Use of passive acoustic monitoring to estimate fishing effort on artificial reefs in Alabama during the recreational red snapper fishing season

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ABSTRACT

Estimating fishing effort is an important aspect of effective fisheries management for populations such as red snapper (*Lutjanus campechanus*) in the Gulf of Mexico. Monitoring effort, however, can be limited by where and when anglers can be easily observed, such as boat launches or aerial surveys. Passive acoustic monitoring (PAM) can be used to detect boat presence spatially and temporally, which can be used to infer fishing effort. In this study, we deployed PAM devices at multiple artificial reef sites (up to three at a time) in federal waters of the Alabama Reef Permit Zone during the recreational red snapper fishery in 2017 and 2018. Reefs at our deployment sites included multiple structure types (concrete and steel pyramid modules, bridge rubble reefs, chicken coops, and M1 tanks). Reef sites included a mix of publicly available reef coordinates (published reefs) and unpublished sites. To improve reliability of estimates of site-specific fishing activity from captured boat noise, we developed a method to automatically detect sounds indicative of idling vessels maintaining station (live-boating) near an artificial reef. Detections of boat gearshift sounds were consistent with our prediction that fishing effort would be reduced on unpublished sites, decrease as the season progressed, and show a strongly diurnal pattern. Counter to our prediction, fishing effort as measured by boat detections did not appear to differ between open and closed recreational fishing days at our sites, which may be partially explained by commercial fishers that operate on an individual quota system that allows for fishing on days closed to recreational fishers. Our results indicate that PAM in conjunction with this novel method could be an effective way to monitor daily and longer-term patterns of live-boating fishing vessel presence at specific artificial sites for the red snapper fishery in the Gulf of Mexico.

1. Introduction

Fisheries management requires estimation of fishing effort, which can vary spatially, diurnally, and over the course of a managed season. This variation increases the difficulty of obtaining reliable estimates of fishing effort and has implications for sampling design. A variety of technologies are used to monitor fishing effort, such as direct observation or video of boat launches (Powers and Anson, 2016, 2018; Hartill et al., 2020), long-range cameras to observe fishing grounds (Flynn et al., 2018; Becker et al., 2020), aerial surveys (Askey et al., 2018), dock-side intercept (Rocha et al., 2004; Liu et al., 2017), phone/mail interviews (Brick et al., 2012), and smartphone apps (Liu et al., 2017; Midway et al., 2020). Camera based analyses of fishing grounds may be restricted to daylight hours or require thermographic cameras that may

limit the sampling area and distance to a monitored site (Taylor et al., 2018). Further, monitoring fishing effort can be costly and may limit the duration of observation and require many personnel to aid in analysis.

Passive acoustic monitoring (PAM) technology can be used to detect underwater vessel sound and thus may be advantageous for studying fishing activity. PAM devices operate for extended time periods and can monitor activity at all hours of the day. Further, PAM is non-obtrusive and can be deployed underwater and thus is unlikely to be seen and influence angler behavior. Small vessels produce harmonic sound that is distinct from most natural sound sources and can be detected and classified with PAM (Pollara et al., 2017). The use of multiple PAM devices may allow for spatial and temporal information on fishing boat detection. PAM has been used to discriminate between different kinds of vessel sound associated with legal and illegal fishing in the north Pacific

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and Bering Sea based on spectral characteristics (Abileah and Lewis, 1996). Simard et al. (2016) used PAM to estimate boat visitation rates between natural and artificial reefs off western Florida. Thus, PAM data can be used to quantify differences in fishing vessel presence among locations over time.

The red snapper (*Lutjanus campechanus* [Poey]) fishery in the Gulf of Mexico (GOM) is a major commercial and recreational fishery that has profound economic and cultural importance to the region. Management of this fishery has been controversial (Cowan et al., 2011) and methods to effectively study fishing effort are important for stock management. PAM may be a useful method for producing estimates of fishing effort for GOM red snapper and such methods could be refined to reduce the workload for studying fishing effort and to improve reliability of estimates obtained from acoustic observations.

PAM recorders can easily obtain sounds from the intense noise produced by boats and larger vessels (Barlett and Wilson, 2002; Simard et al., 2016). Fishing vessels produce relatively tonal sounds that can be detected once sound levels exceed a signal-to-noise ratio (SNR) threshold as the vessels approach a site. However, vessels leaving a fishing ground or passing a fishing ground at a sufficiently close distance will also be detected. Simard et al. (2016) recently applied a model based on empirical evidence of how frequently boat noise events detected on a fishing ground were associated with boats stopping at a site to fish. However, in some cases it may not be practical to model the likelihood of vessels to stop at a reef.

Fishing on offshore artificial reefs typically involves maintaining station on the reef by switching between neutral and in gear to counteract currents and wind, termed 'live-boating.' Live-boating is used to maintain a station while anglers are fishing or used temporarily while a vessel homes in on a site to anchor. Therefore, both live boating and anchoring produce distinctive intermittent sounds as vessels shift in and out of gear that could be recorded on PAMs. In the present study, we developed a new method for automated detection of live-boating fishing vessels on offshore artificial reefs. We then show how PAM data and this novel method can be used to quantify spatial, diurnal, and longer temporal patterns of fishing boat presence in studies on fishing effort.

We examined the efficacy of PAM to detect fishing vessels during the recreational red snapper fishery in federal waters in Alabama. In this study, we aimed to detect vessels that stopped to fish at sites within the Alabama Reef Permit Zone by designing a detection algorithm for identifying these intermittent boat sounds that are associated with live boating at artificial reefs. We tested the efficacy of this method by estimating false positive and false negative rates. We then used this algorithm to examine patterns of boat detections at published and unpublished reefs in 2017 and 2018 on both open and closed red snapper fishing days. We predicted that fishing effort would be greatest on published reefs and on open fishing days, that fishing effort would wane as the red snapper season progressed, and that fishing boat detections would show a strong diurnal pattern.

2. Materials and methods

2.1. Passive acoustic monitoring effort

Three 'SNAP recorders' from Loggerhead Instruments (www.loggerhead.com, Sarasota, FL, USA) were used as PAM devices. The SNAP recorders used in this study have an HTI96-min hydrophone (High Tech, Inc., Long Beach, MS, USA) with sensitivities of − 169.6, − 170.2, and − 170.4 dB re V/μPa. Recordings were sampled at 44.1 kHz and stored as. WAV format files. In 2017, the SNAP recorders were programmed for continuous recording stored as individual five-minute.WAV files, which allowed for up to eight-day continuous recordings. In 2018, the SNAP recorders were programmed for 60 s recordings every five minutes. This 20% duty cycle allowed for up to 40 days of recording.

Recorders were deployed by scuba divers and placed on reefs by means of a ratchet strap and cable ties tied to the reef or to a sand screw

anchor adjacent to the reef (<3 m away). The recorder was mounted so that the hydrophone was oriented vertically. We did not randomly sample sites in this study. We chose sites based on logistical considerations that included a limited number of unpublished reef locations of which we were aware, costs of fuel and transport, the training depth limits of divers involved. We intentionally chose a variety of artificial reef types (pyramid, chicken transport device [TD], M-1 tank, and bridge rubble) and sampled an equal number of reefs with published and unpublished locations at the time of our study (Outdoor Alabama, 2017, 2018). Reefs for simultaneous deployments were a minimum of 2.5 km apart for all but one deployment series, in which two reefs 0.44 km apart were chosen to assess detection distances of boats (Fig. 1). In total, seven unpublished and seven published reef sites at depths between 21.6 and 30.2 m deep were sampled in 2017 and two unpublished and two published reefs between 28.0 and 31.1 m deep were sampled in 2018 (Fig. 1).

