

**INTERACTING EFFECTS OF RECRUITMENT, EELGRASS (*ZOSTERA MARINA*),
AND HUMAN ACTIVITY ON RESTORED OLYMPIA OYSTER (*OSTREA LURIDA*)
BEDS AND THEIR PROVISION OF ECOSYSTEM SERVICES**

A Thesis By

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Abstract:

Oysters are foundation species utilized in Living Shorelines projects due to their potential to attenuate wave energy and stabilize shorelines. These potential benefits have created recent interest in restoring Olympia oysters (*Ostrea lurida*), the only oyster species native to the US west coast. However, little is yet known about what site characteristics are necessary to successfully restore functional, self-maintaining Olympia oyster beds. Furthermore, the degree to which Olympia oyster beds attenuate wave energy is not yet known. I examined the effects of annual recruitment, eelgrass presence, and human activity on restored oyster bed integrity and adult oyster density at four sites in Newport Bay, California between 2019-2021. I assessed wave attenuation and shoreline stabilization by measuring the height of boat wakes passing over oyster beds and associated control plots and by tracking changes in grain size profiles upshore of the oyster beds. Oyster beds at sites with higher levels of destructive human activity experienced more rapid bed breakdown, but breakdown was reduced when eelgrass density was higher. Oyster density increased with higher larval recruitment during the previous year, but this relationship weakened as bed breakdown increased. I did not find evidence of wave attenuation by the restored beds. The results of my study suggest that Olympia oyster beds restored at sites with high levels of human activity require additional protective measures to prevent premature breakdown, especially when year-to-year recruitment is variable.

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CHAPTER 1

INTRODUCTION

Shoreline loss and degradation of valuable coastal habitat is tightly linked with activities associated with human development (Hartig et al. 2002; Coverdale et al. 2013; Cellone et al. 2016; Goldberg et al. 2020). Human populations in coastal regions are 2.6 times higher than in inland regions and are projected to climb from 23 million (year 2000) to up to 44 million (year 2060) in the United States alone (MEA 2005; Neumann et al. 2015). Global development of coastal areas is still in progress to match demands associated with population growth, tourism, and marine industries such as fishing and shipping, which frequently results in the removal of marine habitat (MEA 2005; Seto et al. 2011; Neumann et al. 2015). Beyond the direct loss of valuable marine ecosystems, this habitat removal leaves shorelines vulnerable to erosion by eliminating structural complexity that would otherwise buffer wave energy and retain marine sediments (Wilson 1949; Shadrin 2013).

Shoreline armoring structures such as bulkheads and riprap have been built to protect coastlines, but these structures can negatively impact local marine communities, preventing the provisioning of valuable ecosystem functions such as water filtration (Currin et al. 2010) and wave attenuation (Gittman et al. 2015; Prosser et al. 2018). For example, armoring structures can deflect wave energy in a manner that increases scour and erosion at the “toe” or bottom of the structures (Plant and Griggs 1992; Bozek and Burdick 2005). This can alter or remove native vegetation communities, negatively impacting associated fauna such as birds and fish that rely on these communities for foraging and refuge (Bulleri and Chapman 2010; Prosser et al. 2018). In addition, the physical barrier between the land and sea blocks filtration of runoff water and prevents wetland habitat from migrating upland in the face of sea level rise, a phenomenon referred to as “coastal squeeze” that reduces wave attenuation by such habitat (Pontee 2013). These and numerous other problems associated with shoreline armoring have led marine scientists and stakeholders to seek out “green” approaches to shoreline preservation that prevent erosion while simultaneously restoring marine habitat.

Coastal practitioners are currently exploring the use of Living Shorelines as a “green” approach to shoreline loss. “Living Shoreline” refers to the restoration or placement of natural materials, either alone or in combination with other natural or hard substrate, in a manner that reduces erosion, adds habitat value, and enhances coastal resilience (NOAA 2015; Smith et al. 2020). Low-sloping coastal regions support expansion of natural habitat and do not necessarily require rigidly-structured armoring techniques, and therefore provide an opportunity to utilize nature-based solutions for shoreline protection (Priest III 2017). Foundation species including seagrass, oyster reefs, and salt marsh vegetation such as cordgrass *Spartina alterniflora* are commonly selected to create a Living Shoreline (Smith et al. 2020) due to the suite of benefits they provide the surrounding ecosystem and humans alike (hereafter ecosystem services, Daily 1997). Foundation species heavily influence an ecosystem by providing a complex habitat that may be used by other organisms, subsequently increasing biodiversity (Dayton 1972). For example, commercially valuable blue crabs *Callinectes sapidus* exhibit higher growth rates and survival by using seagrass meadows in Chesapeake Bay as protection from predators, subsequently increasing foraging efficiency (Wilson et al. 1987; Perkins-Visser et al. 1996).

Oyster habitat restoration is of particular interest in the context of Living Shorelines due to the loss of 85% of oyster reefs worldwide (Beck et al. 2011). Oysters form rugose vertical reefs and beds and are a foundation species that provisions habitat for a host of invertebrate, fish, and bird species (Posey et al. 1999; Dealteris et al. 2004; Herbert et al. 2018b; Shaffer et al. 2019; Theuerkauf et al. 2022) while providing a wide range of ecosystem services (Coen et al. 2007). Oysters increase water clarity and quality through their filter-feeding behavior which reduces total suspended solid (TSS) and phytoplankton concentrations (Gerritsen et al. 1994; Nelson et al. 2004), subsequently increasing light availability for submerged aquatic vegetation (SAV) (Cerco and Noel 2007). Their complex, biogenic structure buffers wave energy, allows sedimentation and prevents erosion (Meyer et al. 1997; Wiberg et al. 2019). Recently, an experiment in Bangladesh demonstrated significant wave reduction and a 54% decrease in erosion associated with oyster breakwater reefs (Chowdhury et al. 2019). The ability to

reduce erosion (and therefore stabilize shorelines) while improving water quality and providing habitat for other species makes oysters an attractive option to use to create a Living Shoreline.

Olympia oysters (*Ostrea lurida*) are the only native oyster species on the west coast of North America and were once widely abundant from Baja, Mexico to British Columbia, Canada (Dall 1914; Baker 1995). However, their population has decreased precipitously since the early 1900s due to a combination of overharvesting (Baker 1995; Peter-Contesse and Peabody 2005), pollution (Steele 1957), and habitat loss. At present, Olympia oysters are considered “functionally extinct”, meaning remnant populations can be found but no fully formed beds exist (White et al. 2009; Zu Ermgassen et al. 2012). On the U.S. east coast, restoration of eastern oysters (*Crassostrea virginica*) has produced ample evidence of this species’ ability to reverse shoreline erosion (Piazza et al. 2005; McClenachan et al. 2020), increase water filtration (Nelson et al. 2004; Grizzle et al. 2008), and increase the abundance of resident reef-associated marine species (La Peyre et al. 2014). These demonstrated benefits of oyster restoration and the desire to preserve native west coast biota has motivated a growing interest in restoring Olympia oysters in a manner that returns important ecosystem services. However, efforts to restore this species began more recently on a scientific timescale, with approximately 20 years of Olympia oyster restoration research (Peter-Contesse and Peabody 2005) compared to 60 years of Eastern oyster restoration research (Bersoza Hernández et al. 2018). Coupled with limited historical data due to their early decline, there is little information about site characteristics that are required to restore self-sustaining Olympia oyster populations (Ridlon et al. 2021, but see Wasson et al. 2015). Restoration practitioners have reported that burial by sediment and lack of recruitment are the primary challenges to restoration success (Ridlon et al. 2021). While this information is useful in the context of site selection, the effects of a great number of other site characteristics on restoration success are not well understood. Successful restoration relies on a well-developed understanding of species-specific threats of destruction and required environmental conditions (McDonald et al. 2016) and filling this information gap will guide the selection of restoration sites that maximize the success of future restoration efforts and ensure

resilient, self-sustaining oyster beds. Some characteristics that may influence restoration success include the presence of adjacent submerged aquatic vegetation (SAV), the amount of annual larval recruitment, and the level of human activity at a prospective site.

On the US west coast, the dominant SAV species is eelgrass (*Zostera marina*). Eelgrass is another foundation species that has experienced precipitous declines worldwide and has been targeted for restoration to create Living Shorelines (Orth et al. 2006; Busch et al. 2010; Thom et al. 2012). Several projects have combined eelgrass restoration with Olympia oyster restoration as multi-species Living Shorelines with the intent of amplifying the return of ecosystem services (Boyer et al. 2017; Briley et al. 2021). However, predicted interactions between these two species are conflicting, and little is known about whether the presence of eelgrass is beneficial or harmful to Olympia oysters (and vice-versa). Like oysters, seagrasses reduce water velocity which allows fine-grain sediment to fall out of the water column (Harlin et al. 1982; Christianen et al. 2013). While this benefits shorelines by reducing erosion, increased sedimentation is regarded as a major stressor for Olympia oysters (Wasson et al. 2015) and may induce mortality due to gill clogging and reef burial (Lenihan 1999; Valdez et al. 2016). Conversely, this increased sedimentation may benefit oysters by filtering problematic sediment from the water column away from oyster habitat, reducing overall sediment loading (Wood 2018). However, benefits derived from filtration may be negated if filtration subsequently reduces food availability and larval transport to restored oyster habitat (Reusch 1998; Allen and Williams 2003; Wood 2018). This complex relationship between potential benefits and stressors produced by eelgrass has been observed as part of an ongoing study in Newport Bay, California, USA that restored Olympia oysters alone and adjacent to eelgrass (Wood 2018). When restored adjacent to eelgrass, sedimentation on oysters was reduced in the first year following restoration but oyster density was either unaffected or lower. Lowe et al. (2019) found evidence of conflicting effects of eelgrass on oysters, with overall increased shell growth but reduced survival of Olympia oysters and Pacific oysters in the presence of eelgrass at six sites in Willapa Bay and Padilla Bay, Washington. However, their results were spatially-dependent and

differed based on the bay and location relative to the bay mouth, suggesting that the effect of eelgrass is mediated by local environmental conditions. Taken as a whole, these two studies highlight the context-dependency of the relationship between eelgrass and Olympia oysters. Additional research is necessary to understand whether these species can be restored simultaneously in order to maximize the return of valuable ecosystem services to coastal areas.

Larval recruitment is defined as the continued survival of settled larvae (spat) over an arbitrary period of time (Keough and Downes 1982; Jenkins et al. 2009), and a reliable recruitment rate is necessary to build and maintain oyster habitat (Mann and Powell 2007). Oysters require hard substrate to settle, and restoration is often accomplished by the placement of hard substrate at the appropriate tidal elevation depending on the targeted species (Baker 1995; Brumbaugh and Coen 2009). Oyster larvae present in the water column settle on this substrate, and subsequent generations of larvae settle on top of adult oysters and dead oyster shell (cultch), building the reef or bed over time (Powell et al. 2006). To build self-maintaining oyster habitat, the rate of shell addition via death of adult oysters and continued recruitment of oyster larvae must equal or outpace the rate of shell loss from processes like burial, shell dissolution, and removal by fishers (Powell et al. 2006; Mann and Powell 2007). Higher larval recruitment may increase the rate of shell addition by adding future generations of adult oysters whose shells will become available upon their death. If increased recruitment causes shell addition to outpace shell loss, a restored bed may be more likely to grow rather than degrade. While low recruitment is a known challenge to restoration success (Wasson et al. 2015; Ridlon et al. 2021), the relationship between recruitment and restored bed integrity has not been examined directly.

A third characteristic that may influence Olympia oyster restoration success is the amount of human activity at a prospective restoration site. Human development activity is associated with habitat degradation and the damaging effects of human activity on marine communities is varied and abundant. A 2009 review by Crain et al. listed habitat loss, overexploitation of resources, hypoxia, eutrophication, invasive species, altered salinity and sedimentation regimes, disease, ocean acidification, and climate

change as the major human-mediated threats to marine environments world-wide. Marine intertidal communities, such as those located along rocky shores and wetlands, are particularly vulnerable to human-mediated damage due their accessibility from both the land and sea (Thompson et al. 2002). On the landward end, trampling and bait collection by fishers and recreational visitors reduces cover of foliose algae and barnacles, and increases fragmentation in mussel beds both directly by crushing and indirectly by weakening mussel attachment which leaves them vulnerable to removal by waves (Brosnan and Crumrine 1994; Smith and Murray 2005). This damage can be exacerbated in the presence of natural disturbances such as shell-weakening parasitism (Nicastro et al. 2019). In soft-sediment wetlands, trampling increases sediment compaction which significantly reduces the presence of benthic macrofauna such as polychaetes and burrowing clams (Hsu et al. 2009), subsequently reducing food available for foraging shorebirds (Evans et al. 1999).

From the seaward end, many anthropogenic disturbances are associated with recreational and commercial boats. These vessels transport non-native species (Ruiz et al. 1997), leach toxic chemicals into the water (Ytreberg et al 2010), and produce energetic wakes that suspend sediment, thereby increasing turbidity and intensifying shoreline erosion (Zaggia et al. 2017; Bilkovik et al. 2019). Boat wakes in particular are also known to impact Eastern oyster reefs by removing clusters of live oysters and preventing survival of settled oyster larvae (Wall et al. 2005; Campbell 2015). Furthermore, in Mosquito Lagoon, Florida the location of dead oyster reefs has been correlated with the location of boating channels (Wall et al. 2005). While the damaging effects of human activity on oysters and other marine communities are well-documented, it is not yet known how these activities might impact Olympia oyster restoration projects specifically.

A thorough understanding of the site conditions necessary to ensure successful Olympia oyster restoration is critical to motivate communities and funders to engage in these often-costly projects. Equally important, however, is determining the true economic value of ecosystem services provided by Olympia oysters based on the degree to which they offset costly environmental problems (Nelson et al.

2009). Oyster habitat is estimated to be valued at \$5,500 - \$99,000 per hectare due to their ability to provision various ecosystem services, such as water filtration and shoreline stabilization. However, the nascent stage of Olympia oyster research precludes us from being able to reliably apply these values to this particular species (Grabowski et al. 2012). On the east coast, restoration of native Eastern oysters increased upshore sedimentation and stabilized shorelines (Piazza et al. 2005). However, this oyster species forms tall and complex reefs, dissimilar to the low-relief beds formed by Olympia oysters. For this reason, Eastern oysters may not be an appropriate analogue to use to predict the Olympia oyster's ability to stabilize shorelines. The San Francisco Bay living shorelines project demonstrated that there was sediment accumulation and wave energy reduction associated with restored Olympia oyster beds (Boyer et al. 2017). However, these results may be dependent on the initial height or "relief" of the habitat that was restored. Oyster reefs that experience more frequent inundation are less effective at attenuating wave energy (Wallis et al. 2016; Wiberg et al. 2019; Morris et al. 2021). Therefore, taller restoration substrate may experience less inundation time and be more effective at attenuating wave energy and contributing to shoreline stabilization. Further work is necessary to develop better understanding of these processes so that a true economic valuation of services provided by this species may be produced.

Beginning June 2016, a team of scientists at CSU Fullerton in collaboration with colleagues at CSULB and Orange County Coastkeeper, restored Olympia oyster beds and eelgrass beds alone and adjacent to each other at four sites in Newport Bay, Newport Beach, California to create Living Shorelines (hereafter UNBLS) in a region where historically present oyster beds have been lost to development (Gilbert 1889). This study design was developed to investigate the possible compounded benefits of restoring multiple foundation species as opposed to just one. In the years since oysters were restored, the sites experienced differential success in terms of maintenance of oyster bed height and overall consolidation. Previous research associated with this project found negative or neutral effects of eelgrass presence on oyster density, with results varying by site (Wood 2018). My project expands on

this preliminary finding by studying additional factors that may affect restoration success, in terms of bed consolidation and adult oyster density. I selected human activity because the most easily discernable difference among sites is the level of permitted human access. In addition, previous studies have shown damaging effects of trampling and boat wake on bivalve communities (Smith and Murray 2005; Campbell 2015; Herbert et al. 2018a). I selected annual recruitment due to availability of long-term recruitment data for each site, as well as the understanding that a strong larval source is necessary to colonize restoration substrate (Wasson et al. 2015). I also measured sedimentation dynamics derived from changes in upshore grain size distribution at each restoration treatment (oyster, oyster/eelgrass, eelgrass, control) to determine the ability of Olympia oysters to stabilize shorelines. Finally, I used water level loggers to measure wave action at each site in a manner that allowed me to both compare differences in wave energy by site and directly measure wave attenuation by oyster beds.

