and current direction on video detection were inconsistent among species, as were the effects of maximum substrate relief, bottom depth, water temperature, and percent of the bottom that was rock. Video detection of predatory and scavenging fish species was not strongly affected by characteristics of the water or seafloor, but video also clearly did not detect all fish species at a site. Therefore, imperfect detection must be acknowledged and accounted for in video surveys, perhaps by using a paired-gear sampling approach.

KEY WORDS: BRUVS · Detectability · Detection probability · Occupancy · GAM · Fishery-independent · Survey · Catchability

1. INTRODUCTION

Surveys of aquatic or terrestrial organisms typically make inferences about a population of interest across space, time, or both using a single sampling gear (Williams et al. 2002). These studies can be informative as long as sampling intensity is high enough to address study objectives and assumptions are described clearly. It is commonly assumed in surveys that the probability of detection (i.e., detectability or the probability of catching or observing a species that is present at a site) is 100%, even though it is rare for a sampling gear to have perfect detection of all species present at a site (Yoccoz et al. 2001, MacKenzie et al. 2002, Thompson 2004, Bacheler et al. 2017). Another common and perhaps more tenuous assumption is that detectability is constant over space and time, but this is rarely tested because it is difficult to quantify what is not caught or seen at a site (Arreguín-Sánchez 1996, Moriarty et al. 2020). For example, inferring habitat selection from differences in catch rates (Manley et al. 2002) inherently presumes that the probability of detection is constant among habitat types (Bacheler & Shertzer 2020).

Innovative approaches have been developed in recent years to quantify variable detection, such as multiple observers, mark-recapture, distance sampling, removal techniques, and paired sampling gears (Katsanevakis et al. 2012). For instance, Issaris et al. (2012) used multiple observers (divers) to account for imperfect detection and estimate occupancy rates of whelk *Stramonita haemastoma* and the invasive green algae *Codium fragile fragile* in coastal waters of Greece. Ronconi & Burger (2009) used distance sampling to account for the fact that seabirds closer to vessel transect lines had higher probabilities of detection than those further from the line. Paired sampling gears have also been used to estimate gear-specific detection probabilities, catchabilities, occupancy rates, or relative abundance for various reef-associated fish species

(Coggins et al. 2014, DuFour et al. 2019, Gwinn et al. 2019). Methods accounting for variable detection have improved our understanding of the strengths and weaknesses of sampling gears and have resulted in less biased occupancy rates or abundance estimates (MacKenzie et al. 2002, Royle & Nichols 2003, Royle 2004).

Video is commonly paired with trawls, traps, gill nets, and longlines to understand the limitations and quantify variable detection rates of traditional sampling gears (Graham et al. 2004, Ryer 2008, Ward 2008, DuFour et al. 2019, Bacheler 2024). Very little is known, however, about what influences the detection rates of fish on underwater video. The use of underwater video to survey fishes has become widespread in the last two decades given their non-destructive nature, declining cost, and improvements in battery life, video resolution, and low-light sensitivity (Murphy & Jenkins 2010, Mallet & Pelletier 2014, Struthers et al. 2015; Langlois et al. 2020). There are numerous video-based surveys around the world that now quantify the occupancy rates, relative abundance, and distribution of fishes (e.g. Hannah & Blume 2012, Letessier et al. 2013, Klibansky et al. 2017, Bacheler et al. 2019, Langlois et al. 2020, Nalmpanti et al. 2023). The limited work on video detectability has shown that water clarity often influences video detectability (Mueller et al. 2006, Bacheler et al. 2014, Hannah & Blume 2016, Donaldson et al. 2019). Given that video surveys are often baited, the direction of the water current relative to the direction of the camera may also be important because most predatory or scavenging fish species tend to aggregate down-current of the bait to remain in the bait plume (Zhou & Shirley 1997, Bacheler et al. 2014, 2022, Lees et al. 2018).

We quantified video detectability by taking advantage of a paired sampling design where video cameras were attached to baited fish traps in a large-scale, region-wide, fishery-independent survey targeting reef-associated fish species. Specifically, we used trap catches to determine the presence of each species at a site, and then examined whether the corresponding videos detected specific fish species and, if not, why they may have been undetected. Using a nonlinear regression modeling approach, we related the presence or absence of fish on video (when known to be present) to a number of predictor variables. Based on previous work (Bacheler et al. 2014, 2020), we hypothesized that video detection would be positively related to water clarity and also influenced by current direction. We also tested for the influence of maximum substrate relief because fish may be more easily obscured in high-relief habitats compared to flat substrates (e.g. Bacheler et al. 2014). Finally, we tested for differences in video detectability by water depth, water temperature, and the percent of the seafloor that was hardbottom, all while standardizing for variable site abundance using trap catch. These results expand our understanding of video gears as a survey tool and highlight the fact that sampling gears rarely detect all individuals or species at a site.

2. MATERIAL AND METHODS

2.1. Study area

Sampling for reef-associated fish species in this study occurred in temperate and subtropical waters of the southeast United States Atlantic continental shelf and shelf break (hereafter, SEUS) between Cape Hatteras, North Carolina, and St. Lucie Inlet, Florida (Fig. 1). The SEUS continental shelf is large (~100,000 km^2) and varies in width from ~9 km in southern Florida to ~130 km off northern Georgia. The Southeast Reef Fish Survey (SERFS) carried out the sampling approach described below using chevron traps with attached video cameras at patches of rocky, hardbottom reef habitats in the SEUS. These reef habitats ranged from flat rock substrate, sometimes covered by a thin layer of sand, to high-relief, vertical ledges

(Schobernd & Sedberry 2009). Hardbottom reef patches are scattered throughout the SEUS and make up approximately 2.6% of the seafloor in the region (Steward et al. 2022).

2.2. Sampling approach

We used fishery-independent trap and video data collected by SERFS from 2015 to 2023 for this study. Three programs work together using identical methodologies to carry out trap-video sampling and collectively comprise SERFS: (1) the Southeast Fishery-Independent Survey, (2) the Marine Resources Monitoring, Assessment, and Prediction Program of the South Carolina Department of Natural Resources, and (3) the Southeast Area Monitoring and Assessment Program – South Atlantic. All programs were funded by the National Marine Fisheries Service. We included trap and video data from 2015 to 2023 here because sampling and video reading occurred in a consistent manner over this time period, as described below.

A simple random sampling design was used to select stations for sampling each year. Each year, 1,500 stations were randomly selected to be sampled out of a sampling frame of approximately 4,300 stations. The majority of stations included in our analyses were randomly selected stations (77%), but some stations (20%) were sampled in a given year despite not being randomly selected in order to increase sampling efficiency. The remaining stations (3%) included in our analyses were newly sampled stations that were discovered based on information from fishermen, charts, seafloor mapping, or historical data; these stations were only included if hardbottom was detected on video. Sampling occurred during daylight hours spring through fall on one of four research vessels – the RV *Savannah*, the RV *Palmetto*, the NOAA Ship *Pisces*, and the SRVx *Sand Tiger*.