2.2. Detection algorithm

We designed a detection algorithm to search for rapid changes in sound amplitude that are associated with boat sounds as vessels go in and out of gear (Fig. 2). Sounds were high-pass filtered (2 kHz, 4th order Butterworth filter) library 'Signal' (Ligges et al., 2015) because leopard toadfish (*Opsanus pardus* [Goode & Bean]) calls were common at some sites and caused false positives in preliminary testing of unfiltered files. Recordings were then rectified and the median relative amplitude was calculated in 0.1 s increments. We then used an algorithm to save putative detections for adjacent 0.1 s portions on a recording that met two following criteria: (1) a median amplitude of at least 50 samples for the first 0.1 s portion and (2) an amplitude ratio between the first and second 0.1 s portions of > 2. Thus, this algorithm finds areas on the sound file where there is a rapid drop in amplitude (> 2 times) over a 0.2 s period. This threshold was chosen because preliminary testing indicated that it was conservative and would avoid false positives but worked on a limited dataset for testing. The script then saved a.csv file with the (1) file number (from the directory of sound recording [. WAV] files), (2) the location (in samples) of the putative detection within the recording file, (3) the median amplitude of the first 0.1 s region being compared, and (4) the median amplitude of the second 0.1 s region being compared. With this R routine, to scan eight days' worth of continuous recording (1440 h, 2304 five-minute duration.WAV files, 59.5 GB) took approximately three hours on a duo core Windows 64-bit computer with 8 GB of RAM.

2.3. Screening for false positives and false negatives

All putative detections were examined aurally and spectrographically (in Adobe Audition 3.0) for veracity. This was done in Adobe Audition 3.0 software. Locating a putative detection within a five-minute file was expedited by pasting the sample location of the putative detection from the R routine results into the selection view to move the cursor to the location of the putative detection. We refer to boat gearshift sounds that appear to be from idling boats after review as 'confirmed detections'.

To estimate the rate of false negatives in 2017 and 2018, we examined two randomly sampled subsets of our data for each year: 50 files with confirmed detections and 50 files without putative detections. Files with confirmed detections are likely to contain other impulsive boat sounds that may be missed by the parameters of the detection algorithm. Thus, an estimate of the proportion of impulsive boat sounds detected relative to the total number of impulsive boat sounds from these files should provide a conservative estimate of the false negative rate. We also chose to screen a random set of files that lacked putative detections because this method could provide an estimate of how frequent false negatives are among the broader data set. These data distributions were non-normal (Shapiro-Wilk test) and thus we report the median, range,
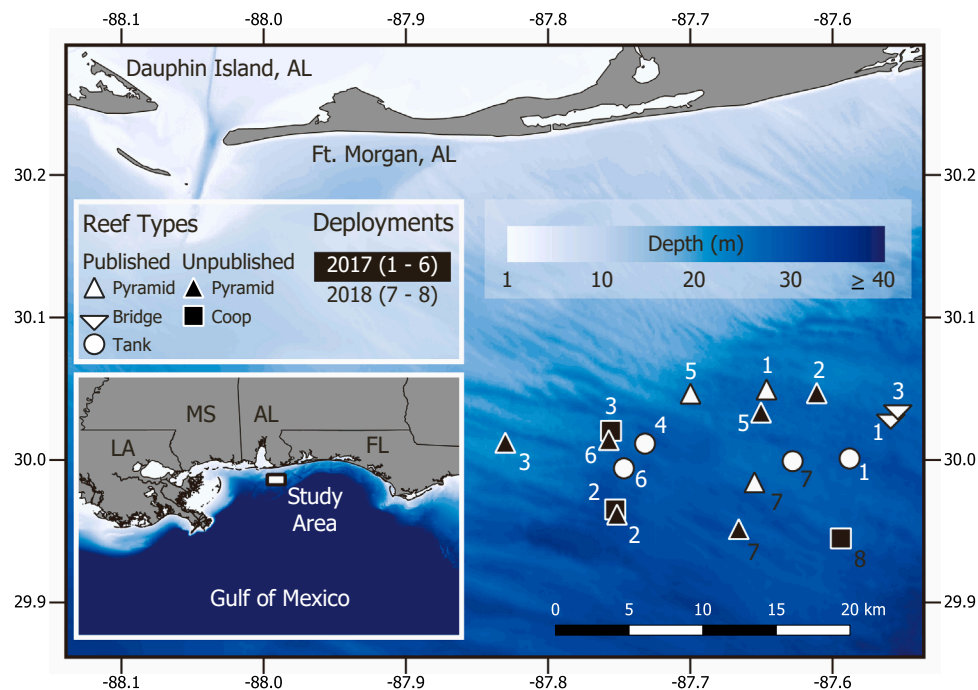
Fig. 1. Locations of 18 artificial reef sites in the Alabama Reef Permit Zone that were examined with passive acoustic monitoring during 2017 and 2018. Deployment numbers correspond to the following dates in 2017 (1 = 30 May, 2 = 18 June, 3 = 10 July, 4 = 18 July, 5 = 1 August, 6 = 8 August) and 2018 (7 = 25 June, 8 = 16 July).

and interquartile range (IQR).

2.4. Data analysis of confirmed detections

Analysis and graphical representation of confirmed impulsive boat sounds began with binning observations into five-minute intervals (i.e., each five-minute.WAV file was classified as either with or without impulsive boat sounds present). We were careful to restrict the analysis to recorded files that were made after deployment vessels were no longer audible. We examined the duration of boat visits to artificial reefs by calculating the median, range, and 95th percentile of the number of consecutive files with boat detections. We also calculated these descriptive statistics for the duration of time (number of five-minute bin files) between consecutive boat detections.

Diel patterns of idling boat presence were examined by calculating the hourly detection frequency (proportion of five-minute bins per hour with detections of boat gearshift sounds). We tested for a difference in detection rate among reefs on open red snapper fishing days and closed days by calculating the proportion of five-minute bins with at least one detection over the available period of time on open and closed days for each reef. Shapiro-Wilk normality tests indicated non-normal data, even after attempted transformation. Because of data non-normality, we used a Wilcoxon signed rank test to compare the difference in relative detection rate on open and closed fishing days among reefs in 2017 and 2018. We tested for differences between detection rates on published and unpublished reefs by first calculating the proportion of five-minute bins with at least one detection for the recording period for each reef in 2017. Data were not normally distributed, so we used a Mann-Whitney *U*-test to compare the boat detection rates between published and unpublished sites from 2017. This comparison was not possible for 2018, because of the small total sample size: two published and unpublished sites, respectively.

We examined relationships of daily boat detections (proportion of files per day where boat gearshift sounds were detected) with date (relative to the start of the recreational season), reef status (published/unpublished), and fishing day (open/closed). Because data were zero-inflated, we tested these relationships with hurdle models that were run using the glm R function (R Core Team, 2019) and consisted of a binomial generalized linear model (family = binomial, link = logit), coupled with a gamma GLM (family = Gamma, link = log) run on non-zero proportion data. For the binomial model, we assigned a value of one to days with at least one detection and a value of zero to days with no detections. In addition to the main effects described above, we included the interaction of date and fishing day and the date by reef status interaction as full model predictor variables in both model types. For each model type, we selected the best fitting model as the one with the lowest corrected Akaike information criteria (AICc) using the R function 'dredge' (Bartoń, 2019). We used the best fitting binomial and gamma GLMs to predict, respectively, the probability of daily detections and the proportion of daily detections when detections were present. We multiplied these predictions to obtain the overall predicted daily detection proportion. Given the differences between 2017 and 2018 data collection, we performed this analysis framework separately for each year.

3. Results

In 2017, a total of 2252.75 h of recordings from 51 days was examined between 31 May–16 August. In 2018, a total of 451.8 h of recordings spanning over 43 days (because of the 20% duty cycle) was examined between 25 June - 6 August. In 2017, when verified boat gearshift sound detections occurred within a five-minute sound file, on average there were 4.8 boat impulsive sound detections per file. Further, 75% of sound files with boat detections in 2017 had two or more detections. Thus, there is potential to record on a duty cycle, thereby extending the runtime, without much reduction in vessel detection within five-minute intervals.