The purpose of my project is twofold. First, I will determine how varied site characteristics (adjacent eelgrass, annual recruitment, human activity) affect the ability of restored oyster beds to maintain integrity and avoid breakdown, and to determine which characteristic has the greatest effect. Second, I will determine the extent that Olympia oyster beds, restored with and without adjacent eelgrass beds, attenuate wave energy and stabilize shorelines. Specific hypotheses are as follows:

- H1. Oyster beds restored adjacent to restored eelgrass will have higher oyster density and lower bed breakdown than oyster beds restored alone.
- H2. Oyster beds at sites with higher annual larval recruitment will have higher oyster density and lower bed breakdown.
- H3. Sites with higher human activity will have lower oyster density and higher bed breakdown.
- H4. The amount of human activity at a site will have the greatest effect on oyster density and bed breakdown relative to eelgrass density and annual recruitment.
- H5. Restored Olympia oyster beds attenuate wave energy.
- H6. Restored Olympia oyster beds increase upshore sedimentation as seen by an overall fining of sediment through time.

CHAPTER 2

METHODS

Study Site and Multi-Habitat Restoration Design

The Newport Bay Living Shorelines project (UNBLS) is comprised of Olympia oyster beds and eelgrass meadows that were restored at four sites in Newport Bay, California, USA (Figure 1) between 2016-2017 in a full-factorial blocked design consisting of four treatments (Figure 2): oyster bed restored alone (“Oyster”), eelgrass restored alone (“Eelgrass”), oyster bed restored upshore of eelgrass (“Oyster/Eelgrass”), and an unmanipulated mudflat (“Control”). This four-treatment design was replicated at four sites in Newport Bay with the treatment blocks ordered randomly at each site. The sites include Deanza Peninsula (33°37'13.18" N, 117°53'54.81" W, hereafter Deanza), Pacific Coast Highway (33°37'9.55" N, 117°54'17.41" W, hereafter PCH), Shellmaker Beach (33°37'21.60" N, 117°53'32.19" W, hereafter Shellmaker), and Westcliff Beach (33°37'16.81" N, 117°54'7.29" W, hereafter Westcliff). Oyster restoration plots were constructed by deploying clean Pacific oyster shell contained within coconut coir mesh bags. Oyster plots and associated control plots were 20 x 1.5 m. Eelgrass plots and associated control plots were 20 x 8 m (Wood 2018). In November 2019 two smaller oyster plots (“High Mini” and “Low Mini”) were deployed alongside a corresponding control plot (“New Control”) at all sites (Figure 3). New restoration plots were 4 x 1 m. This study primarily focused on the original four treatment plots, but utilized the newer, mini beds as part of the wave attenuation component. The newer beds have experienced less breakdown compared to the older beds and therefore have higher vertical relief, providing an opportunity to compare wave attenuation by oyster beds of different heights.

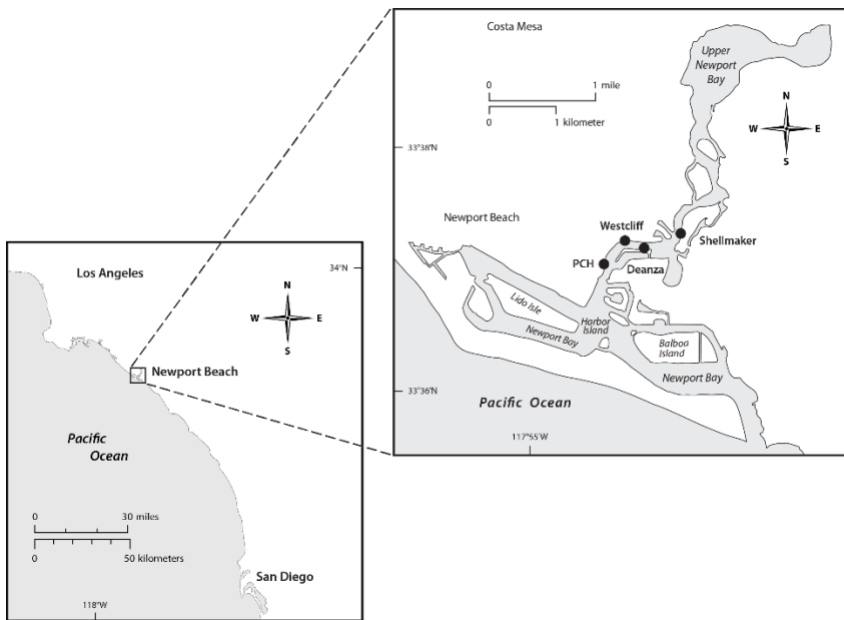


Figure 1. Oyster and eelgrass restoration sites established in 2016-2017 in Newport Bay, CA, USA.

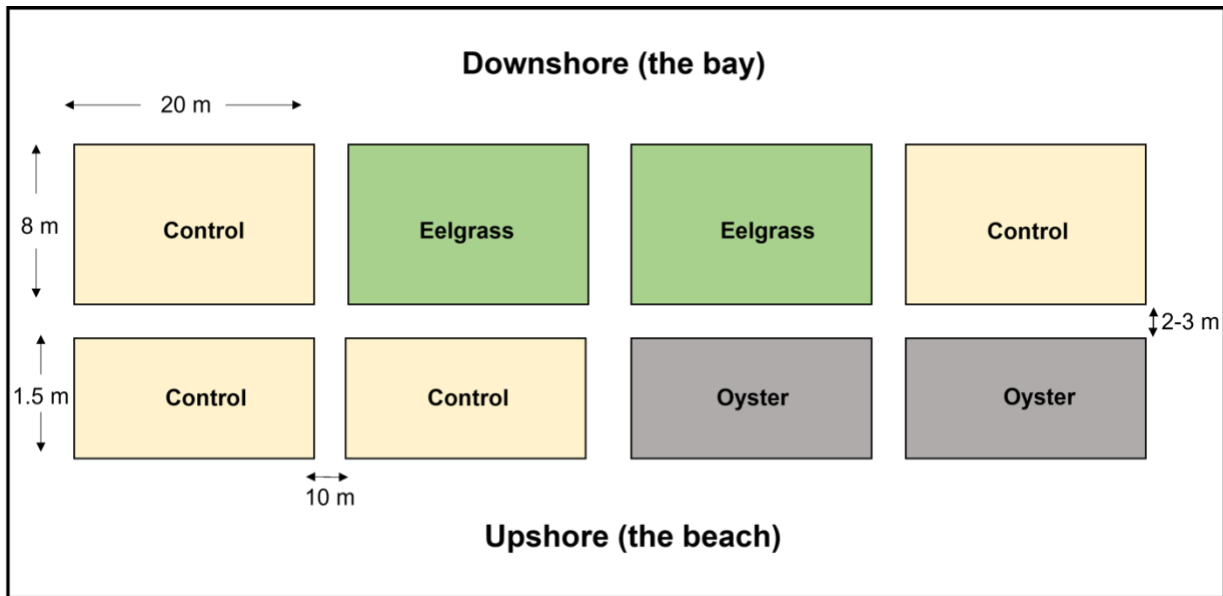


Figure 2. Blocked restoration design consisting of four treatments (left to right): Control, Eelgrass, Oyster/Eelgrass, Oyster in Newport Bay, CA. Treatment order is randomized at each site.

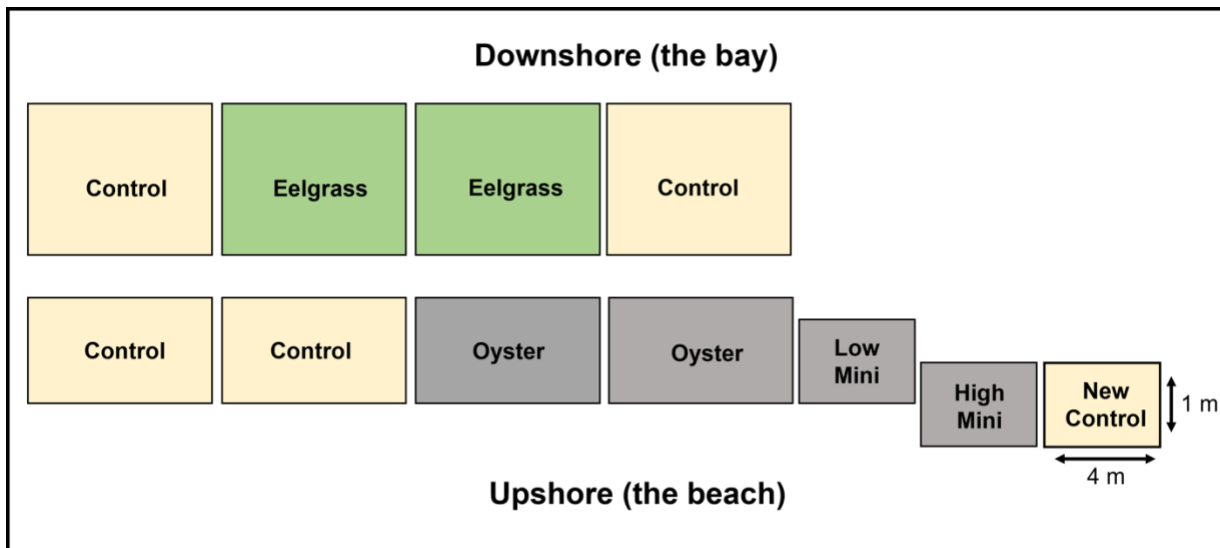


Figure 3. Location of newer “mini” beds relative to original restoration treatment plots

Site Characteristic Variables

Eelgrass Presence and Density

I initially assessed eelgrass presence as a categorical factor based on the original blocked treatment design. However, beginning in 2019 the eelgrass plots expanded to such an extent that the treatments were no longer maintained, as eelgrass began growing into the control plots associated with the Oyster treatment and the Control treatment. To address the loss of treatments I have used eelgrass density data as a continuous factor that has been collected during subtidal SCUBA surveys conducted each summer in May or June. Methods for conducting the surveys and descriptive eelgrass density data by site and treatment are not presented here but can be found in Appendix B (Figure B6) in Emery 2022.

Annual Recruitment

Recruitment is arbitrarily defined as the continued survival of settled oyster larvae over a given time period (Keough and Downes 1982; Osman et al. 1989). I assessed recruitment at each site by deploying ceramic tiles held in mesh cages, which were suspended on PVC “tees” above each treatment plot. The tiles are suspended at -0.5 MLLW approximately 15cm above the bay floor so that they remain within the range of tidal elevations Olympia oyster larvae settle at most frequently (Danielle Zacherl, personal communication). Tiles were deployed over the duration of the Olympia oyster spawning

period, between March and September/October in years 2016-2021, during which time water temperature may partially mediate spawning behavior (Coe 1931, Seale and Zacherl 2009). At the end of this period the tiles were brought into the lab and all live oysters were identified, counted, and measured (length and width, mm) using calipers. Oyster recruit counts were converted to recruits/m² for analysis.

Human Activity and Boat Wake Size

Beginning in July 2019 I conducted 30-minute human activity surveys at each site. Surveys were not confined to specific days, times, or tidal elevations in order to collect the full range of human activity. All instances of human activity were recorded including people walking, domestic animal presence, kayaking, stand up paddleboarding, boating, fishing, etc. In addition, the wake produced by each passing motorized vessel was assigned a score between 0-2 based on how the wake interacted with the shoreline. A score of “0” represented no contact with shoreline, “1” represented small ripples making contact with the shoreline, and “2” represented small waves breaking on the shoreline. This scale was developed to be specific to the range of wake “behavior” observed at Newport Bay and therefore should not be applied to other locations (Gorzelay 2005). Scoring wakes based on how they interact with the shoreline was selected because transmission of wave energy is a function of both wave height and the wave’s interaction with the bottom substrate (Thornton 1983). Due to this interaction it was difficult to predict the amount of potentially damaging energy making contact with the oyster beds by observing the starting size of the wake. Scoring wakes based on their interaction with the shoreline accounted for attenuating and shoaling processes along the path of the wake that I was unable to detect, as bathymetric analysis was beyond the scope of this study.

Oyster Bed Response Variables

Oyster Density

Live oyster density was assessed by excavating randomly selected 0.25 x 0.25m sections of the oyster beds during annual surveys in May ($N = 10$ excavations per bed, 2018-2021). All hard substrate

within the quadrat was collected into a gallon-sized Ziploc bag and replaced with new, clean oyster shell. The samples were carefully cleaned of all mud in the lab and all living oysters were identified and counted. Oysters were converted to oysters/m² for analysis.

Bed Breakdown

Bed breakdown was assessed using point contact surveys conducted each May (2018-2021). A lined 0.5 x 0.5m quadrat was placed at randomly selected locations ($N = 10$) on each bed and a dental probe was used to determine the substrate present at each of the 49 intersecting points on the quadrat. This technique determines the “percent cover” of all surface substrate. I used the percent cover of mud and eelgrass to determine the amount of “soft bottom substrate” exposed. This value represents the amount of area within the original restoration plot that no longer contains hard substrate due to shell spreading and bed breakdown over time, or possibly due to sedimentation and shell burial. In this context, a higher percent cover of “soft bottom substrate” corresponds to a higher degree of bed breakdown.

Upshore Migration

I also assessed bed breakdown and shell spreading in May of 2020 and 2021 by tracking the amount of upshore shell migration observed for each bed. The distance between the midline of each restoration plot and three points along the upper edge of the bed was measured and averaged. The starting upper limit of each original bed was 75 cm and the starting upper limit of each new “mini” bed was 50 cm so this was subtracted from the measured upshore distance during a given year to determine the degree of bed migration.

Ecosystem Service Response Variables

Upshore Grain Size

I collected grain size samples once annually, 10 cm upshore of the upper edge of each bed and 10 cm upshore from the upper edge of each control plot. The upper 1.5 cm of sediment was removed within a 25 cm² section at each location. In the lab, the sediment in each sample was homogenized and

approximately 1 g of wet sediment was removed for grain size analysis. These samples were pretreated with H₂O₂ to remove all organic matter, HCl to remove carbonates such as shell fragments, and NaOH to dissolve biogenic silica (diatoms) as described by Dickson et al. (2022). Cleaned samples were then analyzed using a Malvern Mastersizer 2000 laser diffraction particle size analyzer paired with a Hydro 2000G sample dispersion unit to determine the relative proportion of grain size classes within each sample (Kirby et al. 2010).

Wave Attenuation

I used water level loggers to directly measure wave attenuation by oyster beds and eelgrass (see Appendix A for logger design and instructions for use). Loggers were placed at the upper limit of the original oyster beds (oyster, oyster/eelgrass, “Treatment”) and the newer High Mini bed (“Treatment”) with a control logger (“Control”) placed at the same tidal elevation as the corresponding “Treatment” logger. The tidal elevation of each Treatment logger was determined by referencing an online tidal log at the moment the water line made contact with the logger. The associated Control logger was deployed at the water line at this time. This layout (see Figure 4) allowed me to assess wave attenuation by measuring the difference in transmitted wave energy with and without an oyster bed present. This layout also allowed me to measure the difference in wave energy encountered by a given bed with and without eelgrass present to explore whether eelgrass may protect oyster beds by attenuating wave energy. Prior to analysis, each data set was reduced to an 8-hour period during which time the loggers were underwater. Logger deployment occurred in the late afternoon during low tide and retrieval occurred the following day during the following lowest tide. The selected 8-hour period always occurred during the following day just prior to logger retrieval to maximize the number of boat wake occurrences, as there is typically more boating activity in the morning than in late afternoon in Newport Bay (personal observation). This 8-hour period was consistent between loggers within one deployment, and therefore within one site, so the same individual wake sets could be compared between oyster bed treatments. Three overnight deployments were completed at each site between January-March 2022.