To estimate video detection probabilities, we took advantage of the paired trap-video approach used by SERFS. Chevron traps were shaped like an arrowhead with a size of 1.7 × 1.5 × 0.6 m and an inside volume of 0.91 m^2 (Fig. 1; Collins 1990). Chevron trap mesh size was 3.4 × 3.4 cm, the wire mesh was 2 mm in diameter and coated in plastic, and the trap mouth was shaped like an upside-down teardrop measuring approximately 18 cm wide and 45 cm high (Bacheler et al. 2013). Each trap was baited with 24 whole Atlantic menhaden (*Brevoortia tyrannus*). Each trap was set at least 200 m from any other trap in a given year to provide independence among traps (Bacheler & Ballenger 2015, Bacheler et al. 2018), and traps were deployed individually in clusters of up to six traps in an area to increase sampling efficiency. A soak time of 90 min was targeted for each trap, and any trap that dragged, bounced, had its mouth obstructed, or experienced other issues that impaired sampling was excluded from all analyses.

SERFS attached two high-definition cameras to each chevron trap deployed in this study (Fig. 1). GoPro Hero 3+, 4, or 9 cameras were used with identical settings, resolution (1080p), and fields-of-view (wide digital lens, 118° horizontal and 69° vertical), with one camera looking outward over the trap mouth and one camera looking in the opposite direction outward over the trap nose. For consistency, fish observations were only made using the camera attached over the trap mouth, but both cameras were used to quantify habitat variables, water current information, and water clarity. Samples were removed if videos did not record correctly or videos were too dark or out of focus to read. Only stations with both valid trap and video samples were included in our analyses, and are hereafter referred to as “trap-video samples.” Presence or absence of each species was recorded during a 20-min interval of time that began 10 min after the trap landed on the seafloor (Bacheler et al. 2019).

Following Bacheler et al. (2014), a number of characteristics were quantified at each station sampled in this study. Depth (m) was estimated using the vessel's sonar, bottom temperature was measured for each group of simultaneously deployed traps using a conductivity-temperature-depth cast descended to within 2 m of the seafloor in the vicinity of soaking traps, and the remaining variables were visually estimated using footage from both of the video cameras attached to each trap. Water clarity was scored as "poor" if the substrate could not be seen on video, "fair" if the substrate could be seen but not the horizon, and "good" if the horizon could be seen in the distance. Current direction relative to the camera looking outward over the trap mouth was scored using particle movement and scored as "away," "sideways,", or "towards;" current direction accounts for differences in sightability of fish due to aggregation of predatory and scavenging fish on the down-current side of baited traps (Bacheler et al. 2022). Maximum substrate relief was the highest substrate relief visually estimated across both cameras and categorized as low (< 0.3 m), moderate (0.3 – 1.0 m), or high (> 1.0 m). Percent hardbottom was visually estimated from each camera as the percent of the seafloor that consisted of hard, consolidated sediment at least 10 cm in diameter, and a mean value was calculated for each station. Water clarity, habitat, and current variables were all scored by a single reader to minimize inter-observer bias.

2.3. Analytical approach

Video detection probability was estimated using only those trap-video samples where a particular reef fish species was caught in a chevron trap, verifying that the species of interest was present at a site. The presence or absence of species on video when the species was caught in the corresponding trap was then used as the response variable in a binomial model. We determined from preliminary analyses that models were only informative if a species was caught in at least 1,000 chevron traps. Eight reef fish species met this sample size requirement and were the focus of this work: tomtate (*Haemulon aurolineatum*), black sea bass (*Centropristis striata*), gray triggerfish (*Balistes capriscus*), red porgy (*Pagrus pagrus*), red snapper (*Lutjanus campechanus*), vermilion snapper (*Rhomboplites aurorubens*), white grunt (*Haemulon plumierii*), and bank sea bass (*Centropristis ocyurus*). These species varied substantially in terms of mean length, mean density, coloration, morphology, and swimming behavior.

We used binomial generalized additive models (GAMs) to relate the presence or absence of each species observed on video, when they were known to be present based on trap catches, to seven predictor variables. GAMs are an extension of generalized linear models that use smoothing functions to allow for non-linear relationships between predictor and response variables and can account for various error distributions (Hastie & Tibshirani 1990, Wood 2006). An important assumption of GAMs is that predictor variables are independent. We tested for multicollinearity of predictor variables using the variance inflation factor (VIF), which measures the amount of variance that is inflated for each predictor variable as a result of its collinearity with other predictor variables. The VIF in our study was less than 4 for all predictor variables, below the level thought to be concerning (i.e. 5–10; Neter et al. 1989). Moreover, pairwise correlation plots between all predictor variables did not show any obvious patterns, indicating that predictor variables met the assumption of independence.

The seven predictor variables in our GAMs were included based on our specific hypotheses and previous research. Water clarity was included because we hypothesized that fish video detection probability would be higher when water was clear compared to when it was turbid (Mueller et al. 2006, Bacheler et al. 2014, 2020). Current direction was included in our

GAMs because we hypothesized that video detection probabilities would be higher when the video camera was facing downstream compared to upstream because of the bait plume from bait in the trap (Bacheler et al. 2014, 2022). Maximum substrate relief was included to test the hypothesis that fish could be obscured and therefore detected less often when relief was high compared to low. Percent hardbottom was included to test the hypothesis that fish could be easier to detect on video when there was a white sand background compared to a dark, complex rocky background (often with large amounts of attached biota like soft corals, algae, and sponges that could further obscure fish). We also included the log-transformed catch of each species in traps to standardize for variable relative abundance at a site, hypothesizing that there would be a positive relationship between trap catch and video detection probability. Our last two predictor variables were depth and bottom temperature; depth may influence video detection via light availability, while water temperature may influence video detection by affecting fish swimming behavior.

Thus, the full binomial GAM relating video presence or absence to the seven predictor variables for each of the eight species was:

$$\eta = f_1(wc) + f_2(cur) + f_3(rel) + s_1(\log(catch) + s_2(depth) + s_3(temp) + s_4(ph)$$

where η is the probability of presence for each species on a video when caught in the corresponding chevron trap, $f_{1\text{-}3}$ are categorical functions, $s_{1\text{-}4}$ are cubic spline smoothed functions, *wc* is water clarity, *cur* is current direction, *rel* is maximum substrate relief, log(*catch*) is the log-transformed trap catch, *depth* is bottom depth, *temp* is bottom water temperature, and *ph* is percent hardbottom. All models were coded and analyzed using R version 4.3.3 (R Core

Team 2023) using the mgcv library version 1.9 (Wood 2011). We used the logit link function for all binomial GAMs.