The effectiveness of the boat gearshift detection algorithm was demonstrated by detections of the deployment vessels (*R/V E.O. Wilson* and *Nancy M.*). In 2017, when continuous recording was used, the idling deployment vessel was detected on all deployments (mean number of five-minute files + SD that contained deployment vessel detections:
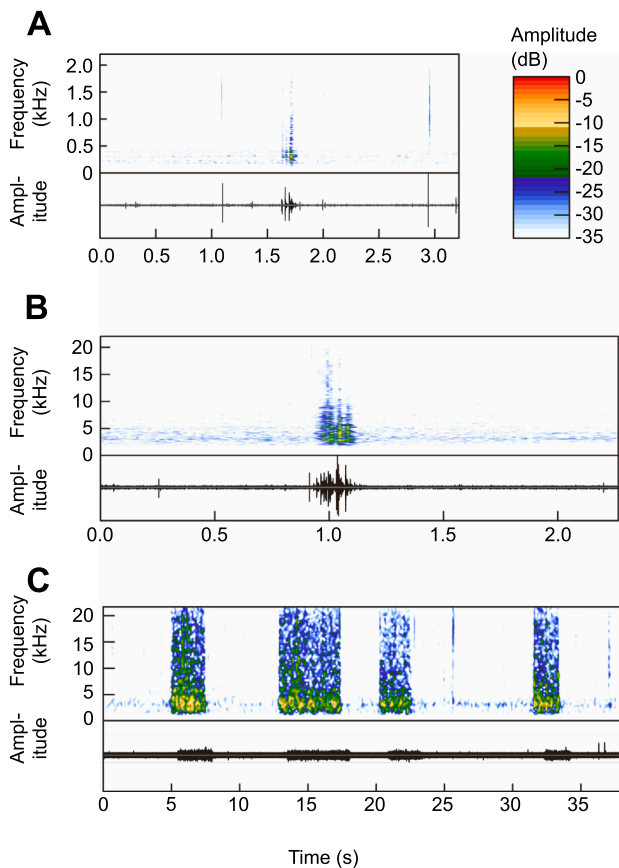
Fig. 2. Spectrograms and oscillograms of three example (A-C) impulsive boat gearshift sounds that occur while boats are maintaining station and were detected with the algorithm described in this study. Oscillograms (bottom) and associated spectrograms (top) are shown for each sound. Sounds were high-pass filtered (fourth order Butterworth filter) before plotting and as part of the algorithm procedure. Boat sounds in A and C are sounds from unknown vessels, while the sound in B is from the deployment vessel. The sound in C is slightly different and appears to occur when thrust is applied to the propeller, but all three sounds are predicted to be associated with vessels maintaining station (live-boating) an artificial reef.

4.29 +1.77 files, range 2–9 files). In 2018, with a 20% duty cycle, the detection rate was slightly lower (mean number of one-minute files + SD with deployment vessel detections: 0.75 +0.96, range 0–2 files). This difference in deployment vessel detection between years is likely explained, at least in part, by the 20% duty cycle in 2018, which lowered the opportunity to detect potential boat sounds. In addition to detection of boat gearshift sounds, in 2018, sounds of scuba divers were observed at a published tank reef (Fig. 1, deployment 7) as a false positive and a boat gearshift sound had been detected at the same reef five minutes earlier. Thus, we predict that the boat that brought the divers was

detected once despite the 20% duty cycle.

3.1. False positives

The number of files in 2017 and 2018 with detections exceeded false positives (Table 1). False positive occurrences were variable in 2017 (Table 1) and some reefs had no false positives. The number of total false positives at reefs was somewhat higher, as files with false positives often had multiple occurrences (Table 2). Total false positives averaged over six events per day in 2017 and over two events per day in 2018 (Table 2). In both 2017 and 2018, the greatest source of false positives was something making physical contact with the hydrophone, possibly invertebrates (Tables 1 and 2). Other relatively rare sources of false positives were atypical sounds from running (non-idling) boats, whistles from dolphins (possibly common bottlenose dolphins, *Tursiops truncatus* [Montagu]) (Hayes et al., 2019), and one instance of scuba divers detected in 2018 (Tables 1 and 2). In 2017, alpheid snapping shrimp sounds (Au and Banks, 1998) were a common source of false positives at a single bridge rubble reef (Tables 1 and 2).

3.2. False negatives

The algorithm used in this study had modest false negative rates (Table 3). When idling boats were present, the algorithm missed 39 + 35% (mean+SD) of gearshift sounds per five-minute file in 2017 and 20 + 28% of gearshift sounds per one-minute file in 2018. Because we analyzed detections in five (2017) and one-minute bins (2018) and there are more opportunities for detections of at least one gearshift sound event over a sound file, false negatives among bins likely occur at a much lower rate. Estimated false negatives among bins from randomly screened files indicated a false positive rate of 2% in 2017 and 0% in 2018.

3.3. Double detections

In some cases, two sequential putative detections from the algorithm in this study occurred for the same impulsive boat sound – double detections. Two subsamples of 50 files examined for false negatives in 2017 and 2018 indicated that in both cases, 12% of files had at least one double detection. Double detections occurred because of imprecision of the detection algorithm resulted in some cases when boat gearshift sounds continued to decay after the second 0.1 s sound segment used by the detection routine. Because the next iterative screening of raw data began at the start of the second 0.1 s segment of the former screening iteration, it was possible to have cases of two subsequent detections (double counts) separated by 0.1 s. Double counts had no impact on interpretations of boat presence because our subsequent analyses were binned over five-minute intervals as boat presence/absence.

3.4. Detection distance

The deployment of two recorders on reefs (deployment 2) 0.44 km

Table 1

Frequency of idling boat detections, false positives (total), and false positives by sound source from 2017 and 2018 passive acoustic monitoring devices on artificial reefs in Alabama. Data are percentages of individual sound files containing detections or false positives. SD=standard deviation.

	2017 Percent of files					2018 Percent of files				
	mean	SD	min	max	median	mean	SD	min	max	median
Detections	1.52	1.97	0.00	6.61	0.44	0.75	1.22	0.00	2.56	0.22
Total False Positives	0.81	0.85	0.00	2.82	0.55	0.07	0.03	0.03	0.10	0.07
Object contacting hydrophone	0.45	0.61	0.00	2.44	0.28	0.46	0.47	0.00	0.89	0.48
Boat sound, not idling	0.14	0.16	0.00	0.46	0.12	0.26	0.51	0.00	1.03	0.00
Dolphin whistle	0.05	0.09	0.00	0.37	0.04	0.21	0.25	0.00	0.48	0.18
Snapping shrimp	0.17	0.64	0.00	2.40	0.00	0.00	0.00	0.00	0.00	0.00
Scuba divers	0.00	–	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00

Table 2

Rate of total false positives and false positives by sound source from 2017 and 2018 passive acoustic monitoring devices on artificial reefs in Alabama. Data are the rate of false positives per 24 h of recording. SD=standard deviation.

	2017 Rate (no. per day)					2018 Rate (no. per day)				
	mean	SD	min	max	median	mean	SD	min	max	median
Total false positives	6.73	13.24	0.00	50.89	2.18	2.12	1.67	0.60	4.11	1.88
Object contacting hydrophone	5.12	13.12	0.00	50.03	1.29	0.29	0.50	0.00	1.03	0.06
Boat sound, not idling	0.57	0.64	0.00	1.84	0.38	0.12	0.24	0.00	0.48	0.00
Dolphin whistle	0.21	0.41	0.00	1.58	0.12	1.03	2.06	0.00	4.11	0.00
Snapping shrimp	0.84	3.13	0.00	11.70	0.00	0.00	0.00	0.00	0.00	0.00
Scuba divers	0.00	–	0	0.00	0.00	0.30	0.60	0.00	1.20	0.00

Table 3

Estimated false negative rates of boat gearshift sounds from 2017 and 2018 recordings from passive acoustic monitoring devices on artificial reefs in Alabama. A conservative estimate of false negative rates was determined by manually screening 50 files with detections from the algorithm used in the study for both 2017 and 2018 datasets and counting the total number of gearshift sounds. This total was used to determine the number of missed detections (false negatives) by the algorithm. False negatives estimated from 50 randomly selected files that lacked detections (50 ea. in 2017 and 2018), an estimate of how likely the detection routine is to miss all cases of boat gearshift sounds over an entire five-minute (2017) or one-minute (2018) file, indicated a low overall (2% for 2017 and 0% for 2018) false negative rate among files.