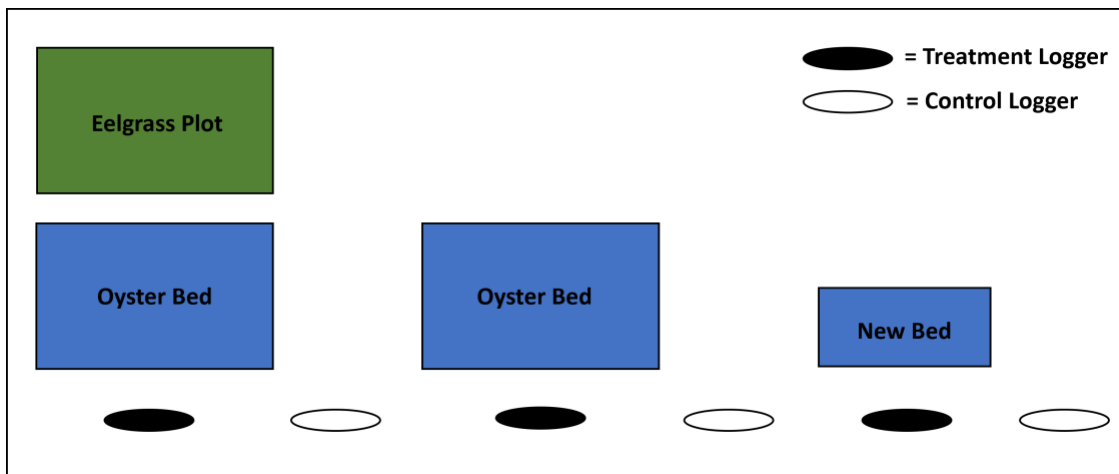


Figure 4. Locations of water loggers relative to oyster beds during wave attenuation study in Newport Bay, CA. I completed three wave attenuation trials at three oyster beds (high mini bed, oyster bed, oyster/eelgrass bed) per site between December 2021-February 2022.

Statistical Analyses

The effects of eelgrass (H1), prior year recruitment (H2), and human activity (H3) on oyster density and bed breakdown were addressed using a combination of ANOVA and linear mixed modeling. Heteroscedasticity was checked by visually examining residuals in predicted, studentized and normal quantile plots for all ANOVAs. Data that did not meet the assumptions of the model were log transformed ($\log(x+1)$) or square root transformed. Transformations are noted in table captions listing the statistical results. Two-way ANOVA was used to test the effects of site and year on levels of human activity (total activity, onshore activity, offshore non-motorized activity, number of boats, destructive activity, number of large boat wakes, percent large boat wakes) and annual recruitment. Three-way ANOVA was used to test the effects of site, treatment, and year on oyster density and bed breakdown. Linear mixed modeling was used to test the effects of human activity, eelgrass density, and prior-year annual recruitment on oyster density and bed breakdown. Oyster density and bed breakdown data were collected by re-sampling the same experimental oyster plots once annually, so samples within the same plot are technically not independent between years. To avoid issues with this lack of independence, each explanatory variable was treated as fixed effect with year included as a random effect. This allowed me to look at variation among years in slopes and intercepts and address the lack of independence

associated with yearly re-sampling of the restored oyster plots. When the model was fit with year as a random slope many of the models were singular indicating that the variances estimated for the random effects are small or zero (Bolker, 2015). This could be because the models were too complex to be supported by the data, possibly due to the low sample size ($N = 24$). I utilized a step-down approach (Zuur et al 2009) to simplify the initial models by refitting year as a random intercept using the lmerTEST package in R (Kuznetsova et al 2017). The R script used to produce linear mixed models and all analysis output is found in Appendix B.

Hypothesis 4 addresses the relative influence of various site characteristics (human activity, eelgrass, annual recruitment) on oyster density and bed breakdown. This was analyzed using multivariate two-way PERMANOVA and canonical analysis of principle coordinates (CAP). CAP analysis was selected as the appropriate ordination approach due to *a priori* groups (site, year) established by PERMANOVA. Draftsman plots for each variable were examined to assess normality. Oyster density and prior year recruitment were right skewed and were therefore transformed ($\log(x+1)$) prior to analysis. All variables were normalized prior to analysis to compare variables on different scales.

Wave attenuation by oyster beds (H5) was analyzed in R using pressure data (mBar) collected by water level loggers. The truncated 8-hour data sets were detrended by removing mean water level from the time series data to remove the tide and isolate boat wakes. A fast Fourier transformation (FFT) was computed on the detrended data to calculate the wave spectral density within frequency bands between 0-2 Hz within 30-second windows across the time series. This was used to create a three-dimensional spectrogram wherein the wave spectral density (mBar^2/Hz), corresponding to the amount of wave energy, within each frequency band was plotted over time (Figure 5). This spectrogram was used to identify the timing of individual boat wake events which are displayed as bright signals between 0.05-1 Hz (Sheremet et. al 2013). Single boat wake events were then isolated from the full 8-hour data set for the “Treatment” and corresponding “Control” logger and plotted over time to compare progression of

the same wake set with and without an oyster bed present (Figure 6a). Each “single wave” data set was detrended and an FFT was computed and plotted (Figure 6b). The peak spectral density of the most prominent frequency band of each logger was obtained to compare the amount of wave energy transmitted to each logger. In addition, the total spectral density across all computed frequencies (0-2 Hz) was obtained to understand how the oyster bed may change the structure of the passing wake set relative to the control. A paired t-test was used to analyze the difference in peak spectral density and total spectral density between each “Treatment” logger and corresponding “Control” logger for each boat wake event. See Appendix C for a complete set of spectrograms, plotted “single wake” sets, and corresponding FFT plots.

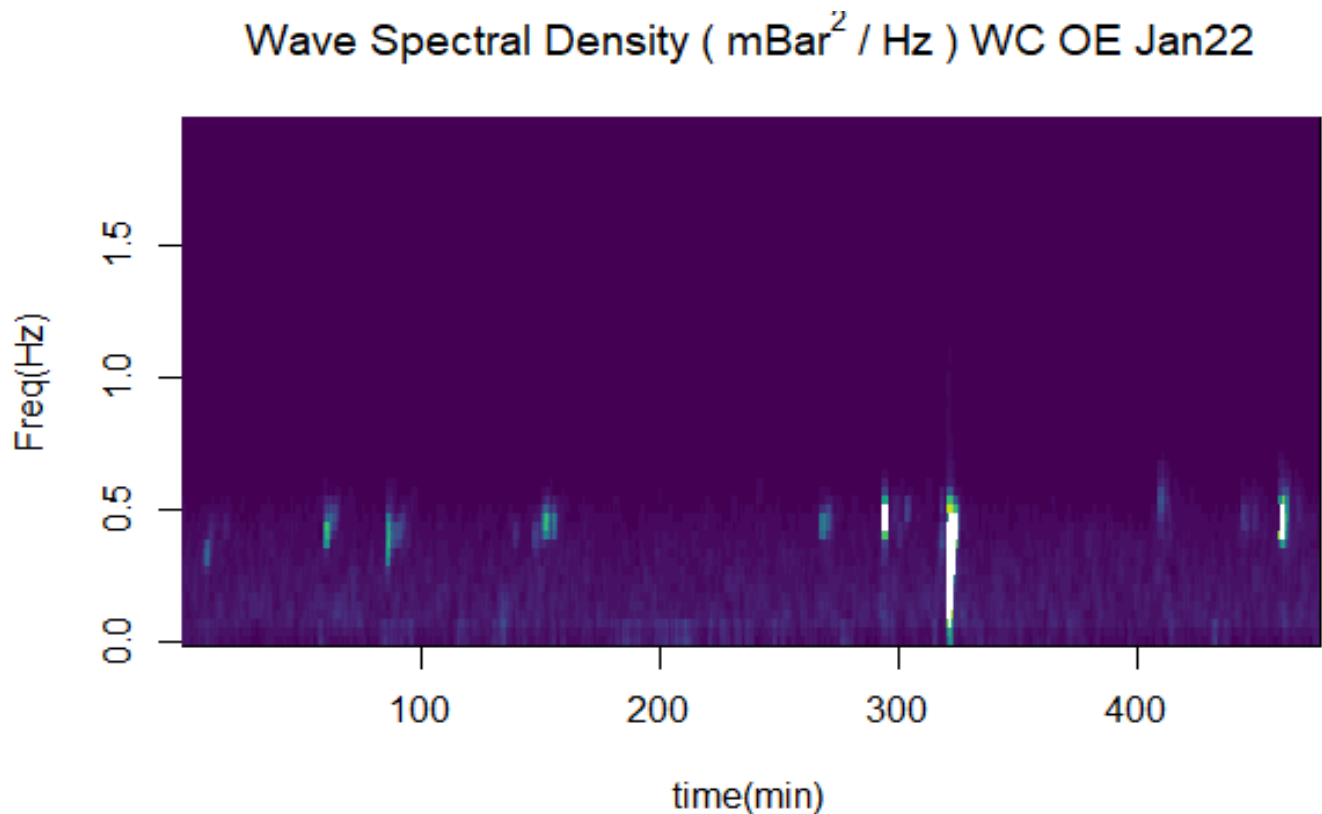


Figure 5. Example of spectrogram produced from the first logger deployment at Westcliff Oyster-Eelgrass treatment in December 2021 in Newport Bay, CA. Color values represent spectral density at frequencies between 0-2 Hz over the 8-hour time period. Individual boat wake events are represented by bright signals between 0.05-1 Hz.

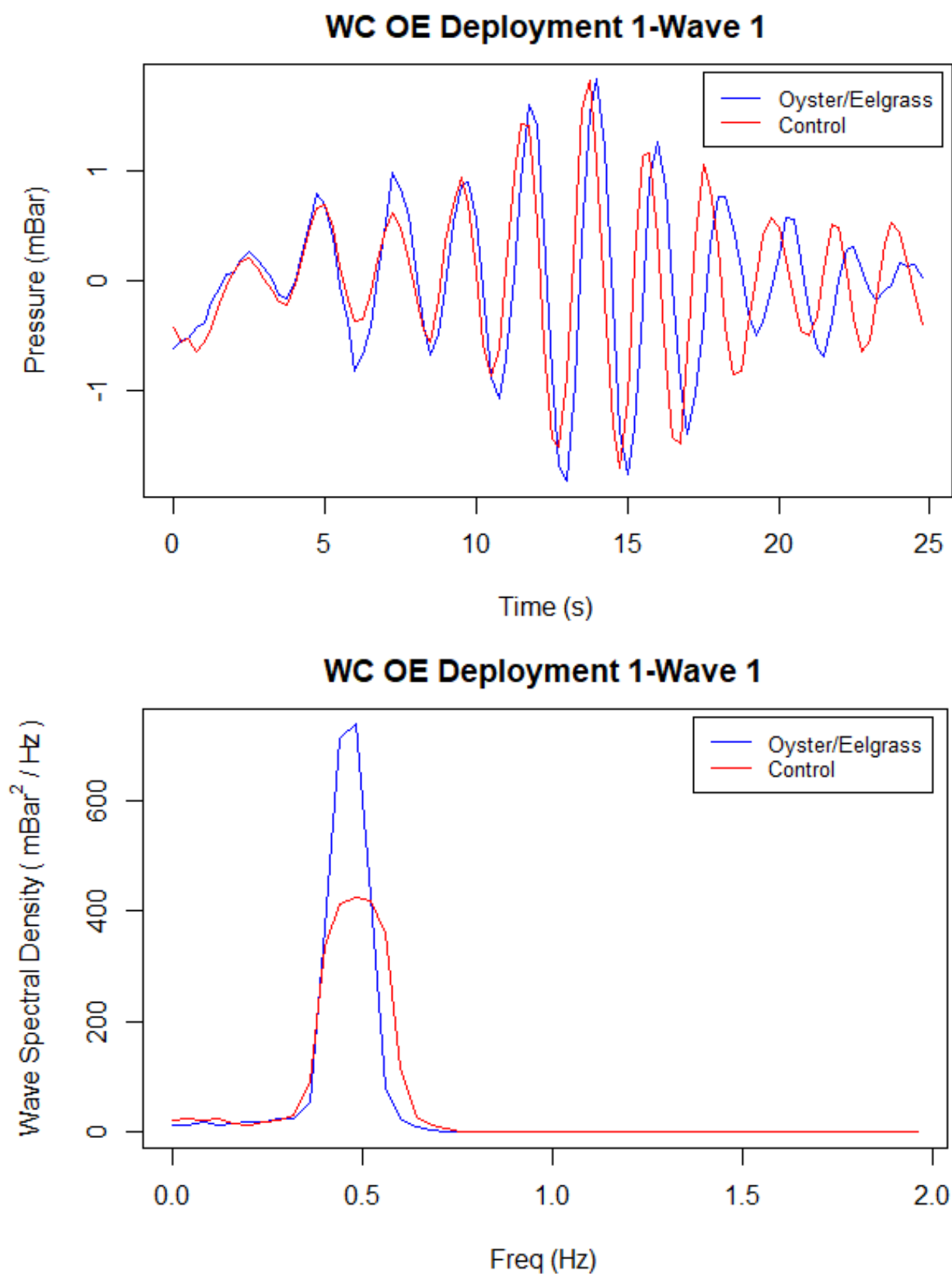


Figure 6. (a) Single wave at Westcliff Oyster/Eelgrass “Treatment” and “Control” loggers over time and (b) FFT results corresponding to single “Treatment” and “Control” waves in December 2021 in Newport Bay, CA.

The effect of restored oyster beds on changes in upshore grain size (H6) was addressed using the median grain size of each sediment sample, which allowed me to examine whether the sediment has become more fine (increased sediment accumulation or reduced erosion) or more coarse (reduced sediment accumulation or increased erosion) since the restoration plots were implemented. Median grain size values were standardized (after Kirby et al. 2010) to the starting conditions (Year 0) at each site using Equation 1, where X represents an observation, μ represents the mean of all starting values at a site ($N = 4$), and σ represents the standard deviation. Standardizing to the starting conditions allowed me to account for inherent differences in the grain size profile at each site, which made it possible to compare changes in median grain size among treatments. In this context, each value represents the number of standard deviations from the average median grain size during year 0 at a given site. Positive values represent sediment coarsening and negative values represent sediment fining. One-way ANOVA was used to assess differences in mean change in median grain size between sites and treatments four years post-restoration. Linear regression was used to assess changes in median grain size with increasing time since restoration. Heteroscedasticity was checked by visually examining residuals in predicted, studentized and normal quantile plots for all ANOVAs.

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

CHAPTER 3

RESULTS

Site Characteristic Variables

Annual Recruitment

Annual recruitment between 2016 – 2021 ranged from 0 – 4711.11 oysters/m² and varied by site (Figure 7, Table 1, 2-way ANOVA, $p = 0.0221$). Mean recruitment at Deanza (1061.11 ± 103.66) was highest and significantly greater than at Westcliff (257.41 ± 106.50), but neither could be distinguished from PCH or Shellmaker (376.85 ± 103.66 to 487.96 ± 3.66).