For the species-specific GAMs, we compared models containing all predictor variables (hereafter, “full” models) to reduced models containing fewer predictor variables. Model selection used Akaike information criterion (AIC) to determine which predictor variables should be included in the best models (Burnham & Anderson 2002). For each species, the model with the lowest AIC score was considered to be the most parsimonious and was selected as the best model. For ease of interpretation, we present ΔAIC scores for each species, where the best model has a ΔAIC of 0 and models with less evidence have values greater than 0 (Burnham and Anderson 2002).

The specific relationship between predictor variables and video detection probability for each species was plotted using a bootstrapping approach. We resampled 10,000 predictions for each model given the estimates of error, assumed to be normally distributed. Predictions were made at middle values of all categorical variables and mean values of all continuous variables except log-transformed trap catch, which used a value of 1 (or 2.7 individuals) so that comparisons could be made across species. The exact values or levels chosen for prediction influenced the absolute values of video detection probability but not the relative pattern, which was our main focus. We calculated 95% confidence intervals using the 0.025 and 0.975 quantiles of the 10,000 point estimates.

3. RESULTS

A total of 11,091 trap-video samples were included in our analyses, ranging latitudinally from Cape Hatteras, North Carolina, to St. Lucie Inlet, Florida (Fig. 2). Sampling occurred each year from 2015 to 2023 (except no sampling occurred in 2020 due to COVID-19), with a minimum of 1,035 trap-video samples occurring annually over similar days of the year, depths, and latitudes (Table 1). Most of the species were observed on video broadly over the study area, but red porgy was seen more frequently in deeper water (> 30 m) and white grunt was seen more frequently in the northern portion of the study area (Fig. 3).

Tomtate were caught in traps most frequently (*n* = 4,216; 38.0% of traps), followed by black sea bass (*n* = 3,353; 30.2%), and gray triggerfish (*n* = 2,767; 24.9%), while bank sea bass were caught in the fewest traps (*n* = 1,507; 13.6%; Table 2). Mean trap catch (when present) was highly variable among species, ranging from 2.8 for bank sea bass to 32.2 for tomtate (Table 2). Likewise, video detection probabilities (i.e. probability of being observed on video when caught in traps) varied among the eight species, with the lowest being bank sea bass (0.49) and the highest being red porgy (0.91; Table 2). Overall, six out of the eight species were seen on video over 75% of the time they were caught in corresponding chevron traps (Table 2).

Based on ΔAIC scores, full models were chosen for two species (vermilion snapper and white grunt) and reduced models were selected for the six other species (Table 3). There were no consistent patterns in which predictor variables were excluded: three GAMs excluded water clarity, two excluded current direction, relief, or bottom temperature, and one each excluded depth or percent hardbottom (Table 3). The only variable included in all GAMs was log-transformed trap catch, a proxy for site abundance. Final species-specific GAMs explained from 9.0 (bank sea bass) to 28.0% (black sea bass) of the deviance in video detection probability (Table 3).

There were inconsistent relationships between categorical predictor variables and video detection probabilities for the eight reef fish species. Video detection probability was positively related to water clarity for black sea bass, white grunt, and bank sea bass, the relationships were much weaker and more uncertain for vermilion and red snapper, and water clarity was excluded from the models for tomtate, gray triggerfish, and red porgy (Table 3; Fig. 4). Note that white grunt were never observed when water clarity was poor, so an estimate of video detection probability was not available for particularly turbid water. Video detection probability was higher for cameras looking down-current than up-current for black sea bass, white grunt, and bank sea bass, the relationships were much weaker for gray triggerfish, vermilion snapper, and red snapper, and current direction was excluded for tomtate and red porgy. There were also modest positive relationships between maximum substrate relief and video detection probability for tomtate, vermilion snapper, red porgy, red snapper, and bank sea bass, there was a slight negative relationship for white grunt, and maximum substrate relief was excluded from models for black sea bass and gray triggerfish (Table 3; Fig. 4).

There were also inconsistent relationships between the smoothed continuous predictor variables and video detection probabilities. There were strong negative relationships between depth and video detection for tomtate, black sea bass, and white grunt, weaker negative relationships for vermilion snapper, red porgy, and red snapper, a positive (or dome-shaped) response for gray triggerfish, and depth was excluded from the bank sea bass model (Table 3; Fig. 5). Similar inconsistent relationships were observed between bottom temperature and video detection, with two being positive (black sea bass, white grunt), two being negative (tomtate, vermilion snapper), two being fairly flat (gray triggerfish, red porgy), and two that excluded bottom temperature (red snapper, bank sea bass; Fig. 5). Percent hardbottom was positively related to video detection for white grunt, black sea bass, and bank sea bass, displayed a dome-shaped relationship for tomtate, gray triggerfish, and vermilion snapper, displayed a mostly flat relationship for red porgy, and percent hardbottom was excluded from the red snapper model. For all species, there were positive (and mostly asymptotic) relationships between log-transformed trap catch and video detection, being strongest for black sea bass, bank sea bass, tomtate, and white grunt, and weaker for the other four species (Table 3; Fig. 5).

4. DISCUSSION

Video has become one of the most commonly used fish sampling gears worldwide because it is non-extractive, can be used in deep water where divers are generally precluded, is thought to be less selective than other sampling gears, can provide behavioral and habitat information, and provides a permanent record that can be viewed many times (Willis et al. 2000, Mallet & Pelletier 2014, Bacheler et al. 2016). It is commonly implied or assumed that video has perfect detection, but this assertion is tenuous because imperfect video detection could cause occupancy rates to be underestimated, community structure to be distorted, habitat relationships to be biased, and management recommendations to be incorrect (Tyre et al. 2003). We used eight years of regional-scale, paired trap-video sampling to investigate how video detection probabilities for various reef-associated fish species might be influenced by environmental and site characteristics. We found that video detection probabilities were highly species-specific, varying in the strength and direction of relationships between video detection probabilities and predictor variables, including water clarity and current direction. The only predictor variable that was always strongly positively related to video detection probability was trap catch, which was included to control for site abundance of each species. These results improve our understanding of the video sampling process and provide a novel method to account for imperfect video detection.