	2017 No. of cases per five-minute file			2018 No. of cases per one-minute file		
	median	range	interquartile range	median	range	interquartile range
Method 1						
False negatives	1.5	0–55	0–7	0	0 – 6	0–1
Detections by algorithm on same files	2	1–82	1–9	1	1–12	1–3

apart provided an opportunity to assess detection distance of boat sounds using this method (Fig. 1). During deployment at the second site (a pyramid), the deployment vessel was recognized twice by the automatic detection algorithm 0.44 km away at the first site (a coop) and once at the second site. Poor signal-noise ratio at the pyramid site caused by scuba noise from divers during deployment may have contributed to the missed detection. In the subsequent 15 min, the deployment vessel was detected automatically seven times at the nearest pyramid reef, but not automatically detected at the more distant coop site. Aural examination of files from both reefs at this time indicated that 63.6% of the gearshift sounds from the deployment vessel were detected in these 15 min at the closer pyramid reef, while no sounds were automatically detected at the site 0.44 km away.

Among these two reefs, automatic detections from unknown vessels only occurred at the coop site. Aural examination of sound files from both reefs over this period (9:11–9:31 on 19 June 2017) indicated that 71 impulsive vessel sounds were audible on recorders from both sites, but louder at the coop site that was presumably closer to the vessel and 46.5% of these sounds were automatically detected at the coop site.

3.5. Duration of boat presence and time between boat visits at artificial reefs

Reef visits by boats usually appeared to of brief duration. The median duration of consecutive detections (number of five-minute bins) was 10 min, ranged between range 5–85 min, and 95% of observations were < 38.5 min. The median amount of time between boat detections was 50 min, ranged from 5 min (< 5% of observations) to 20 days (unpublished pyramid, deployment 7 in 2018, Fig. 1), and 95% of observations were < 2.8 days.

3.6. Boat detections on open and closed fishing days and at published and unpublished reefs

In 2017, the difference between boat detections (proportion of five-minute intervals with detections) on open (median = 0.0041) and closed fishing days (median = 0.0049) was greater than would be expected by chance (Wilcoxon Test $V = 58$, $n = 7$, $p = 0.029$) (Fig. 3 A). In 2018, the

median proportion of time with boat detections was 0.018 on open fishing days and 0.007 on closed fishing days. This observed difference was not greater than would be expected by chance ($V = 3$, $n = 4$, $p = 0.371$), but the low sample size ($n = 4$) results in low statistical power. Overall rates of 2017 boat detections between published reefs (median = 0.023) and unpublished reefs (median = 0.002) were not different than would be expected by chance (Mann-Whitney $U = 12$, $n = 7, 7$, $p = 0.124$; Fig. 3B). On open fishing days, however, boat detections were greater on published reefs (median = 0.041) than unpublished reefs (median = 0) (Mann-Whitney $U = 6$, $n = 7, 7$, $p = 0.020$; Fig. 3C). On closed fishing days, differences between boat detection rates on published (median = 0.007) and unpublished reefs (0.003) were not greater than would be expected by chance (Mann-Whitney $U = 19$, $n = 7, 7$, $p = 0.514$; Fig. 3D).

3.7. Daily boat detections across the 2017 and 2018 seasons

A negative relationship between boat detections and days since the start of the 2017 red snapper recreational fishing season was present in our hurdle model. The best fitting binomial model component (Supplemental Table 1) predicted that the probability of boat detection decreased by a factor of 0.97 ($p = 0.002$) with each subsequent fishing season day (Table 4). Furthermore, boat detection probability was 3.75 ($p = 0.004$) times greater on open fishing days than closed (Table 4). The best fitting gamma model component (Supplemental Table 1) exhibited a similar pattern with fishing days; predicted boat detections were 2.10 ($p = 0.013$) times greater on open fishing days, but no date effect was present. Neither reef status (published or unpublished) nor interactions were significant in either model components. When both model types were combined, the proportion of boat detections decreased as the fishing season progressed and daily boat detections were greater on open fishing days (Fig. 4).

In 2018, boat detection probability decreased on unpublished reefs with elapsed fishing season, but this relationship was not present on published reefs. This effect was captured by a significant interaction between date and reef status ($p = 0.002$) in the best fitting binomial hurdle model component for 2018 (Supplemental Table 2, Table 5), however, the overall effect of date was not significant ($p = 0.094$), but
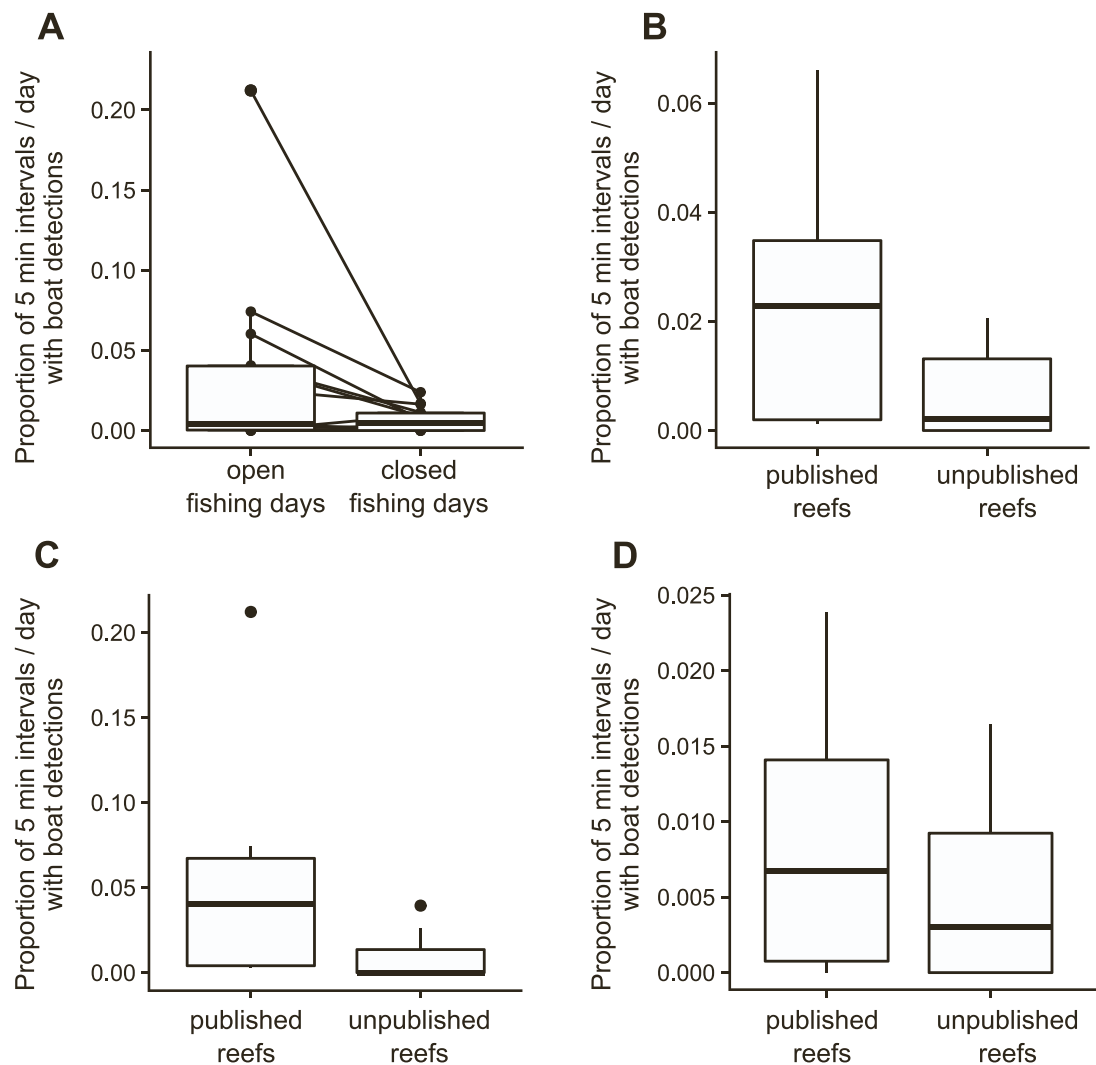
Fig. 3. Comparison of the average daily boat detections from Alabama artificial reefs in 2017 on open and closed days among reefs (A) and between published and unpublished reefs on all days (B), open fishing days (C), and closed fishing days (D). Daily boat detection frequency was estimated by calculating the proportion of five-minute intervals that contain one or more impulsive boat sounds per day. The quartiles are indicated by the span of each box, the median by the horizontal line within the box, and the whiskers denote the range of data within an additional 1.5X the interquartile range above. Note the differences in scale between plots A - D.