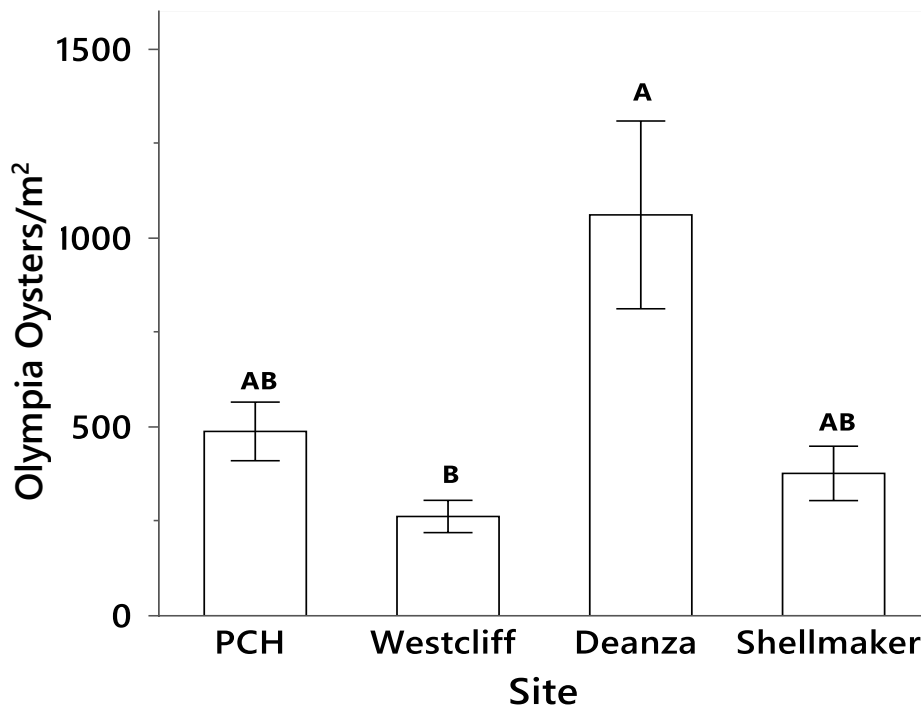


Figure 7. Differences in mean annual recruitment per site ($N = 4-8$ recruitment tiles per site and year) between 2016-2021 Newport Bay, CA based upon two-way ANOVA. Error bars are ± 1 SE. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 1. Two-way ANOVA results for effect of site and year on $\log(x + 1)$ transformed annual recruitment between 2016-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	13.915212	3.4083	0.0221
Year	5	98.893775	14.5335	<.0001
Site*Year	15	24.01446	1.1764	0.31
Error	71	96.62433		
Total	94	233.28292		

Significant Values Displayed in Bold

Annual recruitment also varied by year (Figure 8, Table 1, 2-way ANOVA, $p < 0.0001$). Mean recruitment in 2019 (122.22 ± 126.96) was lower than all other years (363.89 ± 132.14 to 1227.78 ± 126.96). No other years could be statistically distinguished.

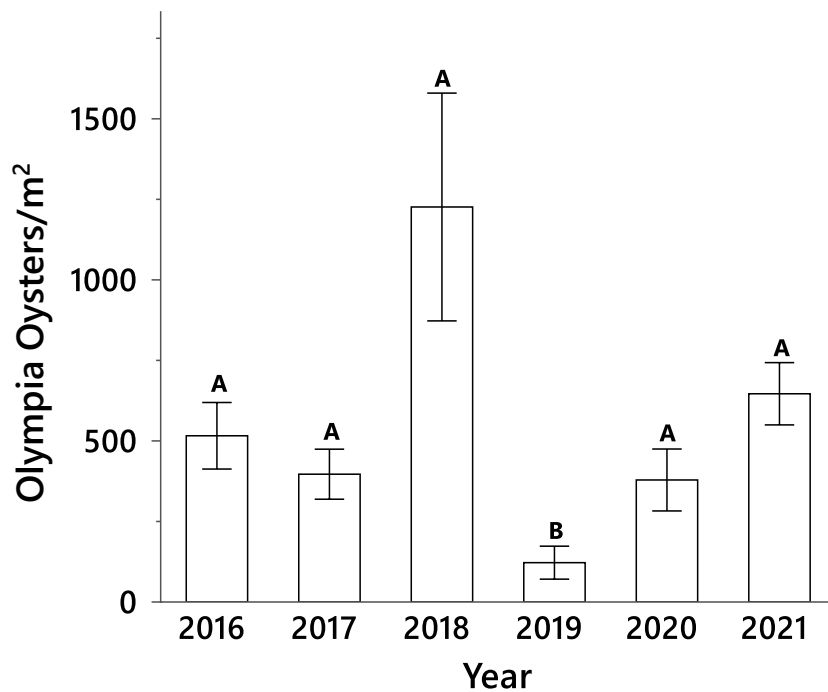


Figure 8. Differences in mean annual recruitment per year ($N = 4-8$ recruitment tiles per site and year) between 2016-2021 Newport Bay, CA based upon two-way ANOVA. Error bars are $\pm 1 SE$. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Human Activity

Total human activity per survey between 2019-2021 ranged from a mean of 23.10 ± 2.56 to 33.15 ± 2.54 instances per 30-minute survey and did not vary by site (Figure 9, Table 2, 2-way ANOVA, $p = 0.2487$). Human activity was subsequently divided into three categories to characterize each site: non-motorized offshore activity (stand up paddleboarding, swimming, kayaking, sailing), motorized boats, and onshore activity (fishing, recreation, domestic animals). Offshore non-motorized activity ranged from a mean of 9.16 ± 2.06 to 26.69 ± 2.02 instances per 30-minute survey and was higher at Deanza and Shellmaker than at PCH and Westcliff, presumably due to the proximity of Deanza and Shellmaker to a kayak and standup paddleboard rental center (Figure 10, Table 3, 2-way ANOVA, $p < 0.0001$). Onshore activity ranged from a mean of 0.28 ± 0.34 to 4.35 ± 0.35 instances per survey and was higher at PCH and Westcliff than at Deanza and Shellmaker presumably due to PCH and Westcliff being located on public beaches (Figure 11, Table 4, 2-way ANOVA, $p < 0.0001$). There were more boat passes per survey at PCH, Westcliff, and Deanza (mean of 10.46 ± 0.88 to 12.22 ± 0.88) than at Shellmaker (mean of 2.28 ± 0.87), presumably due to a lack of accessibility by boats either by law or by nature of the shallower subtidal slope present there (Figure 12, Table 5, 2-way ANOVA, $p < 0.0001$).

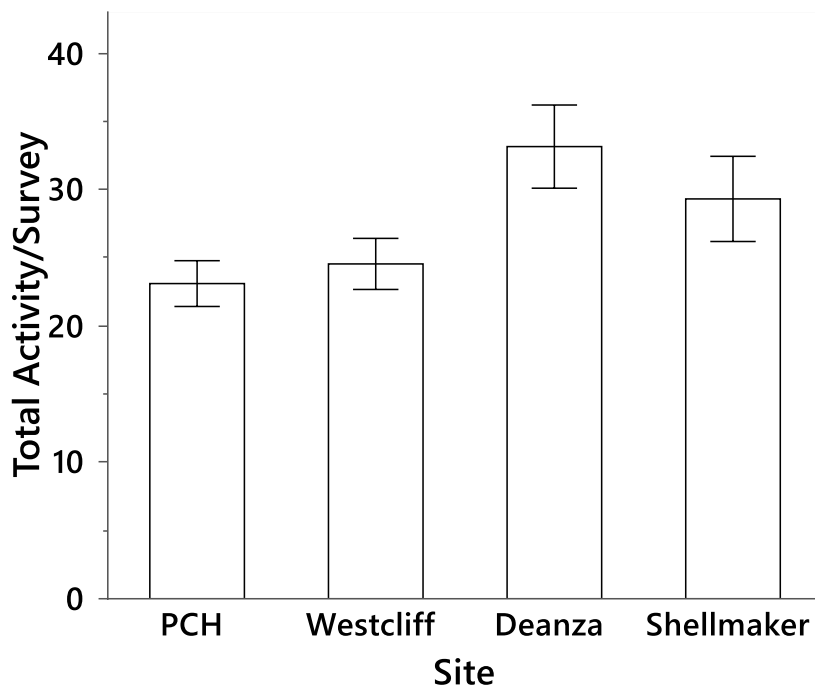


Figure 9. Mean instances of total activity per site ($N = 68-71$ surveys per site) between 2019-2021 in Newport Bay, CA. Error bars are $\pm 1 SE$.

Table 2. Two-way ANOVA results for effect of site on $\log(x + 1)$ transformed total human activity per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Year	2	0.0291474	0.0218	0.9784
Site	3	2.7700587	1.3819	0.2487
Year*Site	6	3.5645226	0.8891	0.5033
Error	264	176.39613		
Total	275	183.00976		

Significant Values Displayed in Bold

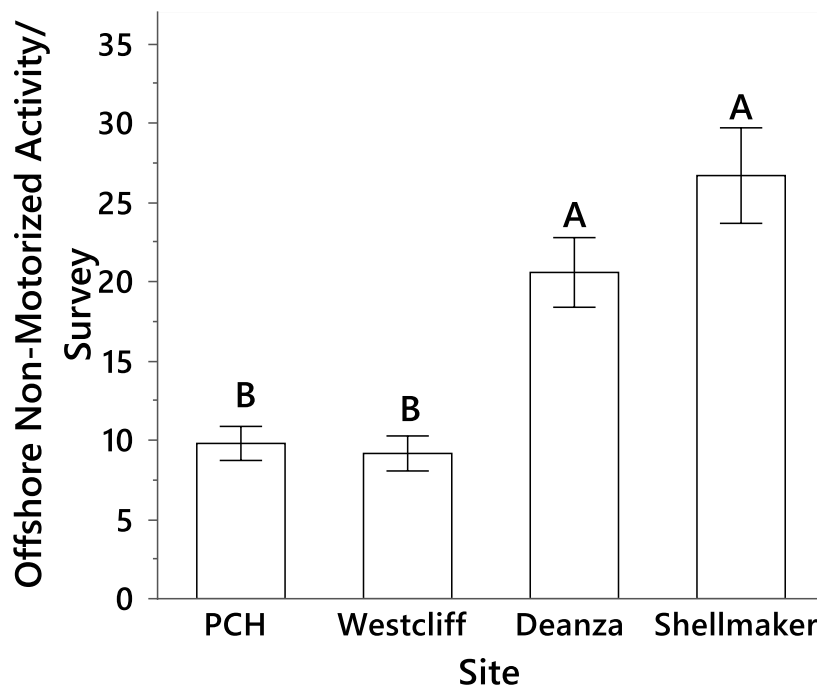


Figure 10. Differences in mean offshore non-motorized activity per site ($N = 68-71$ surveys per site) between 2019-2021 Newport Bay, CA based upon two-way ANOVA. Error bars are $\pm 1 SE$. Variations in bold letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 3. Two-way ANOVA results for effect of site on $\log(x + 1)$ transformed offshore non-motorized activity per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Year	2	1.46215	0.7231	0.4862
Site	3	28.562653	9.4168	< 0.0001
Year*Site	6	2.188032	0.3607	0.9033
Error	264	266.91865		
Total	275	305.96845		

Significant Values Displayed in Bold

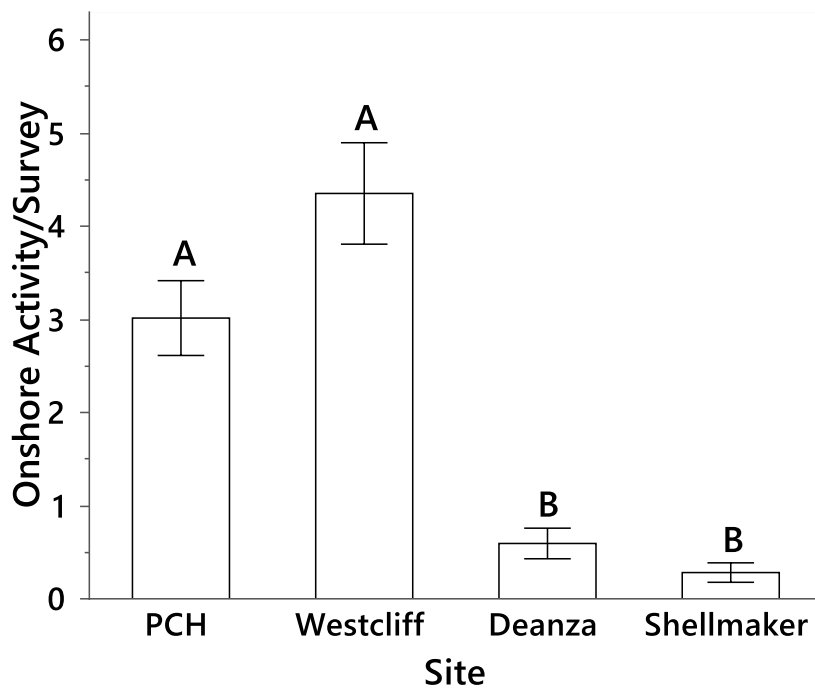


Figure 11. Differences in mean onshore activity per site ($N = 68-71$ surveys per site) between 2019-2021 in Newport Bay, CA based upon two-way ANOVA. Error bars are $\pm 1 SE$. Variations in bold letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 4. Two-way ANOVA results for effect of site on $\log(x + 1)$ transformed onshore activity per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Year	2	3.275534	3.3469	0.0367
Site	3	37.26519	25.3844	<.0001
Year*Site	6	5.602611	1.9082	0.0798
Error	264	129.18685		
Total	275	205.76116		

Significant Values Displayed in Bold

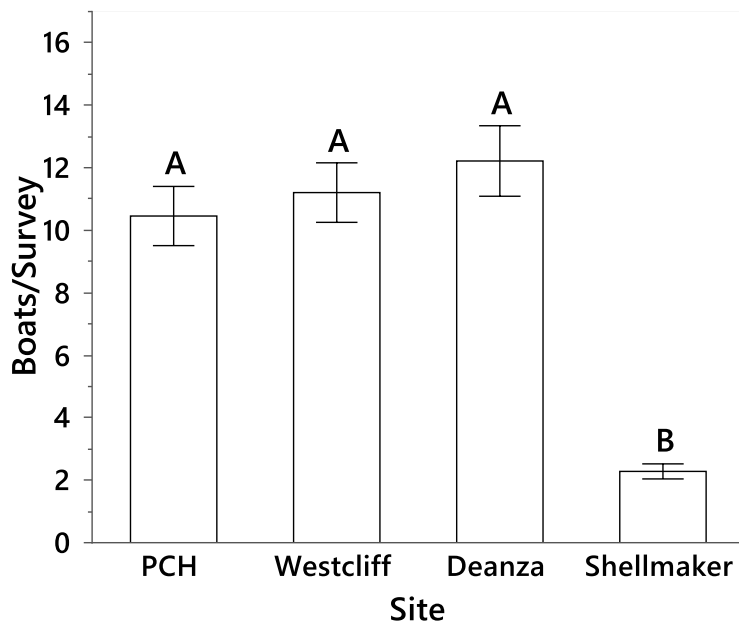


Figure 12. Differences in mean number of boat passes per site ($N = 68-71$ surveys per site) between 2019-2021 in Newport Bay, CA based upon two-way ANOVA. Error bars are ± 1 SE. Variations in bold letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 5. Two-way ANOVA results for effect of site on $\log(x + 1)$ transformed number of boat passes per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Year	2	0.470408	0.5126	0.5996
Site	3	59.451321	43.1859	<.0001
Year*Site	6	2.659048	0.9658	0.4488
Error	264	121.14417		
Total	275	214.6707		

Significant Values Displayed in Bold

When “non-destructive” offshore non- motorized activity was excluded from the analysis (Figure 13, Table 6, 1-way ANOVA, $p < 0.0001$) PCH, Westcliff, and Deanza (mean of 12.81 ± 1.01 to

13.47 $\pm$ 1.02 instances/survey) had significantly higher amounts of “potentially destructive” activity (boating and onshore activity) than Shellmaker (mean of 2.56 $\pm$ 1.0 instances/survey).