Water clarity had inconsistent effects on video detection probabilities for reef fish, similar to previous studies (Mueller et al. 2006, Bacheler et al. 2014, Hannah & Blume 2016, Donaldson et al. 2019). Water clarity was excluded for three species, and for the remaining five species, water clarity was only weakly or moderately related to video detection probability. In our baited trap-video study, all eight species were often detected regardless of water clarity, probably due to their predatory or scavenging behavior in the vicinity of the traps. Moreover, when site abundance of a particular species was high, that species was almost always detected on video, regardless of water clarity. The main exception to this rule was bank sea bass, which is attracted to bait but has low site abundance. It is possible that the lower detection probability of bank sea bass was a result of their low site abundance combined with their relatively small body size (Table 2) and lack of distinctive coloration or morphology. Thus, water clarity may influence video detection more strongly for shy and cryptic species that do not approach cameras closely and tend to have low overall site abundance compared to predatory or scavenging species (Bacheler et al. 2014).

Baited video surveys also must account for variable current direction relative to the direction the camera is facing because some species tend to aggregate down-current in the bait plume (Zhou & Shirley 1997, Bacheler et al. 2018, 2022, Lees et al. 2018). In our study, the effect of current direction on video detectability was variable among species. The strongest relationships occurred for black sea bass, bank sea bass, and white grunt, which also happened to be the three species with the lowest overall video detection probabilities. These species were better detected when cameras were facing down-current, suggesting they were more likely to remain in the bait plume compared to the other species. Current direction was also included in the models for gray triggerfish, vermilion snapper, and red snapper but the effects were weak;

current direction was excluded from tomtate and red porgy models, suggesting it had no influence on detection for those species. Whether current direction is important to a particular species appears to depend on its swimming behavior in and around the bait plume (Bacheler et al. 2022).

Empirical estimates of video detection probability were generally quite high but variable among species. Our video detection estimates were higher than those for four species estimated by Bacheler et al. (2014), likely due to differences in video reading approaches. In Bacheler et al. (2014), presence or absence was determined by reading 41 individual frames over a 20-min interval of time (i.e., the "MeanCount" method; Schobernd et al. 2014), whereas here we read a continuous 20-min segment of video. Video detection appears to be related to the behavior of fish around baited video and their size, morphology, and coloration (Bacheler et al. 2017). Species like red snapper and red porgy are relatively large, distinct from other species, and tend to circle the baited trap-video array, whereas other species like black and bank sea bass are smaller, more plainly colored, not as easily distinguished from other species, and tend to stay near the seafloor. Black and bank sea bass are also so attracted to baited traps that they do not tend to circle baited trap-video array, but rather enter the trap or stay in one place once they reach the outside of the trap (Cullen & Stevens 2017).

We hypothesized that high vertical relief of bottom substrate might obscure fish, resulting in lower video detection probabilities. This hypothesis was mostly not supported by the evidence; models for six out of eight species included maximum substrate relief, but five of those species displayed positive (not negative) relationships between video detection probability and maximum substrate relief. It is unclear why a majority of species had higher detection in higher relief habitats, but perhaps fish in these habitats swim around more or tend to swim further off the bottom, making them more obvious on video. White grunt were the only species displaying a slightly negative relationship between video detection and maximum substrate relief, which is consistent with observations from SERFS video readers that white grunt are shy and tend to stay hidden in rocks, algae, and sponges (Ogden & Ehrlich 1977, Tulevech & Recksiek 1994). This result suggests that it is possible that white grunt could be modestly obscured by higher relief habitats, thus reducing their detectability on video. We also hypothesized that fish might be detected more easily over white sand substrates compared to dark, rocky substrates, but this hypothesis was rejected because there were no obvious negative relationships between video detection and percent hardbottom for any species. Thus, substrate and habitat variables do not appear to greatly influence whether reef fishes are detected by video.

Our binomial GAMs explained a relatively small amount of deviance in the video detection for each species (9–28%), suggesting that either unmeasured variables are important or video detection is highly variable (or both). Depth was included to test for the effects of light availability on detection (deeper videos tend to be slightly darker) and water temperature was included to test for the effects of swimming behavior on detection (fish tend to be more active in warmer water). We found that these variables were ultimately included in GAMs for most species and they explained some of the variation in video detection. Detection was negatively related to depth for 6 of 7 species, but temperature relationships were variable among species and effects were generally weak. It is also possible that these variables are proxies for other unmeasured variables that are more likely to influence video detection, such as ontogenetic size changes across depths or species interactions in and around baited traps (Mitchell et al. 2014, Glasgow 2017, Phenix et al. 2019).

There are various approaches that can be used to estimate and account for imperfect detection (Katsanevakis et al. 2012). The most common approach to estimate detection is to conduct repeated site visits, but a critical assumption of this approach is that occupancy status does not change among visits, i.e. "temporal closure" (MacKenzie et at. 2002). A better approach is to use multiple observers at the same time or in quick succession to reduce or eliminate the temporal closure assumption (Issaris et al. 2012). Alternatively, we used a paired gear approach to estimate detection at the same place at the same time (e.g. Graves et al. 2011, Coggins et al. 2014, Gwinn et al. 2019), so fewer assumptions were required. Not all sampling gears, however, are amenable to being paired with other sampling gears. For instance, traditional sampling gears are difficult to pair with one another because most are extractive. The most logical gear pairing is for a traditional gear like a trawl, gill net, longline, or trap to be paired with a non-extractive gear like video, acoustics, or eDNA (Somerton et al. 1999, Williams et al. 2015, Lugg et al. 2018, Stoeckle et al. 2021).

There were some shortcomings in our study. First, we used trap catch as a proxy for site abundance, but these results should be interpreted with caution because traps do not always catch reef fish in proportion to their site abundance (High & Ellis 1973, Bacheler 2024). Second, although the pairing of gears has many advantages, one disadvantage of pairing traps and video is that traps may have caught some species early in the deployment that may have then been unavailable to be seen on video. Trap catchability tends to be low for most species (Bacheler & Shertzer 2020), however, so we assumed that the effects of trap capture on video detection were negligible. Third, our results only apply to predatory or scavenging reef fish species that were attracted to bait and were caught in traps often enough to allow for GAM modeling. Fourth, we only read 20 min of video during a 90-min trap deployment (~22%), and reading more video would have increased the absolute video detectability for all species. But we read 20 min of video to match the read time of many other video surveys (e.g., Switzer et al. 2023), and the primary goal of our work was to determine the relative influence of various factors on detectability, not the absolute values. Last, it is likely that finer-scale quantification of predictor variables, especially water clarity or current direction, would help explain more of the variability in video detection.