Table 4

Results of our hurdle model on boat detection rates on artificial reefs in Alabama over the length of the 2017 recreational red snapper season, including the best fitting binomial and gamma components. The coefficients and their estimates are reported, along with the exponentiated estimates (e^{Est}) which are the factor change in odds and magnitude for the binomial and gamma model components respectively. Standard errors (SE), z and p values are also reported for each parameter. Open indicates days when the fishing season was open.

Binomial					
Coefficient	Estimate	e^{Est}	SE	z value	p value
Intercept	-0.109	0.896	0.363	-0.301	0.764
Date	-0.029	0.971	0.009	-3.110	0.002
Fishing Day (Open)	1.322	3.754	0.460	2.878	0.004
Gamma				**t value**	
Intercept	-3.551	0.029	0.200	-17.759	< 0.001
Fishing Day (Open)	0.739	2.095	0.283	2.615	0.013

there was a significant main effect of reef status (published or unpublished) (p = 0.016). Boat detection probability boat was 3.15 times higher (p = 0.026) on open fishing days than closed, similar to observations in 2017. The best fitting gamma hurdle model component only included the intercept term (Supplemental Table 2, Table 5). The same

overall relationships were present when component model predictions were combined. Boat detection proportions were higher on open fishing days and decreased with fishing season on unpublished reefs (Fig. 5).

3.8. Diel patterns

In 2017, detections over a 24-hour period followed a largely diurnal pattern (Fig. 6). On unpublished reefs during closed fishing days, the highest detections overall occurred at 10 h and the highest detections in the afternoon occurred at 16 h (Fig. 6A). Published reefs on closed fishing days had peak detections at 13 h, with a morning peak of 9 h and afternoon peak at 17 h (Fig. 6B). On open fishing days, unpublished reefs had detections from 7 to 13 h and 15–18 h, with the most detections at 10 h and most afternoon peaks at 18 h (Fig. 6C). Published reefs on open fishing days had activity from 6 to 16 h, with a morning peak at 9 h (Fig. 6D). In addition, published reefs on open fishing days also had lower amounts of activity detected in some evening hours 20 h and 0 h (Fig. 6D).

Boat detections in 2018 were also mainly diurnal (Fig. 7). Unpublished reefs on closed fishing days had a peak at 9 h and an afternoon peak at 13 h (Fig. 7A). On published reefs on closed days, detections occurred from 7 to 18 h, with a peak at 9 h (Fig. 7B). On open fishing
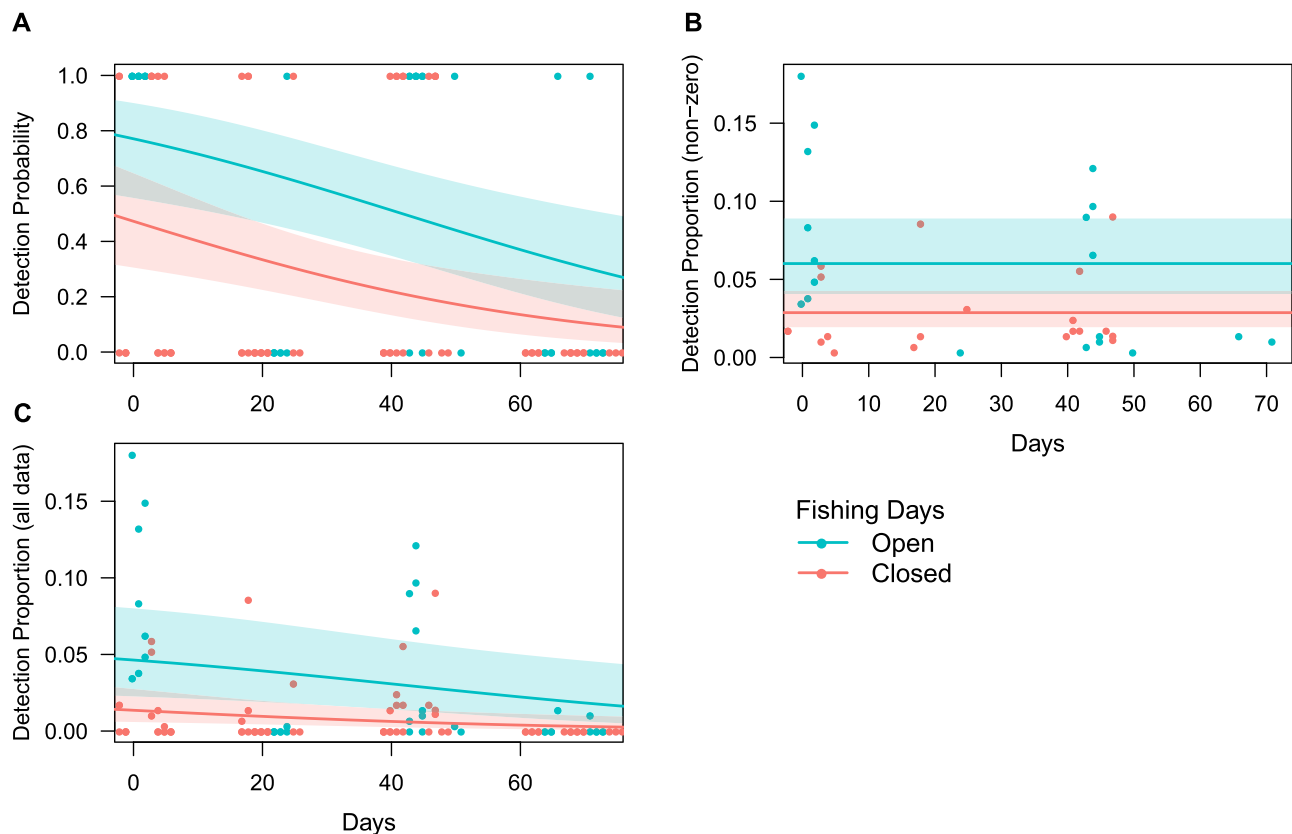
Fig. 4. Predictions from our best fitting hurdle model to describe the relationship between boat detection, fishing day, and time since the start of the recreational red snapper fishing season on Alabama artificial reefs in 2017. The boat detection binomial response (points), the predicted probability (lines), and 95% confidence intervals (shaded regions) for open and closed fishing days from our binomial model plotted against fishing season day (Date, A). Non-zero boat detection proportions (proportion of five-minute bins per day where boat gearshift sounds were detected [points]), the Gamma model predictions (lines), and 95% confidence intervals (shaded region) on open and closed fishing days (B). The combined predictions of both models (C), which we obtained by multiplying the binomial predictions times the gamma predictions (panel A x panel B = panel C).

Table 5

Results of our hurdle model on boat detection rates on artificial reefs in Alabama over the length of the 2018 recreational red snapper season, including the best fitting binomial and gamma components. The coefficients and their estimates are reported, along with the exponentiated estimates (e^{Est}) which are the factor change in odds and magnitude for the binomial and gamma model components respectively. Standard errors (SE), z (binomial), t (gamma), and p values are also reported for each parameter. Open indicates days when the fishing season was open and reef status effects are for unpublished reefs (U).