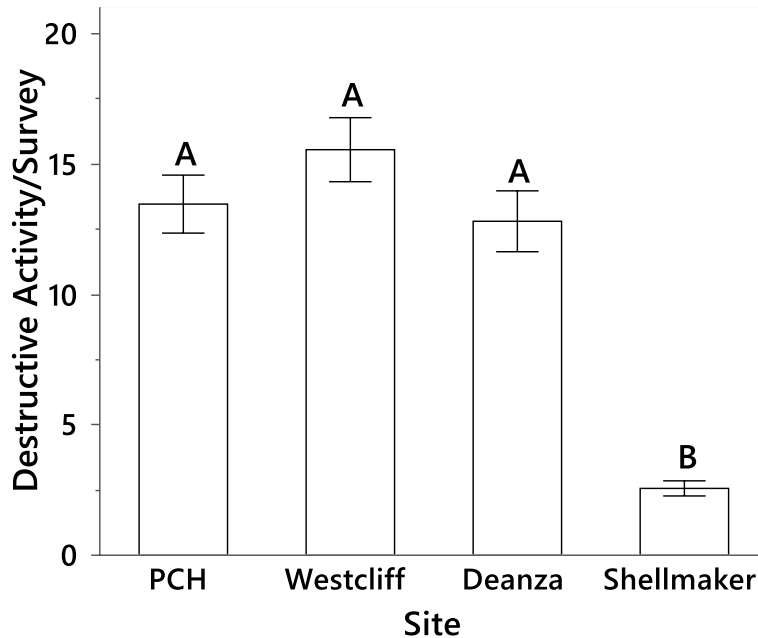


Figure 13. Differences in mean number of boats per site ($N = 68-71$ surveys per site) between 2019-2021 Newport Bay, CA based upon two-way ANOVA. Error bars are $\pm 1 SE$. Variations in bold letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 6. Two-way ANOVA results for effect of site on square root transformed destructive activity per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Year	2	5.03127	1.879	0.1548
Site	3	162.57791	40.4784	<.0001
Year*Site	6	14.1145	1.7571	0.1082
Error	264	353.44441		
Total	275	627.84637		

Significant Values Displayed in Bold

The size of wakes produced by each passing boat was assessed to understand the impacts of *energy* produced by boats on oyster beds rather than the impact of boat presence alone. In this section, the number of “large wakes” observed refers to the number of boats that produced visible breaking waves along the shoreline, rather than the number of individual breaking waves. The number of large wakes observed per survey varied by site but this effect varied by year (Figure 14, Table 7, 2-way ANOVA, $p = 0.0123$). There were no differences between sites in 2019. In 2020, Shellmaker (mean of 0.06 ± 0.11 per survey) had significantly fewer large wakes than PCH, Westcliff, and Deanza (mean of 0.62 ± 0.12 to 1.19 ± 0.12) and Deanza had significantly fewer than Westcliff (mean of 1.19 ± 0.12), but could not be statistically distinguished from PCH (mean of 0.84 ± 0.12). In 2021 Shellmaker (mean of 0.06 ± 0.10) had significantly fewer large wakes than PCH, Westcliff, and Deanza (mean of 1.17 ± 0.10 to 1.63 ± 0.10). Visually, there was a trend towards increasing large wakes over time at all sites except Shellmaker. In addition, in 2020 and 2021 large wakes appeared to be more frequent at PCH and Westcliff than Deanza and Shellmaker, though this relationship could not be resolved statistically.

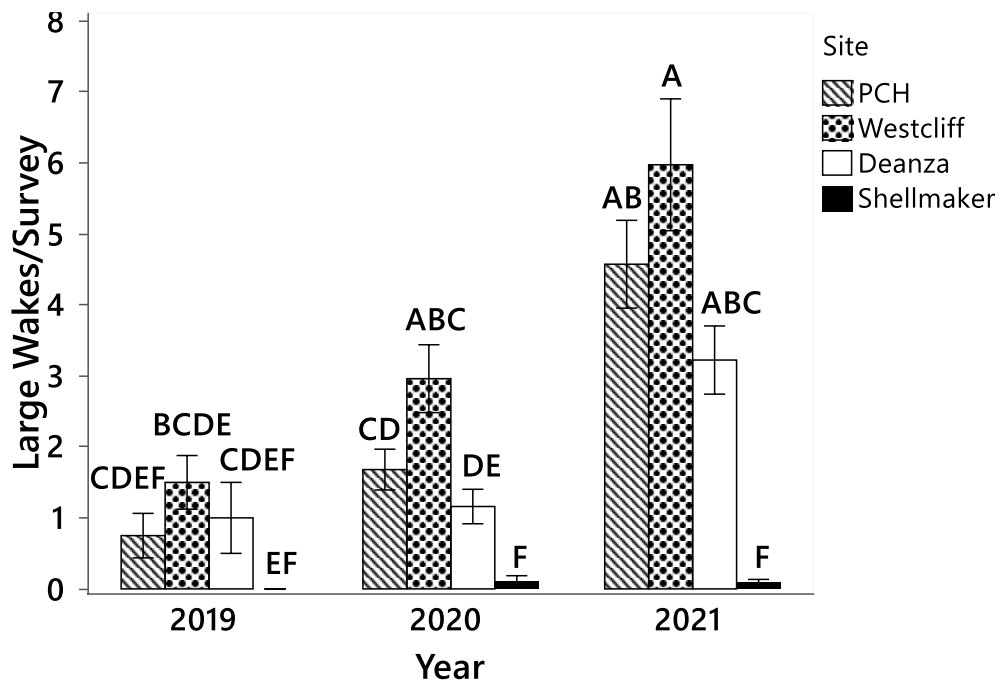


Figure 14. Differences in mean number of large boat wakes per site and year ($N = 68-71$ surveys per site) between 2019-2021 Newport Bay, CA based upon two-way ANOVA. Error bars are ± 1 SE. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 7. Two-way ANOVA results for effect of site and year on $\log(x + 1)$ transformed large wakes per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	2	16.428659	22.9967	<.0001
Year	3	36.085315	33.6746	<.0001
Site*Year	6	5.957549	2.7798	0.0123
Error	264	94.29968		
Total	275	186.39914		

Significant Values Displayed in Bold

The percentage of large boat wakes relative to total boats observed was also assessed to understand the probability of a given boat producing a large wake. This was done to rescale the mean large wake values to deal with the observed infrequency of large wakes (mean large wakes ranged from 0-6 per survey while overall boat passes ranged from 0-46). Like mean large boat wakes, percentage of

large wakes varied by site and this effect varied by year (Figure 15, Table 8, 2-way ANOVA, $p = 0.0027$). There were no differences between sites in 2019. In 2020 Shellmaker (mean of 5.36 ± 3.46) had a lower percentage of large wakes than Westcliff (mean of 28.37 ± 3.66) but not PCH or Deanza (mean of 13.27 ± 3.66 to 20.28 ± 3.66). In 2021 Westcliff and PCH (mean of 40.90 ± 3.10 to 43.98 ± 3.10) had the highest percentage of large boat wakes followed by Deanza (mean of 25.38 ± 3.05), then Shellmaker (mean of 1.52 ± 3.09).

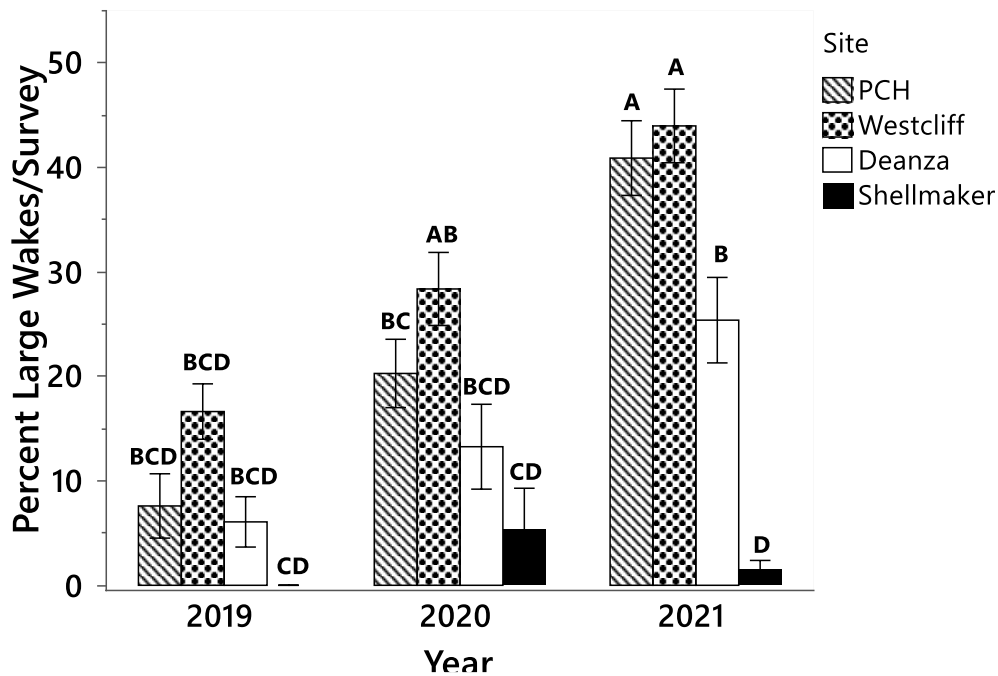


Figure 15. Differences in mean percent large boat wakes per site and year ($N = 68-71$ surveys per site) between 2019-2021 Newport Bay, CA based upon two-way ANOVA. Error bars are ± 1 SE. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 8. Two-way ANOVA results for effect of site and year on percent large wakes per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Year	2	14311.732	21.3322	<.0001
Site	3	19546.248	19.423	<.0001

Year*Site	6	6923.499	3.4399	0.0027
Error	264	88558.52		
Total	275	151451.58		

Significant Values Displayed in Bold

It is important to note that the number of surveys varied by year (8 in 2019, 25 in 2020, 35 in 2021). The reduced number of surveys conducted in 2019 and 2020 relative to 2021 may have reduced the power of the two-way ANOVA which resulted in inconsistent differences between sites among years. If the effect of “Year” is ignored, mean large wakes at PCH, Westcliff, and Deanza were significantly higher than at Shellmaker (Figure 16, Table 9, 1-way ANOVA, $p < 0.0001$) and percent large wakes was highest at PCH and Westcliff, followed by Deanza, then Shellmaker (Figure 17, Table 10, 1-way ANOVA, $p < 0.0001$).

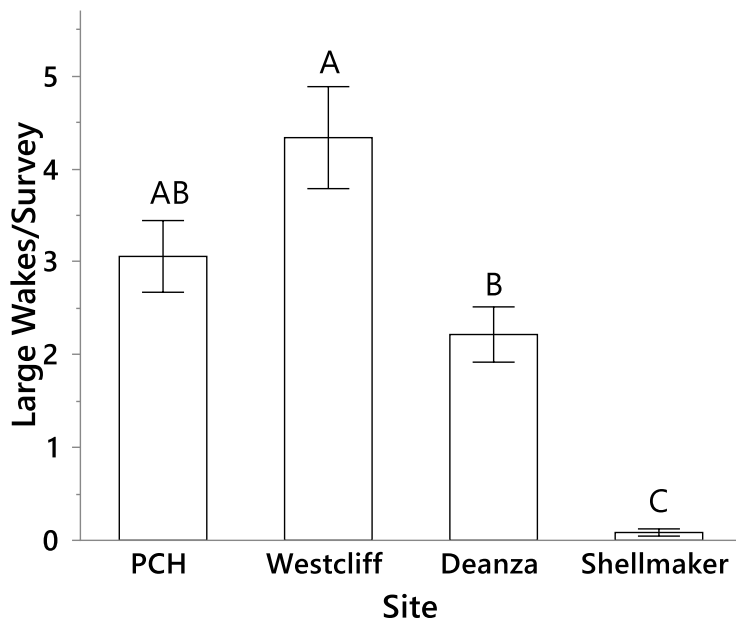


Figure 16. Differences in mean number of large boat wakes per site ($N = 68-71$ surveys per site) between 2019-2021 Newport Bay, CA based upon one-way ANOVA. Error bars are ± 1 SE. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 9. One-way ANOVA results for effect of site on $\log(x + 1)$ transformed large wakes per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	69.89647	54.396	<.0001
Error	272	116.50267		
Total	275	186.39914		

Significant Values Displayed in Bold

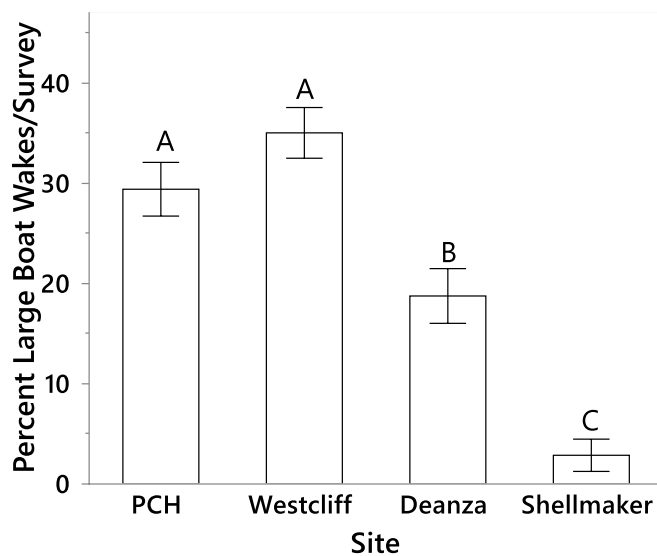


Figure 17. Differences in mean percent large boat wakes per site ($N = 68-71$ surveys per site) between 2019-2021 Newport Bay, CA based upon one-way ANOVA. Error bars are ± 1 SE. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 10. One-way ANOVA results for effect of site on percent large wakes per survey between 2019-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	41842.21	34.611	<.0001
Error	272	109609.37		
Total	275	151451.58		

Significant Values Displayed in Bold

Oyster Bed Response Variables

Oyster Density

Oyster density varied across sites but this effect varied by year (Figure 18, Table 11, 3-way ANOVA, site*year, $p < 0.0123$). In 2018 oyster density ranged from a mean of 51.20 ± 34.93 to 212.00 ± 34.93 oysters/m² and was significantly lower at Westcliff than at Shellmaker. In 2019 density ranged from a mean of 84.00 ± 34.93 to 407.20 ± 34.93 oysters/m² and was significantly lower at Westcliff than at Shellmaker and Deanza. There were no other differences between sites in 2020 or 2021. There was a noticeable drop in density at Deanza and Shellmaker between 2019 and 2020, but density did not vary between years at PCH and Westcliff.

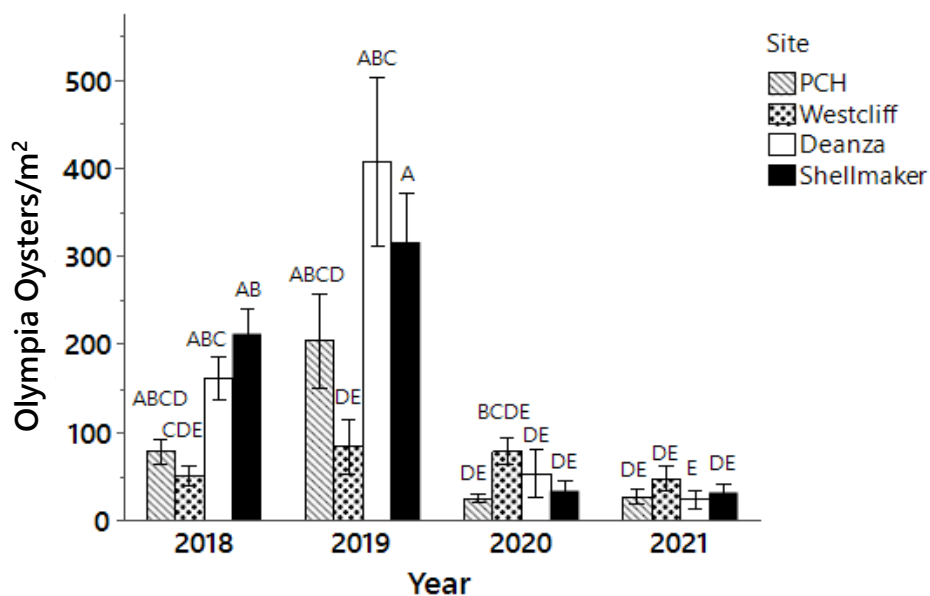


Figure 18. Differences in mean oyster density per site and year ($N = 20$ quadrats per site per year) between 2018-2021 Newport Bay, CA based upon three-way ANOVA. Error bars are ± 1 SE. Variations in letters above bars indicate statistically significant differences based upon post-hoc Tukey HSD.