Monitoring fish populations using underwater video has become commonplace as video technology has improved and the cost of cameras has declined (Mallet & Pelletier 2014, Struthers et al. 2015, Langlois et al. 2020). But despite the numerous advantages of video surveys, it is clear that video does not detect all species present at a site, often missing small, cryptic species (Mallet et al. 2014, Bacheler et al. 2017). Various approaches exist for increasing video detection probabilities for fish species including reading more video (Bacheler & Shertzer 2015) or using rotating cameras (Mallet et al. 2014), 360° cameras (Campbell et al. 2018), or possibly automated video analysis with machine learning (Salman et al. 2020, Marrable et al. 2022). It is also important to understand, estimate, and account for imperfect detection in video surveys regardless of whether detection is low or high. This could be accomplished by pairing video with other sampling gears (DeCelles et al. 2017), incorporating variables that influence video detection in models of relative abundance or stock assessments (Maunder & Punt 2004, Wilberg et al. 2009, Langseth et al. 2016), or by developing occupancy or *N*-mixture models (MacKenzie 2002, Royle 2004). Estimating and accounting for imperfect detection in video surveys will result in more robust survey data that can provide unbiased occupancy rates and reliable management advice.

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Table 1. Yearly information for trap-video samples collected by the Southeast Reef Fish Survey between North Carolina and Florida (2015 – 2023) and included in analyses. No samples were collected in 2020 due to the COVID-19 pandemic.

Year	Number of trap-video samples	Mean date (range)	Mean depth (m; range)	Mean latitude (°N; range)
2015	1,382	3-Jul (21-Apr – 22-Oct)	38 (16–110)	31.9 (27.3–35.0)
2016	1,400	2-Aug (4-May – 26 Oct)	41 (17–115)	32.2 (27.2–35.0)
2017	1,411	4-Jul (26-Apr – 29-Sep)	40 (15–111)	32.0 (27.2–35.0)
2018	1,639	24-Jun (25-Apr – 4-Oct)	40 (16–114)	32.0 (27.2–35.0)
2019	1,529	2-Jul (30-Apr – 25-Sep)	40 (16–110)	32.1 (27.2–35.0)
2020	0	-	-	-
2021	1,364	2-Jul (28-Apr – 30-Sep)	38 (16–109)	31.9 (27.2–35.0)
2022	1,035	11-Jul (26-Apr – 27-Sep)	38 (17–113)	31.8 (27.2–35.0)
2023	1,331	17-Jul (16-May – 11-Oct)	40 (15–121)	31.7 (27.2–35.0)
Total	11,091	6-Jul (21-Apr – 26-Oct)	40 (15–121)	32.0 (27.2–35.0)

Table 2. Species-specific mean length and video detection information from trap-video data collected by the Southeast Reef Fish Survey (2015–2023). A total of 11,091 trap-video samples were included in our analyses.

Species	Mean total length (mm)	Frequency of occurrence in traps	% frequency of occurrence in traps	Mean trap catch (range) when present	Video frequency of occurrence when caught in traps	Overall video detection probability
Tomtate	213	4,216	38.0	32.2 (1–380)	3,745	0.89
Black sea bass	262	3,353	30.2	13.9 (1–282)	2,441	0.73
Gray triggerfish	379	2,767	24.9	3.5 (1–137)	2,175	0.79
Vermilion snapper	299	2,444	22.0	11.2 (1–239)	2,094	0.86
Red porgy	366	2,130	19.2	4.8 (1–61)	1,940	0.91
Red snapper	437	1,834	16.5	5.8 (1–99)	1,645	0.90
White grunt	305	1,572	14.2	6.0 (1–108)	1,190	0.76
Bank sea bass	231	1,507	13.6	2.8 (1–29)	743	0.49

Table 3. Model selection for the top three binomial generalized additive models for eight reef fish species that related the presence or absence of each fish species on video to predictor variables when they were known to be present based on their capture in corresponding traps. Data from 2015 to 2023 were included in analyses, and trap-video samples were collected by the Southeast Reef Fish Survey. Degrees of freedom are shown for categorical predictor variables and estimated degrees of freedom are shown for smoothed predictor variables; asterisks denote significance at the following alpha levels: * = 0.05; ** = 0.01; *** = 0.001. ex = predictor variable was excluded from that particular model, ΔAIC = delta Akaike's information criterion, DE = deviance explained by the model, $f_{1\text{-}3}$ = categorical functions, $s_{1\text{-}4}$ = cubic spline smoothed functions, *wc* = water clarity, *cur* = current direction, *rel* = maximum substrate relief, log(*catch*) = the log-transformed trap catch, *depth* = bottom depth, *temp* = bottom water temperature, and *ph* = percent hardbottom. The best model for each species had a ΔAIC score = 0.

Predictors excluded	ΔAIC	DE	$f_1(wc)$	$f_2(cur)$	$f_3(rel)$	$s_1(depth)$	$s_2(temp)$	$s_3(ph)$	$s_4(\log(catch))$
Tomtate									
cur, *wc*	0.00	20.6	ex	ex	2*	1.0***	3.2***	3.9***	1.6***
cur	1.50	20.7	2	ex	2*	1.0***	3.2***	3.9***	1.6***
wc	2.50	20.6	ex	2	2*	1.0***	3.3***	3.9***	1.6***
Black sea bass									
rel	0.00	28.0	2	2***	ex	5.5***	1.0	5.5***	3.0***
rel, *temp*	0.25	28.0	2	2***	ex	5.5***	ex	5.6***	3.0***
none	3.60	28.1	2	2***	2	5.5***	1.0	5.6***	3.0***
Gray triggerfish									
wc, *rel*	0.00	11.4	ex	2*	ex	6.6**	4.9	3.7***	1.7***
wc	0.30	11.6	ex	2*	2	6.6**	4.9	3.7**	1.7***
rel	1.18	11.5	2	2*	ex	6.7*	4.9	3.7**	1.7***
Vermilion snapper									
none	0.00	9.7	2**	2	2*	1.0**	1.0	6.4*	1.0***

temp	1.69	9.5	2**	2	2*	1.0	ex	6.3*	1.0***
cur	1.85	9.4	2**	ex	2*	1.0**	1.0	6.4*	1.0***
Red porgy									
cur, *wc*	0.00	15.3	ex	ex	2***	2.3	6.7	4.1**	1.5***
cur	2.26	15.4	2	ex	2***	2.3	6.6	4.1**	1.4***
wc	2.56	15.3	ex	2	2***	2.3	6.5	4.1**	1.4***
Red snapper									
ph, *temp*	0.00	16.3	2	2	2***	1.5	ex	ex	1.0***
ph	1.35	16.4	2	2	2***	1.4	1.0	ex	1.0***
temp	1.87	16.3	2	2	2*	1.5	ex	1.0	1.0***
White grunt									
none	0.00	23.3	1*	2***	2*	2.8**	1.6	3.5***	1.8***
temp	0.60	23.2	1*	2***	2**	3.3**	ex	3.4***	1.8***
wc	1.81	23.1	ex	2***	2**	2.9*	1.6	3.6***	1.7***
Bank sea bass									
temp, *depth*	0.00	9.0	2	2***	2	ex	ex	1.8*	3.0***
temp, *depth*, *wc*	0.07	8.9	ex	2***	2	ex	ex	1.8**	3.2***
temp	1.59	9.1	2	2***	2	1.0	ex	1.8**	3.0***