Binomial					
Coefficient	Estimate	e^{Est}	SE	z value	p value
Intercept	-1.940	0.144	1.152	-1.685	0.092
Date	0.041	1.041	0.024	1.673	0.094
Reef Status (U)	4.616	101.098	1.922	2.402	0.016
Fishing Day (Open)	1.148	3.153	0.517	2.221	0.026
Date x Reef Status (U)	-0.146	0.864	0.047	-3.108	0.002
Gamma				**t value**	
Intercept	-2.384	0.092	0.144	-16.572	< 0.001

days, unpublished reefs had a morning peak at 8 h and an afternoon peak at 14 h (Fig. 7C). On published reefs on open fishing days, activity occurred from 6 to 16 h, with a peak at 6 h (Fig. 7D). In addition, published reefs on open fishing days also had activity at 19 h and in the evening at 23 h (Fig. 7D).

4. Discussion

This study demonstrated that PAM can be used to detect impulsive boat sounds from vessels holding station, and these data can be used in studies for estimating fishing effort. Recordings from multiple sites in the Alabama Reef Permit Zone in two seasons showed that, under a variety of background noise levels from biological sounds and vessels underway, it is possible to obtain sounds from boat gearshift sounds from idling boats with sufficient SNR for automated detection. Boat detection patterns from this study generally confirmed our prediction that fishing effort would wane with season, published sites would have more fishing vessel visits than unpublished sites, and that fishing effort would be strongly diurnal.

4.1. Decreasing effort over the recreational red snapper season

In 2017, boat detections decreased with increasing time since the start of the fishing season. The decrease in detections over the season observed in 2017, is consistent with boat ramp observation estimates of fishing effort from 2017 (Powers and Anson, 2018). The 2017 recreational red snapper fishery experienced two fishing seasons, one compressed three-day season and an unanticipated 39-day season. Fishing effort in the second unanticipated 2017 season was reduced relative to the compressed original three days (Powers and Anson, 2018). Similar reductions in effort were observed during the 2017 recreational red snapper fishery in Texas in 2017 (Topping et al., 2019). In our data from 2018, there was also evidence for a decrease in fishing effort on unpublished reefs throughout the fishing season. Angler interest may be higher earlier in the season after a longer hiatus of fishing and may also be motivated to fish early before anticipated quotas are met. A reduction in angler effort over the season could also occur in response to declining
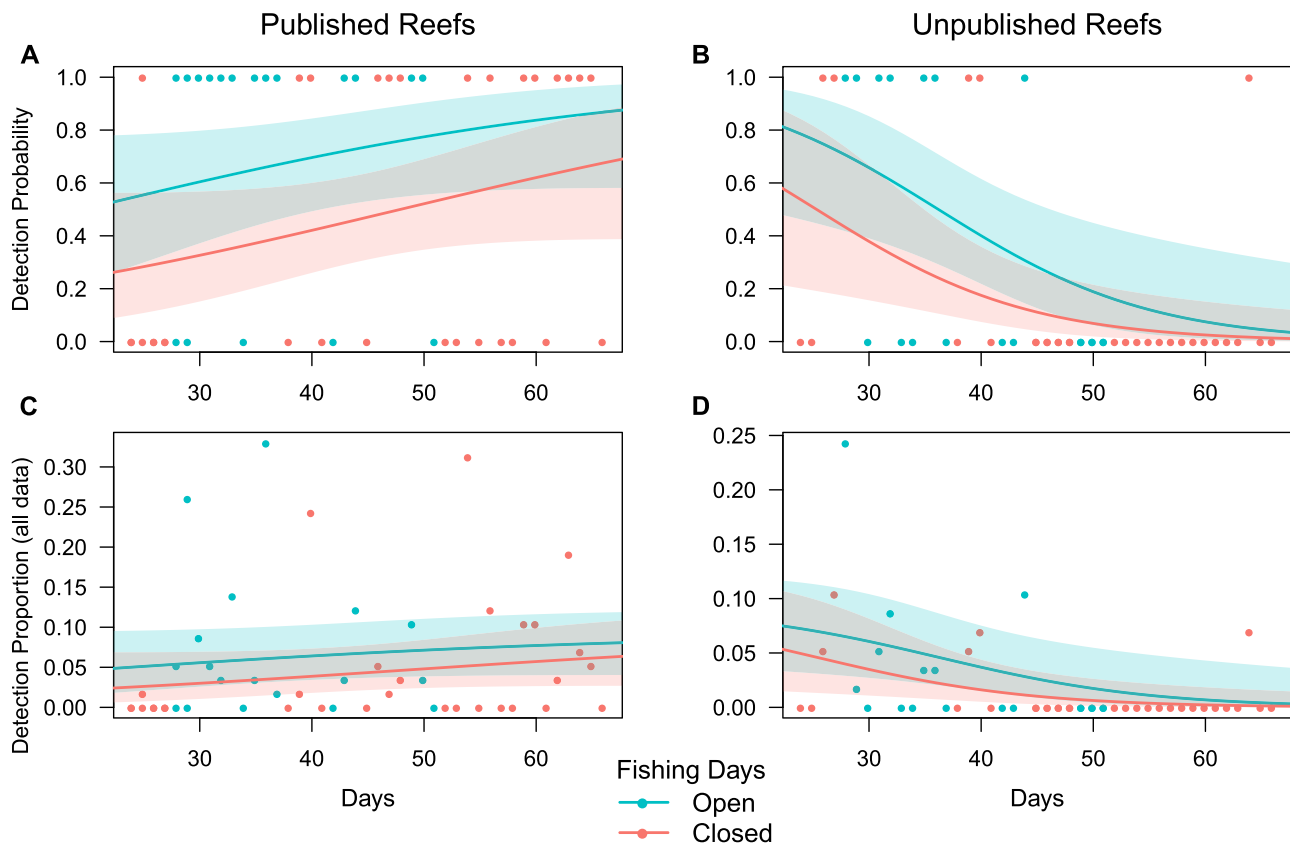
Fig. 5. Predictions from our best fitting hurdle model to describe the relationship between boat detection, fishing day, and time since the start of the recreational red snapper fishing season on Alabama artificial reefs in 2018. The boat detection binomial response (points), the predicted probability (lines), and 95% confidence intervals (shaded regions) for open and closed fishing days from our binomial model on published (A) and unpublished reefs (B). The combined predictions of the 2018 intercept only Gamma model and the binomial model on published (C) and unpublished reefs (D).

CPUE over the season. Anglers may be predicted to reduce fishing if available fish become more scarce ('give-up' density), however angler motivation is likely influenced by a range of factors (Post, 2013). For example, in a study surveying recreational anglers of the red snapper fishery in the Gulf of Mexico, increased season length was preferred even if it resulted in a reduction in allowable catch from two to one fish per angler (Abbott et al., 2018).

When temporal trends were investigated, boat detections on open fishing days were higher than closed fishing days as expected. However, no difference was detected in 2017 when all data (from both open and closed days) were compared across the fishing season. Boats detected on non-open days could have been head boats (larger for-hire vessels that typically carry more than six recreational anglers) or charter vessels (smaller for-hire vessels), both of which were permitted to take passengers for red snapper fishing during the federal for-hire season that included some weekdays in 2017 and 2018 during which private recreational red snapper fishing was not permitted. Detections on closed days also could come from private vessels targeting species other than red snapper, recreational vessels violating regulations in federal waters, or commercial long-line fishing vessels, as some small for-hire vessels and commercial fishing vessels are similar to boats used by recreational anglers. We did not attempt to predict vessel types from acoustic signatures in this study. Using prior probabilities by incorporating other methods for vessel activity could be used to model and predict the activities of vessels on closed fishing days (van Poorten and Brydle, 2018). Discrimination of commercial fishers and head boats from recreational vessels could also be achieved by developing methods to automatically screen and classify features of boat sounds based on acoustic signatures (Pollara et al., 2017; Vieira et al., 2019) or to incorporate vessel monitoring system (VMS) data of commercial vessels in an analysis (O'Farrell

et al., 2017; Ducharme-Barth and Ahrens, 2017; Zhang et al., 2018).