Table 11. Three-way ANOVA results for effect of site, year, and treatment on $\log(x + 1)$ transformed Olympia oyster density between 2018-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	50.65667	4.7654	0.0029
Treatment	1	9.62125	2.7153	0.1005
site*Treatment	3	3.35871	0.316	0.8138
Year	3	282.97692	26.6206	<.0001
site*Year	9	137.97879	4.3267	<.0001
Treatment*Year	3	26.96257	2.5365	0.057
site*Treatment*Year	9	14.2127	0.4457	0.9093
Error	216	870.5065		
Total	239	1177.2597		

Significant Values Displayed in Bold

Bed Breakdown

The degree of bed breakdown was used to assess bed condition. Bed breakdown was represented by the percent cover of “soft substrate”, including mud, eelgrass, and algal attachment points detected during point contact surveys across the bed footprint. A higher percent cover of bottom substrate indicated more “patchiness” and shell dispersal (or burial) observed on a given bed. There was an interaction effect between year, site, and treatment on percent soft substrate (Figure 19, Table 12, 3-way ANOVA, $p = 0.0003$). Overall, breakdown increased progressively over time on each bed, ranging from a mean of 5.00 ± 2.90 to 26.31 ± 2.90 percent cover of soft substrate one-year post-restoration and 37.45 ± 2.90 to 72.35 ± 2.90 percent cover by four years post-restoration. Beds at PCH and Westcliff appeared to experience breakdown at a faster rate than at Deanza and Shellmaker, though Deanza beds experienced a level of breakdown similar to PCH and Westcliff by 2021. However, this pattern was statistically distinguishable only with the Oyster treatment. The effect of treatment was significant

during two years at two different sites. Breakdown was higher in the absence of eelgrass at PCH in 2018. Conversely, breakdown was higher in the presence of eelgrass at Deanza in 2020.

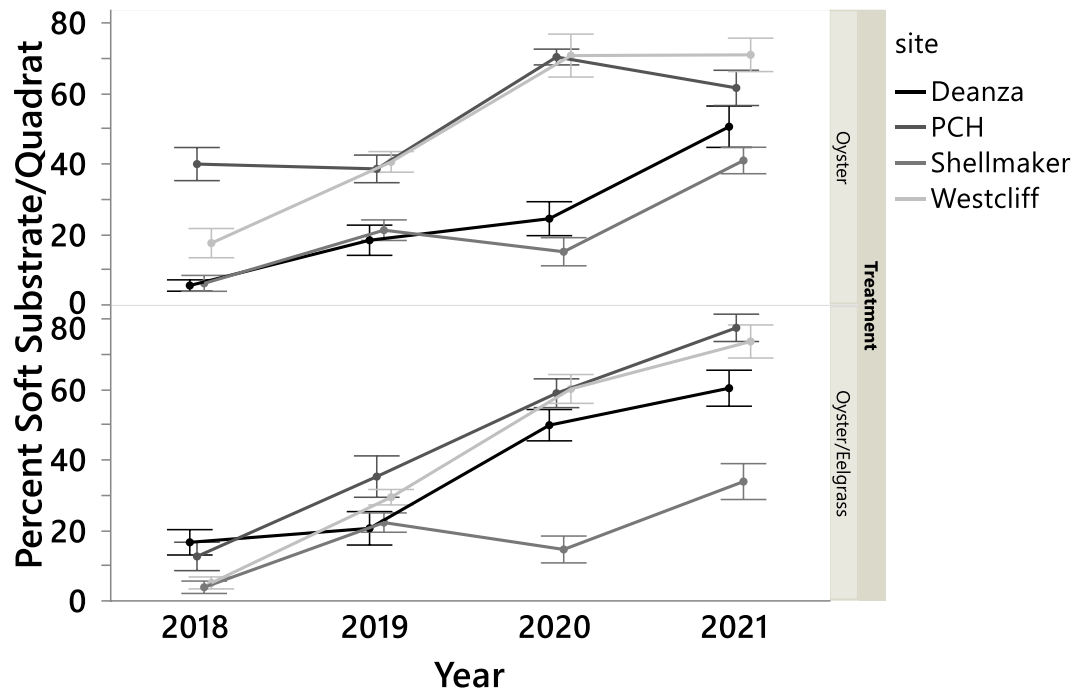


Figure 19. Changes in mean percent soft substrate over time per site by treatment ($N = 10$) between 2018-2021 Newport Bay, CA. Error bars are $\pm 1 SE$. Effect of treatment modified the effect of year and site only twice; once at PCH in 2018 and at Deanza in 2020. These effects are reflected by variations in letters that indicate statistically significant differences based upon three-way ANOVA and post-hoc Tukey HSD presented in Table 13.

Table 12. Three-way ANOVA results for effect of site and year on Olympia oyster density between 2018-2021 in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	45600.714	90.5338	<.0001
Treatment	1	101.951	0.6072	0.4365
site*Treatment	3	5052.34	10.0307	<.0001
Year	3	94045.46	186.7139	<.0001
site*Year	9	15031.142	9.9474	<.0001
Treatment*Year	3	1826.702	3.6267	0.0135
site*Treatment*Year	9	5378.15	3.5592	0.0003
Error	288	48353.99		
Total	319	215390.45		

Significant Values Displayed in Bold

Table 13. Three-way ANOVA post-hoc Tukey HSD results for effect of site, treatment, and year on Olympia oyster density between 2018-2021 in Newport Bay, CA.

Site-Treatment-Year	Tukey letters	Least sq means
PCH-O/E-2021	A	77.55102
WC-O/E-2021	A	73.673469
WC-O-2021	AB	71.020408
WC-O-2020	AB	70.816327
PCH-O-2020	AB	70.408163
PCH-O-2021	ABC	61.632653
DA-O/E-2021	ABCD	60.408163
WC-O/E-2020	ABCD	60.204082
PCH-O/E-2020	ABCD	58.979592
DA-O-2021	BCDE	50.612245
DA-O/E-2020	BCDE	49.906122
SM-O-2021	CDEF	41.020408
WC-O-2019	CDEF	40.623531
PCH-O-2018	CDEFG	40
PCH-O-2019	DEFGH	38.635204
PCH-O/E-2019	EFGHI	35.306122

Site-Treatment-Year	Tukey letters	Least sq means
SM-O/E-2021	EFGHIJ	33.888946
WC-O/E-2019	EFGHIJ	29.448632
DA-O-2020	FGHIJK	24.489796
SM-O/E-2019	FGHIJK	22.244898
SM-O-2019	FGHIJK	21.22449
DA-O/E-2019	FGHIJK	20.612245
DA-O-2019	GHIJK	18.367347
WC-O-2018	HIJK	17.55102
DA-O/E-2018	HIJK	16.638549
SM-O-2020	IJK	15.102041
SM-O/E-2020	IJK	14.608163
PCH-O/E-2018	JK	12.628571
SM-O-2018	K	6.122449
DA-O-2018	K	5.510204
WC-O/E-2018	K	5.102041
SM-O/E-2018	K	3.873469

It would initially be assumed that the relative influence of treatment (oyster vs. oyster/eelgrass) was based on the presence or absence of eelgrass. However, upon comparing the means (based upon post-hoc Tukey analyses) there was no consistent trend that showed significantly higher or lower bed breakdown relative to the presence or absence of eelgrass. Rather, it appeared as though the effect of treatment represented the spatial position of each individual bed relative to the mouth of the bay (treatment order was randomized at each site to avoid block effects). The progression of breakdown on each bed over time was examined by comparing the mean percent bottom substrate between years in one-year intervals (i.e. year 0-1, year 1-2, year 2-3, etc.) and in terms of overall time since restoration (i.e. year 0-1, year 0-2, year 0-3, etc.) based on post-hoc Tukey comparisons. The progression of bed breakdown coincided with the spatial position of each bed, with the bed furthest down-bay experiencing significant breakdown (relative to year 0) first and the bed furthest up-bay experiencing significant breakdown last (see Table 14).

Alternatively, while there was no consistent treatment effect based on the post-hoc Tukey comparisons, breakdown appears consistently higher in the absence of eelgrass at PCH and Westcliff. This suggests that eelgrass may slow the progression of bed breakdown, though not enough to generate a statistical signal in a three-way ANOVA. Eelgrass has been largely absent at Shellmaker and it might therefore be inappropriate to include it in this analysis. However, when Shellmaker was excluded the treatment effect is still limited to PCH in 2018 and Deanza in 2020.

Table 14. Year-to-year and cumulative progression of breakdown of oyster beds between 2017-2021 in Newport Bay, CA relative to upbay-downbay location within the bay, based upon three-way ANOVA post-hoc tukey comparisons. “X” denotes statistically-significant difference between years. Year-to-year columns represent single-year period wherein significant breakdown was experienced. An “X” in the cumulative change columns represent time at which significant breakdown was experienced relative to initial restoration (Year 0).

	Site	Treatment	Year to Year				Cumulative Change			
			Year 0-1	Year 1-2	Year 2-3	Year 3-4	Year 0-1	Year 0-2	Year 0-3	Year 0-4
Downbay	PCH	Oyster	X		X		X	X	X	X
	PCH	Oyster/Eelgrass		X	X			X	X	X
	Westcliff	Oyster		X	X			X	X	X
	Westcliff	Oyster/Eelgrass		X	X			X	X	X
	Deanza	Oyster/Eelgrass			X				X	X
	Deanza	Oyster				X				X
	Shellmaker	Oyster/Eelgrass								X
Upbay	Shellmaker	Oyster				X				X

Upshore Migration

Due to low replication, upshore migration data was not analyzed statistically. Upshore migration measurements were taken in 2020 and 2021 on the original restored oyster beds and the new “mini” beds. Measurements during these years represented upshore migration 3- and 4-years post-restoration on the original beds and migration 1- and 2-years post-restoration on the new beds.

On the original beds, upshore migration appeared highest at PCH and decreased with distance from the mouth of the bay, with Shellmaker having experienced the least amount of migration (Figure 20). The only deviation from this pattern was on the Oyster treatment at Deanza, which experienced an amount of upshore migration similar to that observed at PCH and Westcliff. This may be due to the proximity of a small boating channel to the immediate right of this plot (Figure 21).

Upshore migration on the new “mini” beds did not appear to exhibit a clear pattern (Figure 22). However, subsequent sampling may reveal a pattern similar to that observed with the older plots as breakdown and migration progresses with time.

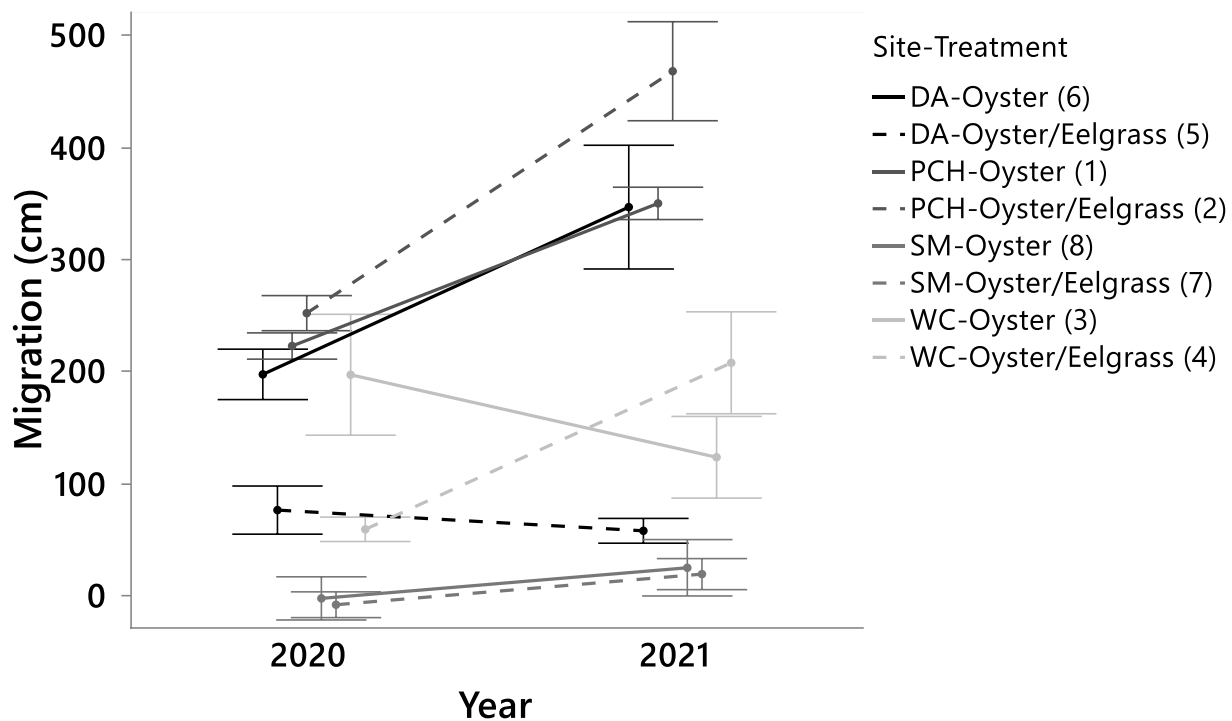


Figure 20. Upshore migration (cm) in 2020 and 2021, 3- and 4-years post-restoration, on original restored beds in Newport Bay, CA. Numbers in legend reflect downbay (1) to upbay (8) position of beds.



Figure 21. Location of oyster beds at Deanza relative to small boating channel directly adjacent to site in Newport Bay, CA. Arrows indicate the location of this channel and the direction of boats moving to and from the bay.