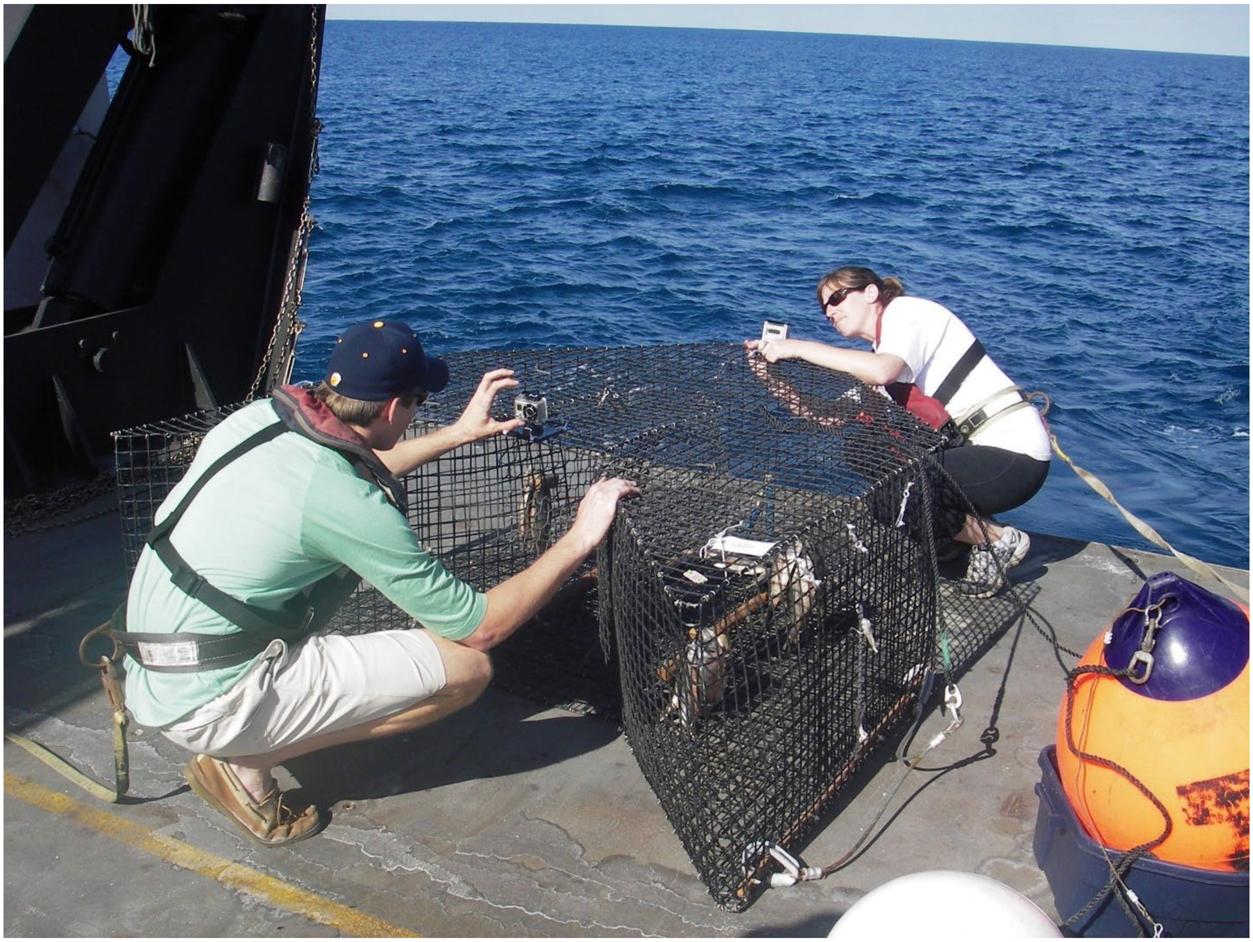

Fig. 1. Baited chevron traps with attached video cameras used by the Southeast Reef Fish Survey between North Carolina and Florida in 2015–2023.