4.2. Fishing effort on published and unpublished artificial reefs

Our study revealed differences in boat gearshift sound detections on published and unpublished reefs during open red snapper fishing days in 2017. This observation was consistent with our prediction. Unpublished reefs are often assumed to have lower fishing pressure and this assumption has even been the basis for deployment of artificial reefs without publicizing reef locations as a fisheries management strategy to increase stocks (Addis et al., 2016). In this study., we found that across the entire recreational red snapper season in 2017, unpublished reefs had comparable fishing vessel presence. On open fishing days, however, published reefs had greater vessel detection rates than unpublished reefs. Further, the highest observed detections on unpublished reefs occurred on closed fishing days but detections on published reefs on open days tended to be an order of magnitude higher. These observations are consistent with the prediction open days have more recreational anglers on the water that may be less aware of unpublished reef locations, while closed days are more likely to have commercial anglers and charter vessel and head boat captains that are more likely to have familiarity with unpublished fishing grounds. This study demonstrated that this simple algorithm can be used with PAM data to detect and test for differences in boat visits at sites predicted to have differences in fishing effort. These methods could easily be applied to test for differences at remote sites (e.g., reefs at the southern end of the Alabama Reef Permit Zone) and unpublished artificial reefs to inconspicuously monitor boat presence in an area over time. Using PAM to monitor efforts at rare sites in conjunction with PAM devices at sites with better estimates of fishing effort, i.e., multiple method estimates employed,
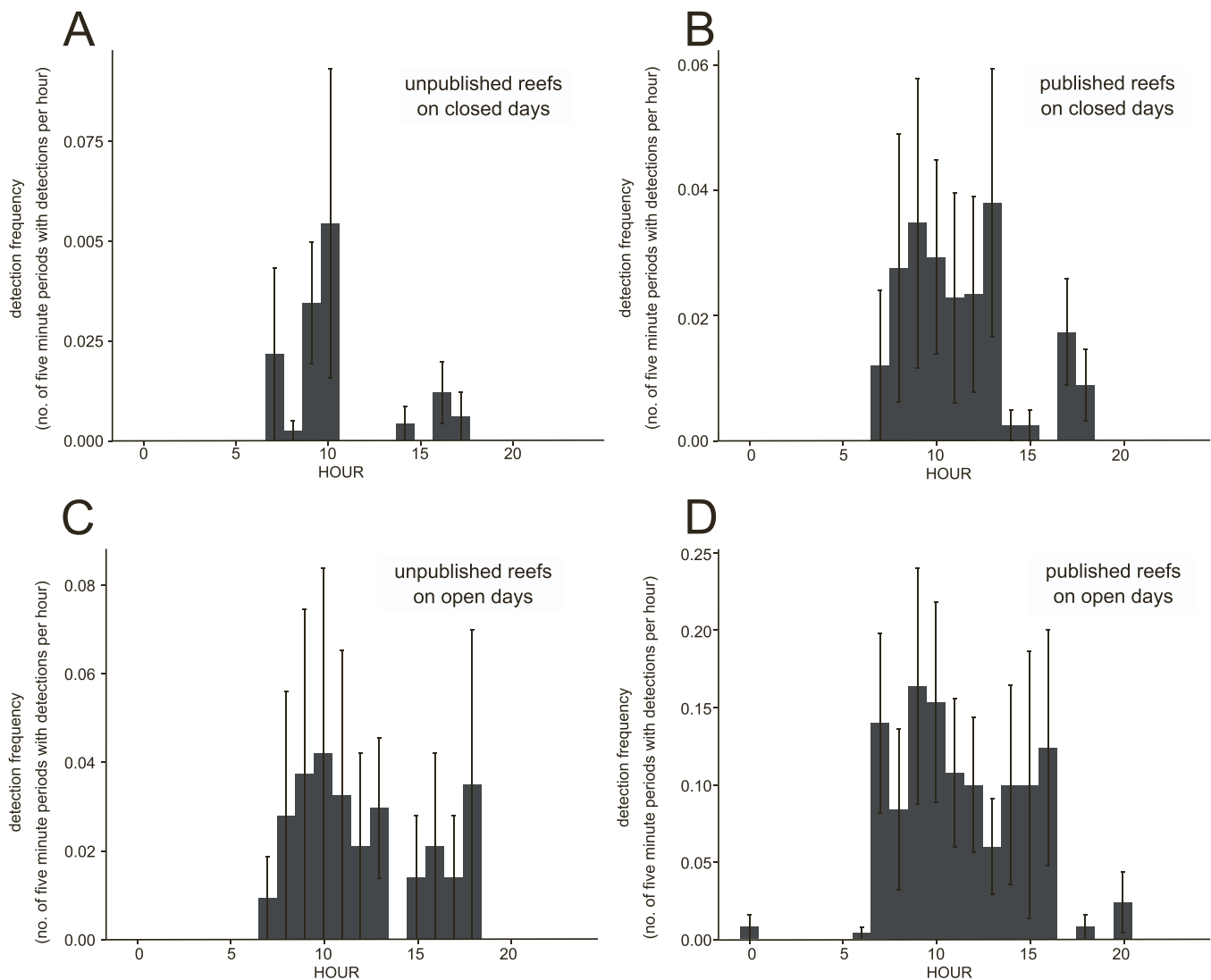
Fig. 6. Average + SE hourly boat detection frequency (proportion of five-minute intervals each hour with one or more boat detections) on Alabama artificial reefs in 2017 from (A) unpublished reefs on closed fishing days, (B) published reefs on closed fishing days, (C) unpublished reefs on open fishing days, and (D) published reefs on open fishing days. Note differences in scale between panels.

would further improve the reliability of this method.

4.3. Diel cycles of fishing activity

Impulsive boat sound detections in this study largely followed our predictions of diel patterns based on assumptions of angler behavior. As expected, nearly all detections occurred during daylight hours. Based on our 2017 data, peak fishing activity appeared to occur mid-morning with a second smaller afternoon peak for both published and unpublished sites. Such a pattern might be expected for anglers slowing down fishing activity during lunchtime, in transit to other sites for afternoon fishing efforts, anchored during a mid-day fishing lull, or perhaps taking shorter morning and afternoon half-day trips. In our 2018 observations a bimodal distribution with morning and afternoon activity peaks was evident at unpublished reefs but not at published reefs. The 2018 sample size, however, is much smaller and may represent a difference in fishing behavior representative of only the sites chosen. These 2018 data are limited to four total sites. Two of these deployments were cut short because the recorder malfunctioned and thus the data mainly represent one published and unpublished reef each.

4.4. Considerations and recommendations for use in other studies

Our observations from continuous recording in 2017 indicate that most five-minute recording files contained multiple impulsive boat sound detections. Thus, it would be possible to record on a duty cycle and maintain a high likelihood of detecting boat gearshift sounds. Use of a duty cycle could reduce costs of more frequent deployments and provide longer term data at a site without a significant loss in vessel detection. On average, there were nearly five boat detections per five-minute sound file. Thus, a 20% duty-cycle (recording one-minute every five minutes) should maintain a similar detection rate but allow the recorder to remain active up to 40 days.