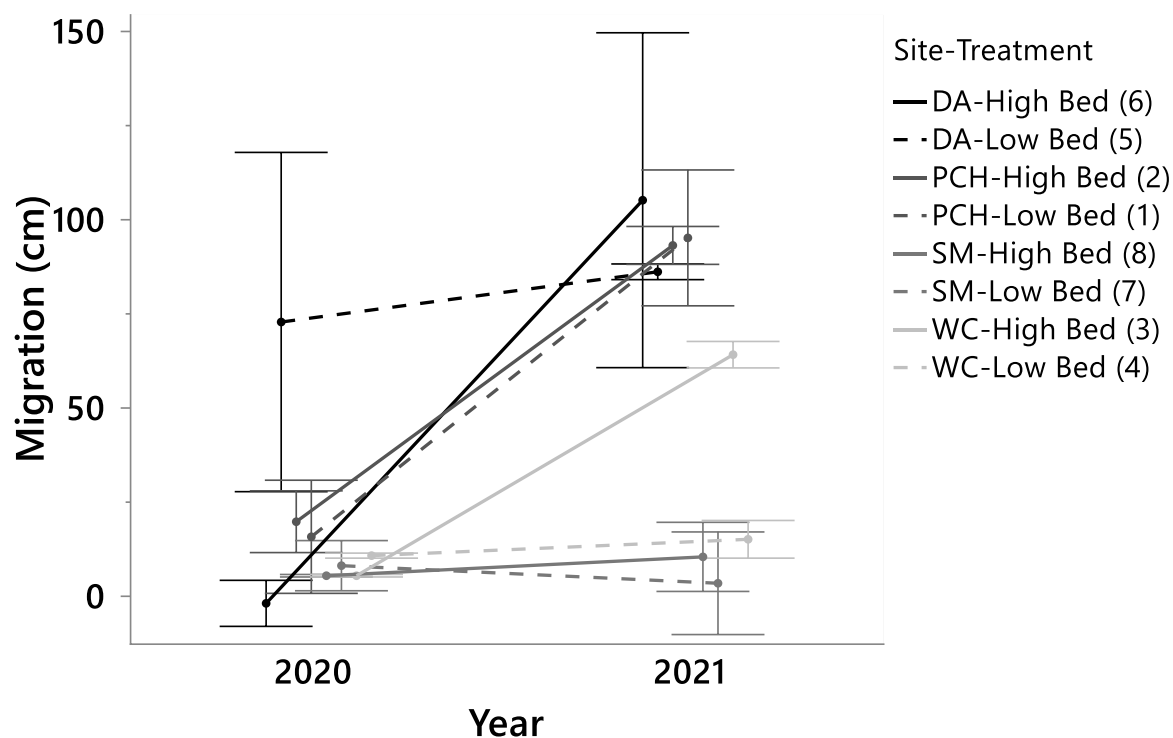


Figure 22. Upshore migration (cm) in 2020 and 2021, 1- and 2-years post-restoration, on new “mini” restored beds in Newport Bay, CA. Numbers in legend reflect downbay (1) to upbay (8) position of beds.

Site Characteristics and Oyster Bed Response Variables

Effects of Human Activity on Oyster Density and Bed Breakdown

The relationship between oyster density and mean onshore activity varied across years (Figure 23, $\chi^2 = 7.61$, $p = 0.02$), and there was no correlation between oyster density and mean onshore activity ($\chi^2 = 9.6 \text{ e}^{-8}$, $p = 0.99$). Therefore, there was no detectable relationship between oyster density and mean onshore activity.

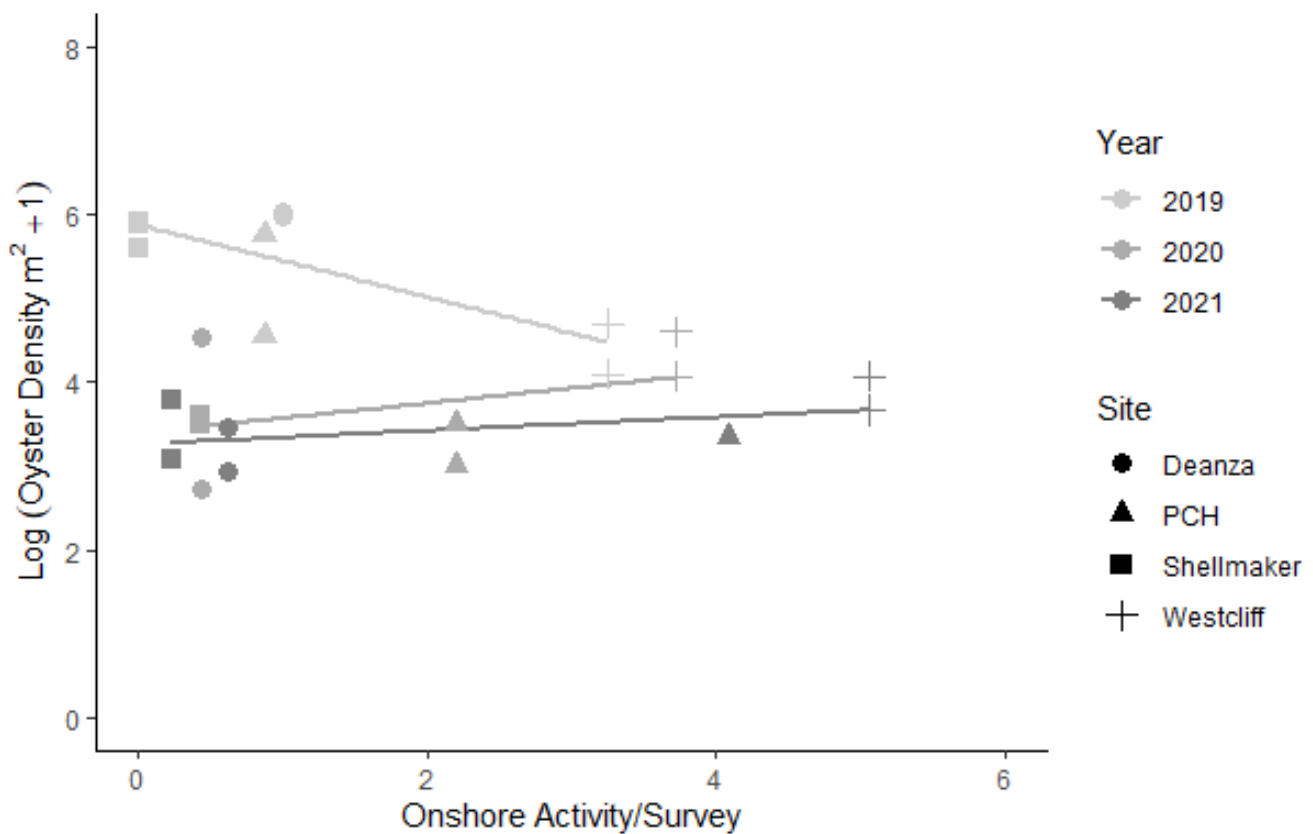


Figure 23. Predicted relationship between mean onshore activity and log-transformed oyster density during each year between 2019-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point). Absence of dashed line indicates no overall predicted relationship.

The relationship between bed breakdown (represented by percent soft bottom substrate) and mean onshore activity is shown in Figure 24. Variation among years in slope did not significantly

improve the model ($\chi^2 = 0.29$, $p = 0.86$) and I refit the model with only random intercepts. In this model, mean onshore activity was positively correlated with bed breakdown ($\chi^2 = 17.68$, $p < 0.0001$).

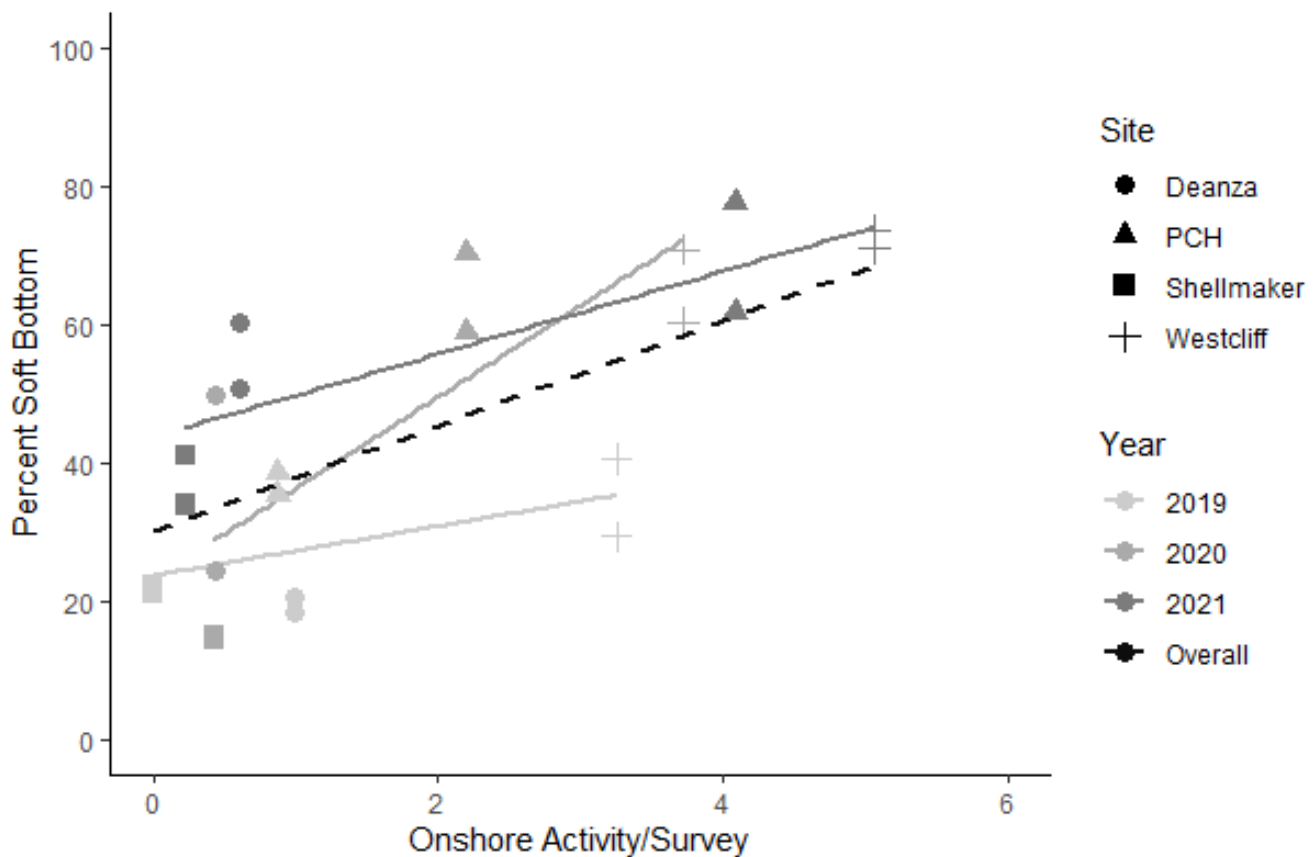


Figure 24. Predicted relationship between mean onshore activity and percent soft bottom substrate during each year between 2019-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). The overall predicted relationship is represented by a dashed line. Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point).

The relationship between oyster density and mean large boat wake passes is shown in Figure 25.

Variation among years in slope did not significantly improve the model ($\chi^2 = 3.52$, $p = 0.17$) and I refit the model with only random intercepts. In this model, there was no correlation between mean large boat wake passes and oyster density (Figure 25, $\chi^2 = 0.1$, $p = 0.75$). Therefore, there was no detectable relationship between oyster density and the number of large boat wake passes.

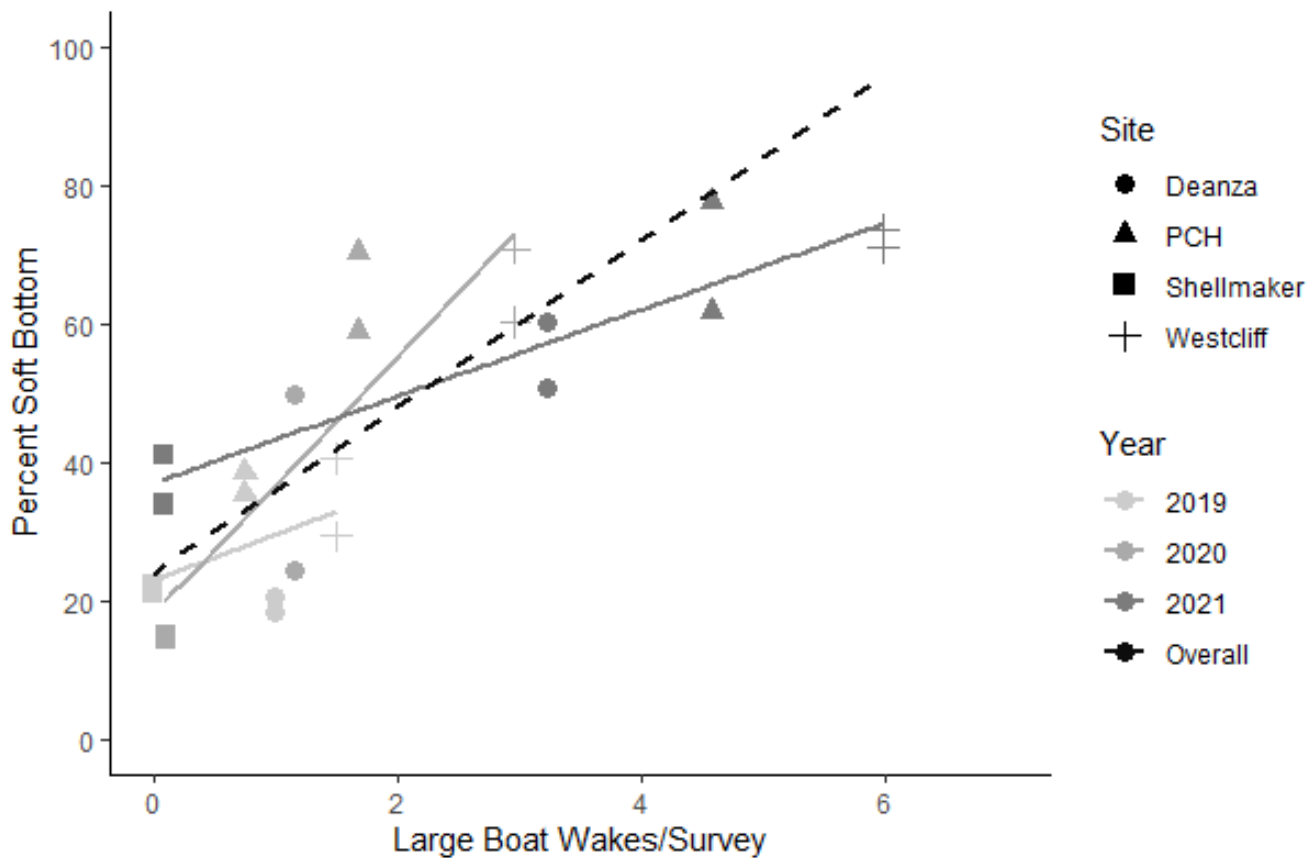


Figure 26. Predicted relationship between mean number of large boat wakes per survey and percent soft bottom substrate during each year between 2019-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). The overall predicted relationship is represented by a dashed line. Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point).

The relationship between oyster density and percent large boat wake passes varied between years (Figure 27, $\chi^2 = 7.03$, $p = 0.03$), and there was no correlation between oyster density and percent large boat wake passes ($\chi^2 = 0.04$, $p = 0.83$). Therefore, there was no detectable relationship between oyster density and percent large boat wake passes.