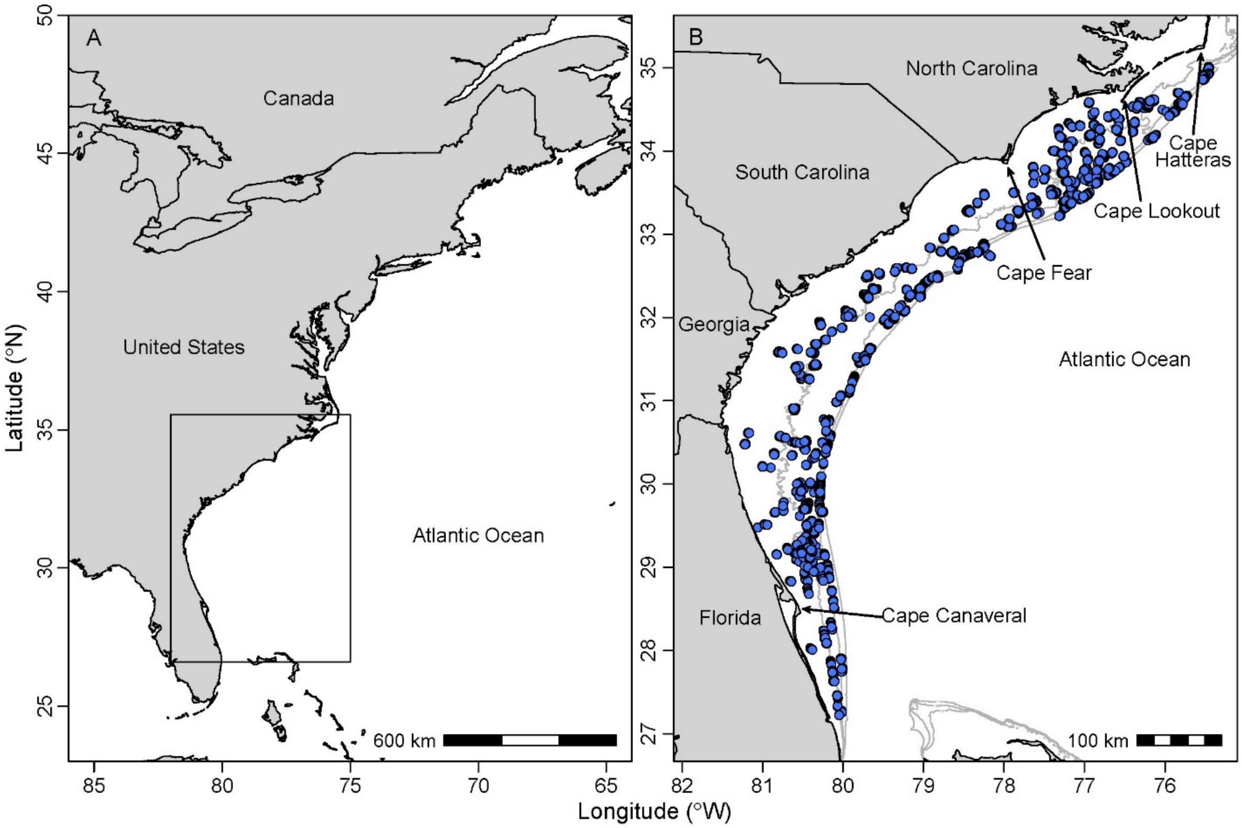

Fig. 2. Locations of trap-video sampling by the Southeast Reef Fish Survey between North Carolina and Florida in 2015–2023. Each blue point is an individual trap-video deployment included in the analyses; note that symbols overlap. Gray isobaths in (B) are 30, 50, and 100 m deep.

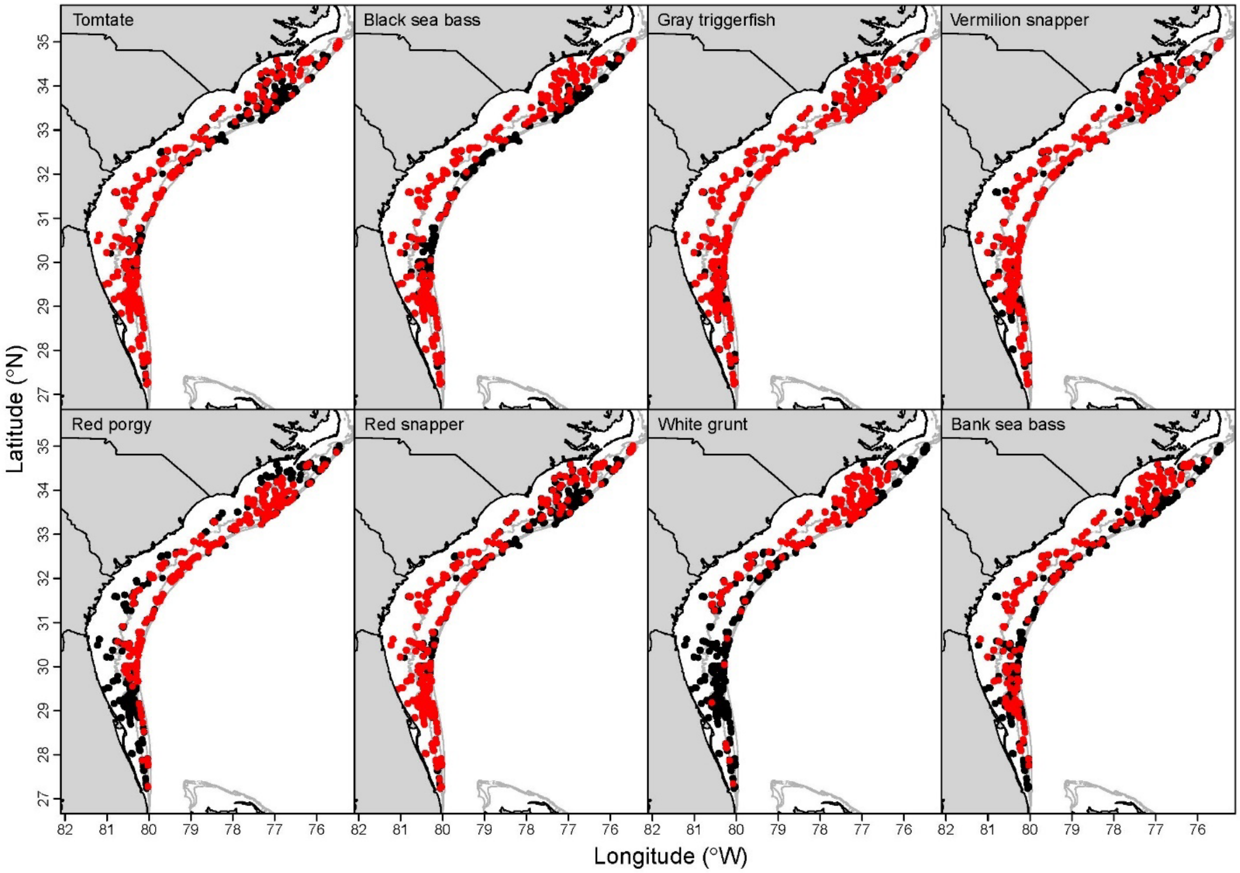

Fig. 3. Patterns of video-based presence and absence of reef fish species across the study area from North Carolina to Florida based on data collected by the Southeast Reef Fish Survey, 2015–2023. Red points indicate where that species was observed on video, while black points indicate where that species was absent on video. Gray isobaths are 30, 50, and 100 m deep. Note that symbols overlap in each panel, and red points are plotted on top of black points