Use of additional methods to infer angler behavior at sites, (e.g., aerial surveys; Askey et al., 2018), may further inform study design with regard to duty cycle and data interpretation. We did not attempt to determine the number of boats present at a reef at a single time or in succession (i.e., two different vessels present in successive five-minute periods). Determining the number of vessels from acoustics alone could be challenging in cases when the vessels are similar. An estimate of the typical duration fishing boats spend at a reef could provide a better estimate of the number of vessels present when vessel detections occur over longer consecutive time periods. In our study, the duration of
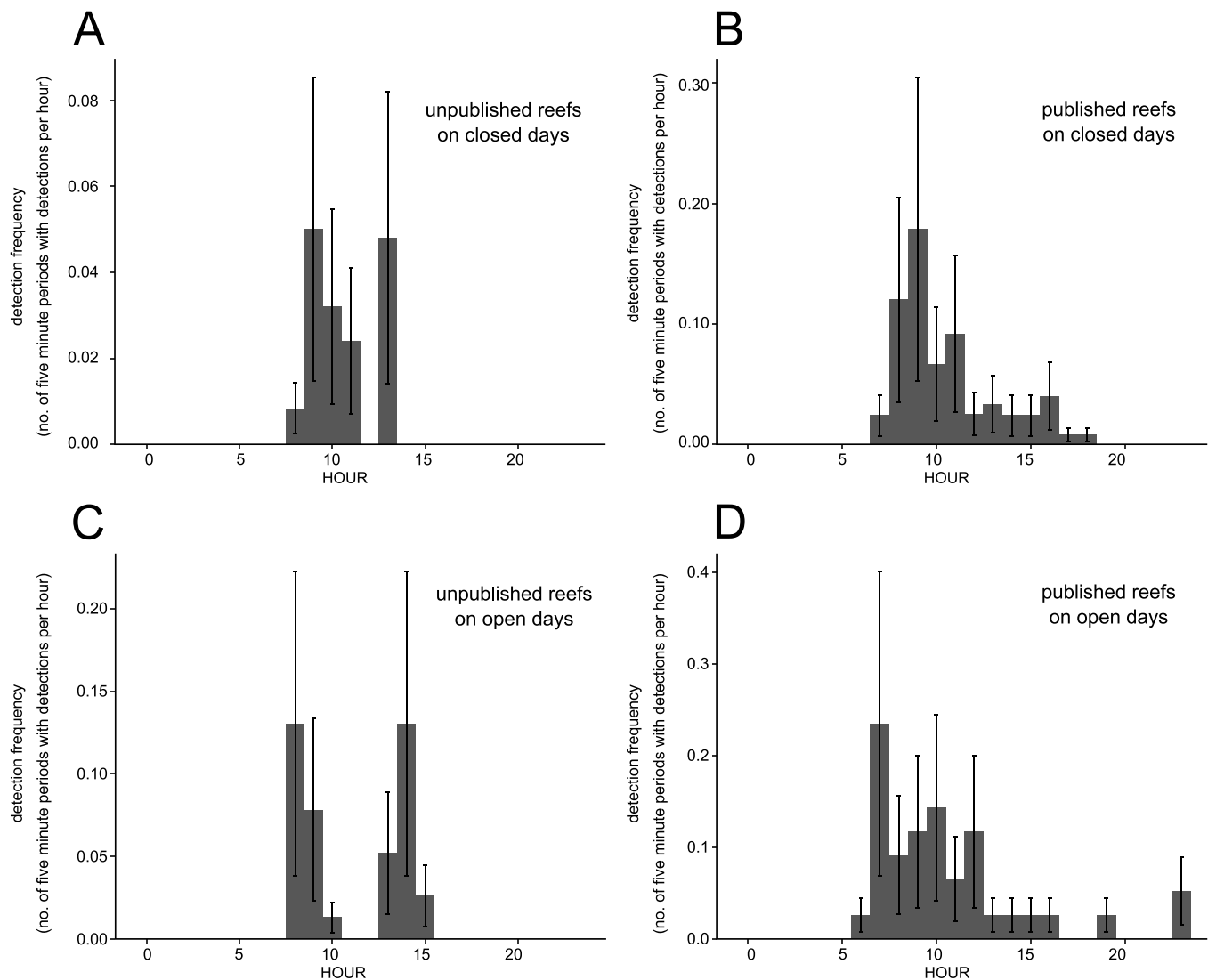
Fig. 7. Average + SE hourly boat detection frequency (proportion of five-minute intervals each hour with one or more boat detections) on Alabama artificial reefs in 2018 from (A) unpublished reefs on closed fishing days, (B) published reefs on closed fishing days, (C) unpublished reefs on open fishing days, and (D) published reefs on open fishing days. Note differences in scale between panels.

consecutive sound files with boat detections tended to be brief; half of all observations were 10 min or less. It is important to consider, however, that reefs with vessels present for the same proportion of time but with differences in the total number of visiting vessels may not have equivalent fishing impacts. Catch limits, such as the two fish per-person limit of red snapper at the time of this study, could result in greater depletion at sites with higher catch rates that have more vessels visiting but for a shorter time spent fishing. Longer durations of vessel presence at a site could also occur with lower catch rates or when anglers voluntarily discard legal-size fish in favor of larger fish. Integrating other data sources, such as electronic surveys (Liu et al., 2017), like 'Snapper Check' for Alabama, may provide further inference on how time of vessel presence may be influenced by angler behavior.

4.5. False positives

False positives using this detection algorithm at most sites were rare, but when they did occur, the most common sound appeared to be the hydrophone making physical contact with an object. We hypothesize that this could be contact with a benthic invertebrate moving over the hydrophone. Thus, hydrophone placement, slightly away from the artificial reef, if boat detection is the sole study objective (i.e., not

bioacoustics of reef fauna) may potentially reduce such false positives further depending on the abundance and habits of reef associated invertebrates compared to invertebrates found in adjacent soft-bottom habitats.

Our use of a high-pass filter eliminated a large source of potential false positives (leopard toadfish) at some reefs and reduced the work effort required to screen detections. We recommend that researchers who wish to use similar methods to the current study but in different regions and habitats consider developing a different filtering procedure to remove common biotic sounds from their dataset, particularly for sounds that are relatively high amplitude or close to the recorder, and last for 0.1 s or longer. Automated screening can be refined by screening first without any pre-filtering, aurally examining putative detections, and identifying false positive rates and acoustic features of false positives to guide refinements such as filter parameters and adjustments to the detection algorithm to avoid biological sounds.

4.6. False negatives

In this study, false negative rates of boat gearshift sounds were relatively low. We expected the probability of finding false negatives would be highest when idling boats were present. From our examination

of false negatives from sound files that had detections, we found that there were approximately four false negatives for each automatically detected impulsive boat sound. This low false detection rate is likely acceptable for most purposes in which boats and anglers are predicted to be at a site for at least five minutes, including time spent detecting the site with sonar and any other pre-fishing activity. Boats present for several minutes will produce multiple sounds and detecting every impulsive sound may not be necessary. Actual false negatives in which boats were never detected were likely lower, as estimates from randomly screened files without detections were quite low (2%).

4.7. Site selection and spatial resolution

In our study, some sounds from vessels were detected at sites 0.44 km apart, however, detections at the more distant site were inconsistent. The precise location of the deployment vessel relative to these two sites was not known, so it is not possible to determine if simultaneous detections occurred at both sites resulted when the vessel was at a position between the two sites. Nevertheless, using the current methodology, it seems prudent to consider that a recorder may detect relatively small vessels within a 0.5 km radius and larger vessels that are louder are likely to be detected from a greater distance. A limitation of the current study was that detection ranges of different types of engines are not known and this should be examined in future research. We recommend placement of recorders at least 1 km apart.

5. Conclusions

Our study shows that live-boating vessels can be easily detected from PAM data with a simple algorithm. This method has the advantage of providing spatial information on where fishing is most likely occurring, as opposed to other methods to estimate effort, such as quantifying the number of vessels at a boat ramp or in transit. Further, this PAM method provides greater temporal information than aerial surveys and at a lower cost. We expect that this algorithm could also be used to detect vessels maintaining station to anchor and thus could be applied for other fisheries where live-boating is less common. We suggest that this method, in conjunction with other tools used to measure fishing effort, can provide a valuable source of data for estimating fishing effort for red snapper and other contentious fisheries in which effort is difficult to quantify.

CRediT authorship contribution statement

Kelly S. Boyle: Data collection, Conceptualization, Methodology, Analysis, Writing – original draft preparation, revising, **T. Reid Nelson**: Data collection, Conceptualization, Methodology, Analysis, Writing – reviewing and editing, **Crystal L. Hightower**: Data collection, Conceptualization, Methodology, Analysis, Writing – reviewing and editing, **Sean P. Powers**: Conceptualization, Writing – reviewing and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fishres.2022.106262.

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