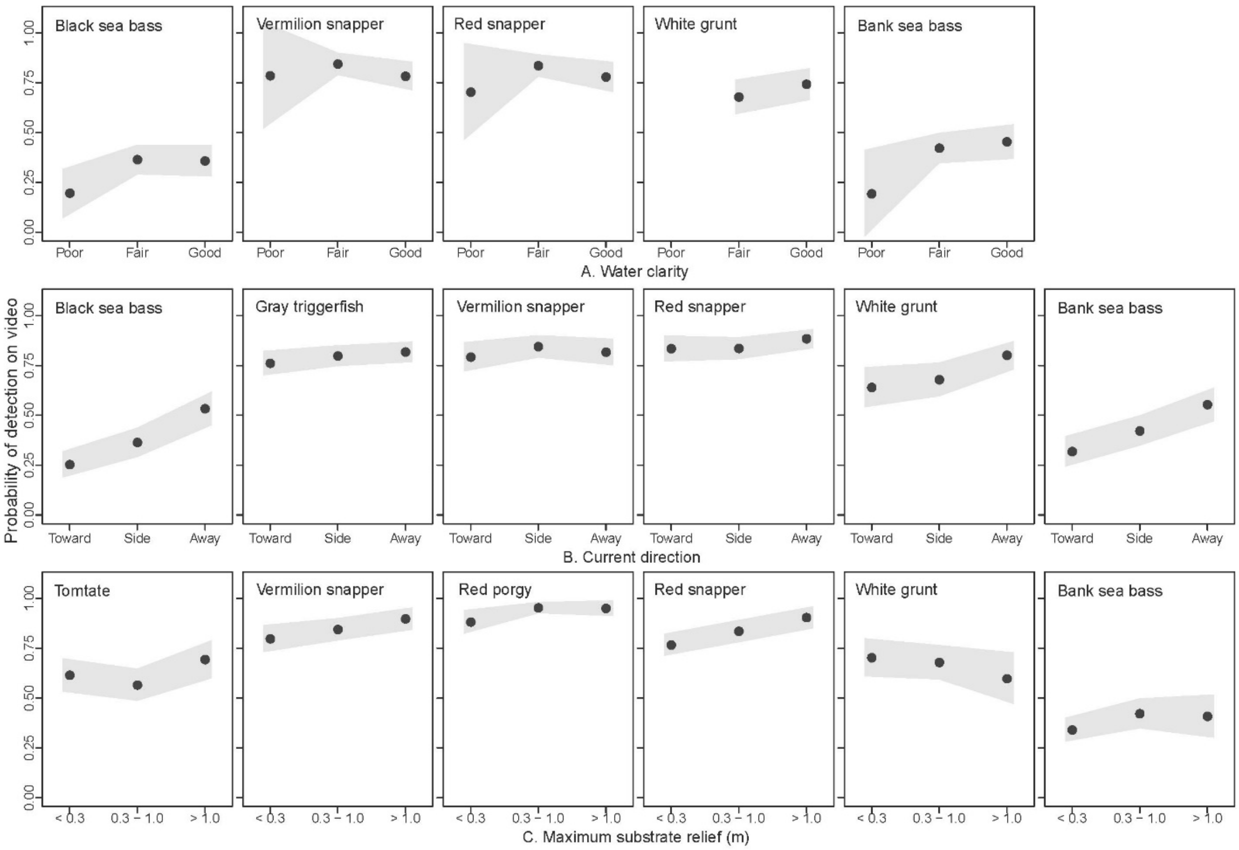

Fig. 4. Video detection probabilities for eight reef fish species related to categorical predictor variables: (A) water clarity, (B) current direction, and (C) maximum substrate relief (m) from Southeast Reef Fish Survey trap-video data (2015–2023). "Poor" water clarity was when substrate could not be seen, "fair" was when substrate could be seen but not the horizon, and "good" was when the horizon could be seen. Current direction relative to the camera looking outward over the trap mouth was scored as "away," "sideways,", or "towards." Points indicate estimated video detection probabilities and gray shaded areas indicate 95% confidence intervals. Data are only shown for species where that predictor variable was included in the final model based on the Akaike information criteria.

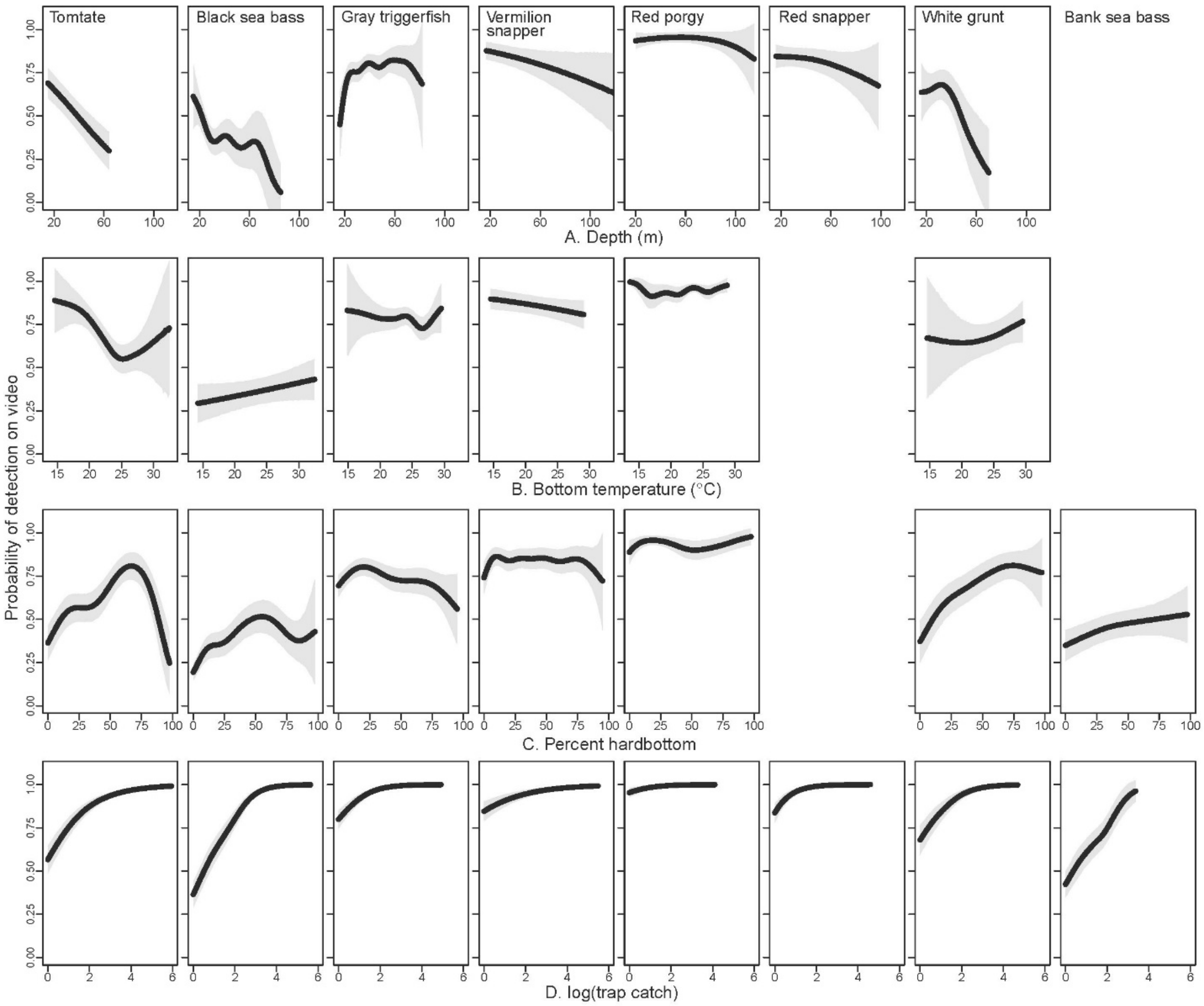

Fig. 5. Video detection probabilities for eight reef fish species related to continuous predictor variables: (A) bottom depth (m), (B) bottom temperature (°C), (C) percent hardbottom, and (D) their own log-transformed trap catch from corresponding traps. Data were collected between North Carolina and Florida in 2015–2023 by the Southeast Reef Fish Survey. Black lines indicate estimated video detection probabilities and gray shaded areas indicate 95% confidence intervals. Data are only shown for species where that predictor variable was included in the final model based on the Akaike information criteria.