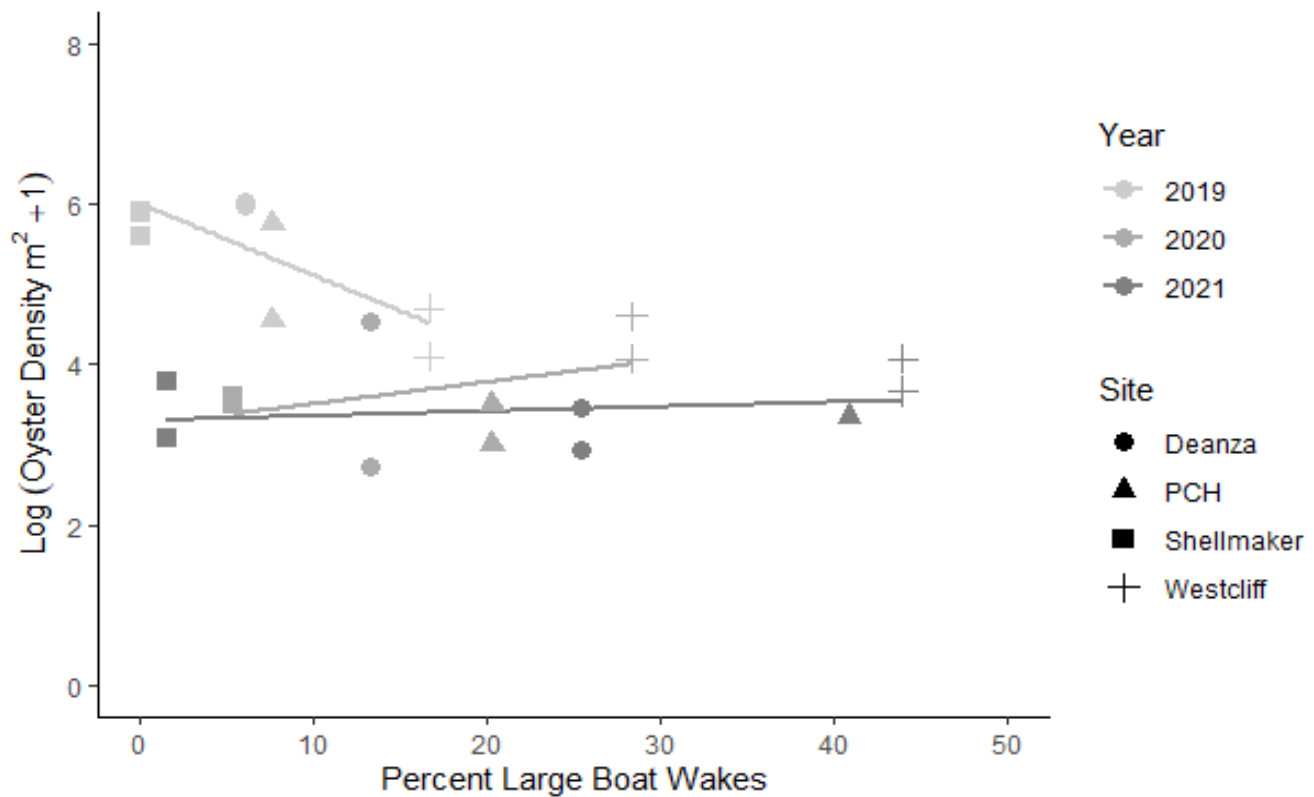


Figure 27. Predicted relationship between mean percent of large boat wakes per survey and log-transformed oyster density during each year between 2019-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point). Absence of dashed line indicates no overall predicted relationship.

The relationship between bed breakdown (represented by percent soft bottom substrate) and percent of large boat wake passes is shown in Figure 28. Variation among years in slope did not significantly improve the model ($\chi^2 = 3.58$, $p = 0.17$) and I refit the model with only random intercepts. Unfortunately, simplifying the model did not improve singularity. This may be due to the large difference in the range of percent large boat wakes between years, with 0 - 16.63% large boat wake passes in 2019, 5.36 - 28.37% in 2020, and 1.5 - 43.98% in 2021. This large disparity between years was likely due to the low number of surveys conducted in 2019 ($N = 8$) relative to 2020 ($N = 25-28$) and 2021 ($N = 35-36$). Therefore, the true percentage of large boat wake passes in 2019 may not have been captured. Simple single-year linear regressions resulted in a significant strong and positive relationship

between percent large boat wakes and bed breakdown in 2020 (Figure 28, $r^2 = 0.76$, $p = 0.003$) and 2021 (Figure 28, $r^2 = 0.86$, $p = 0.0005$) but a non-significant relationship approaching significance in 2019 (Figure 28, $r^2 = 0.29$, $p = 0.1$). In addition, if the singular fit is ignored there was a significant relationship between percent large boat wakes and bed breakdown overall and during each year, where bed breakdown increases with increasing percentage of large boat wakes (Figure 28, $\chi^2 = 28.13$, $p < 0.0001$). The structure of the data makes it difficult to conclude that there was a relationship between percentage of large boat wakes and bed breakdown, but simpler year-by-year analysis provides some evidence that higher bed breakdown was associated with higher percentage of large boat wakes every year and overall.

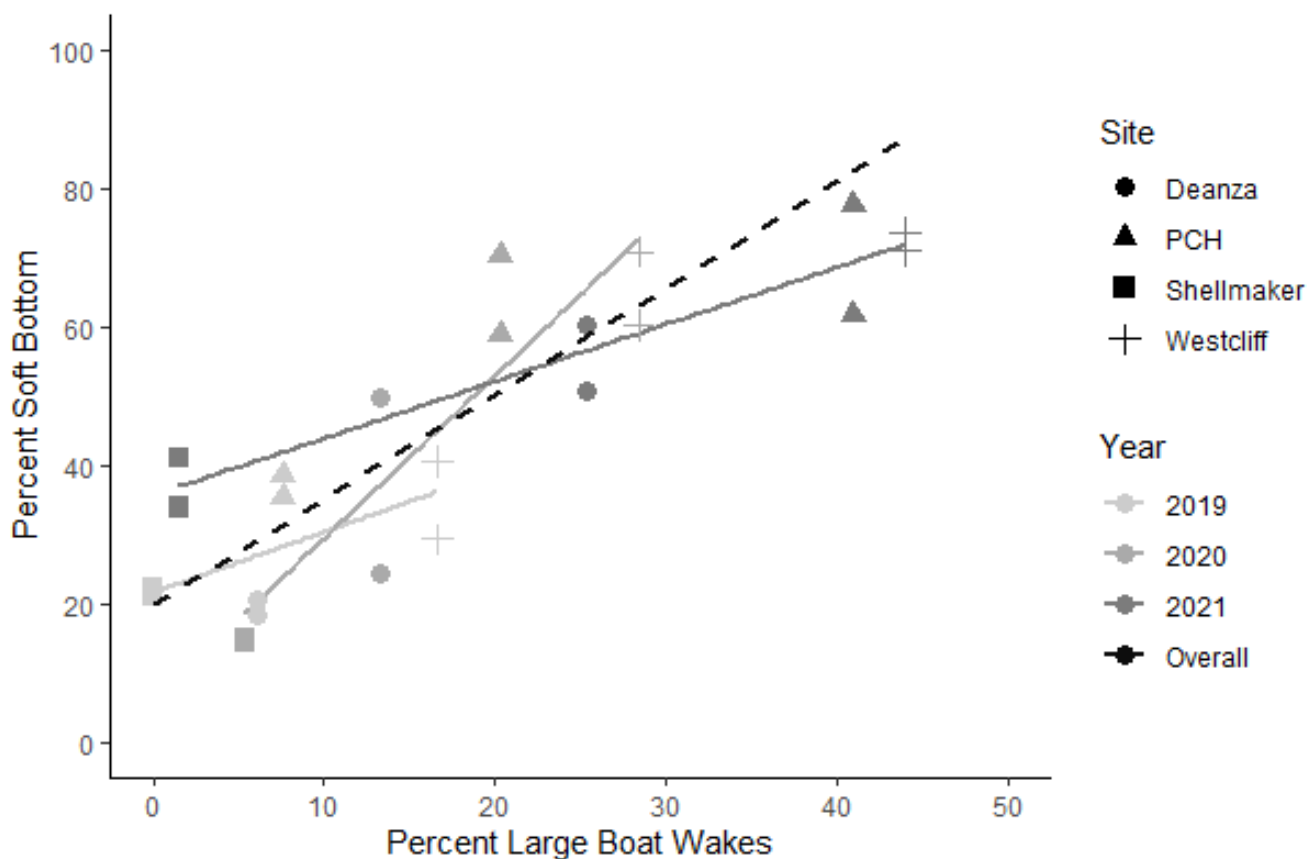


Figure 28. Predicted relationship between percent of large boat wakes per survey and percent soft bottom substrate during each year between 2019-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). The overall predicted relationship is represented by a dashed line. Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point).

Effects of Eelgrass on Oyster Density and Bed Breakdown

The relationship between oyster density and eelgrass density varied across years (Figure 29, $\chi^2 = 6.39$, $p = 0.04$) and there was no correlation between oyster density and eelgrass density (Figure 29, $\chi^2 = 1.04$, $p = 0.31$). Therefore, there was no detectable relationship between oyster density and eelgrass density.

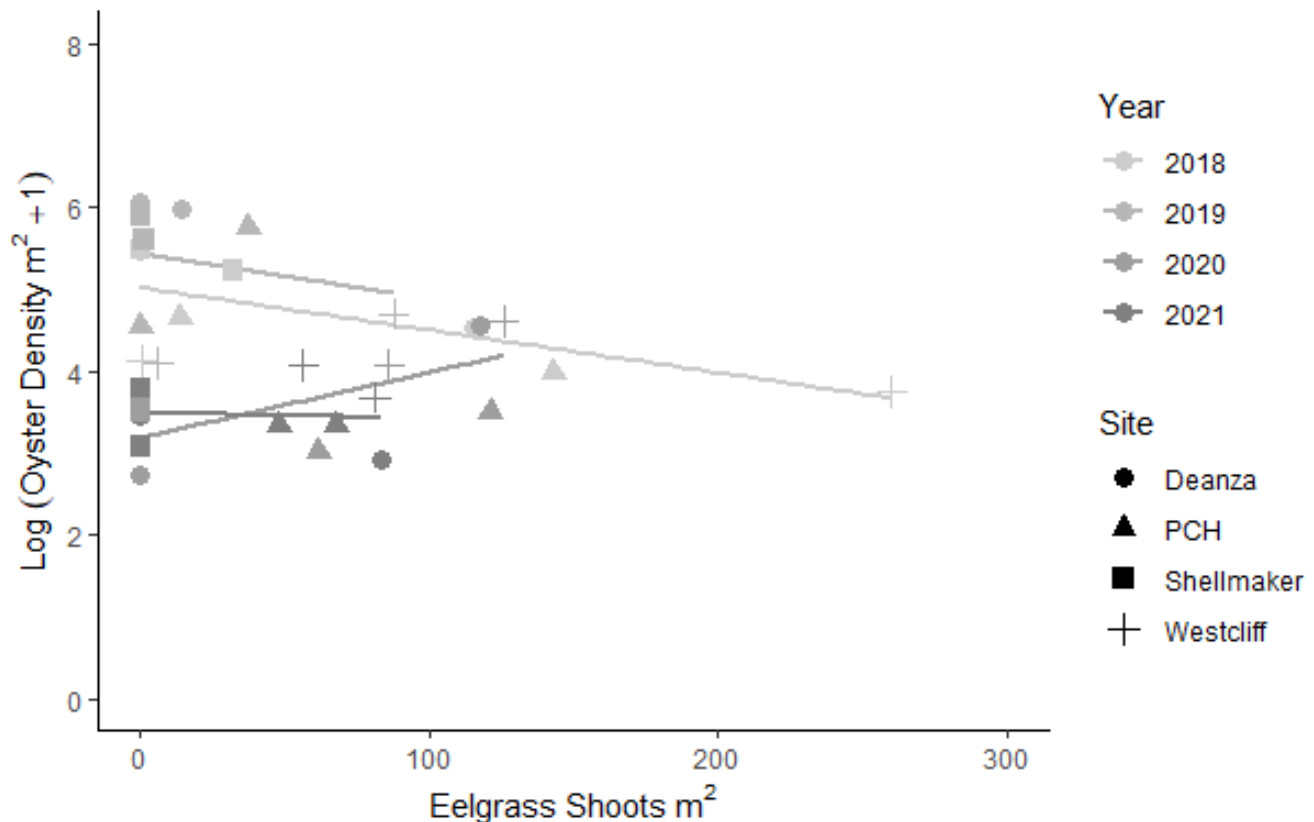


Figure 29. Predicted relationship between eelgrass density and log-transformed oyster density during each year between 2018-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point). Absence of dashed line indicates no overall predicted relationship.

The relationship between bed breakdown (represented by percent soft bottom substrate) and eelgrass density varied across years (Figure 30, $\chi^2 = 13.25$, $p = 0.001$) and there was no detectable relationship between oyster density and eelgrass density (Figure 30, $\chi^2 = 3.21$, $p = 0.07$). This suggests that there was no relationship between bed breakdown and eelgrass density. However, this may have

been due to the differences in human activity among sites. Deanza and Shellmaker experienced less onshore activity and a lower frequency of large boat wake passes than PCH and Westcliff. At sites with higher potential human impacts the eelgrass may have prevented bed breakdown via wave attenuation. At sites with lower potential human impact there would likely not be a detectable relationship between eelgrass and bed breakdown due to the absence of this stressor. When the “low impact” sites were removed from analysis, the relationship between bed breakdown and eelgrass density no longer varied by year ($\chi^2 = 0.94$, $p = 0.63$) and bed breakdown varied significantly with eelgrass density (Figure 31, $\chi^2 = 9.71$, $p = 0.002$), with a lower amount of breakdown associated with higher eelgrass density overall and during each year.

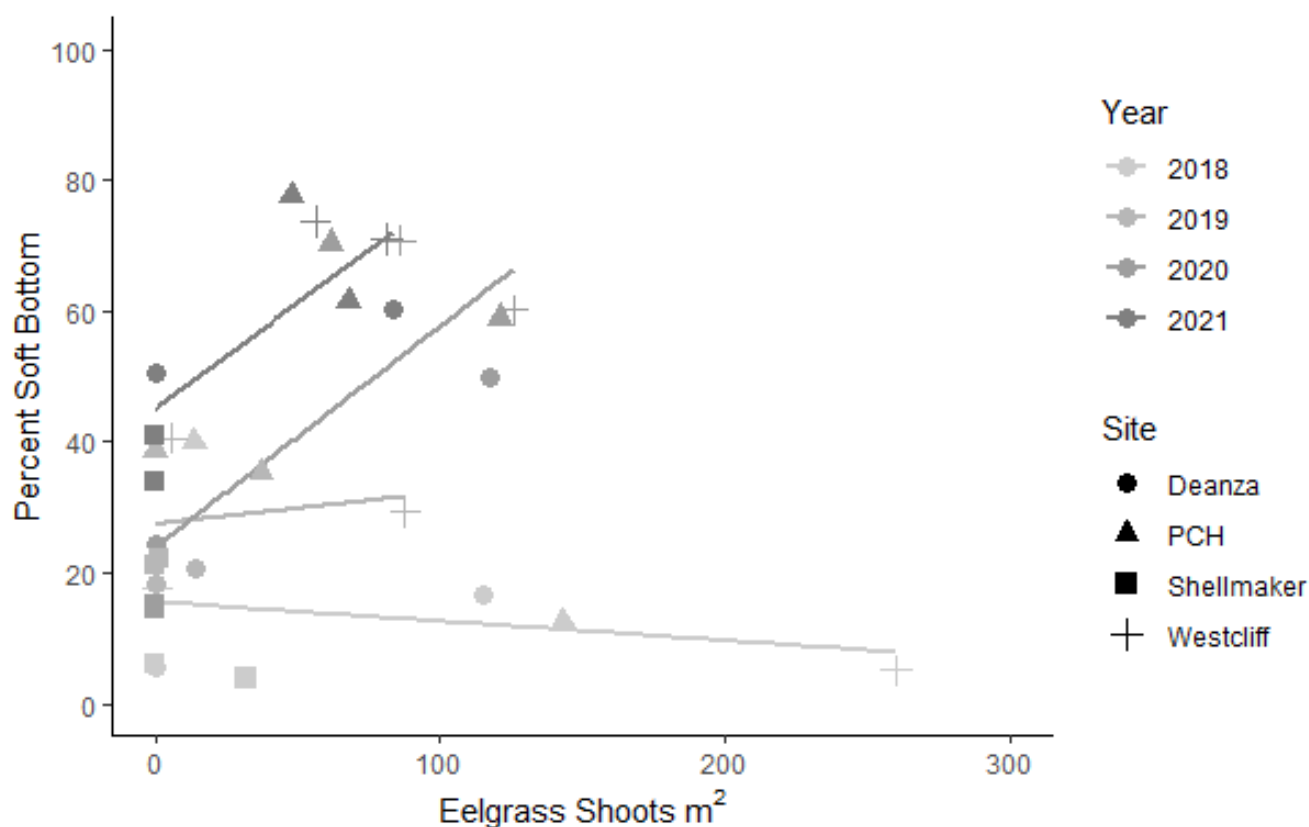


Figure 30. Predicted relationship between eelgrass density and percent soft bottom substrate during each year between 2018-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point). Absence of dashed line indicates no overall predicted relationship.

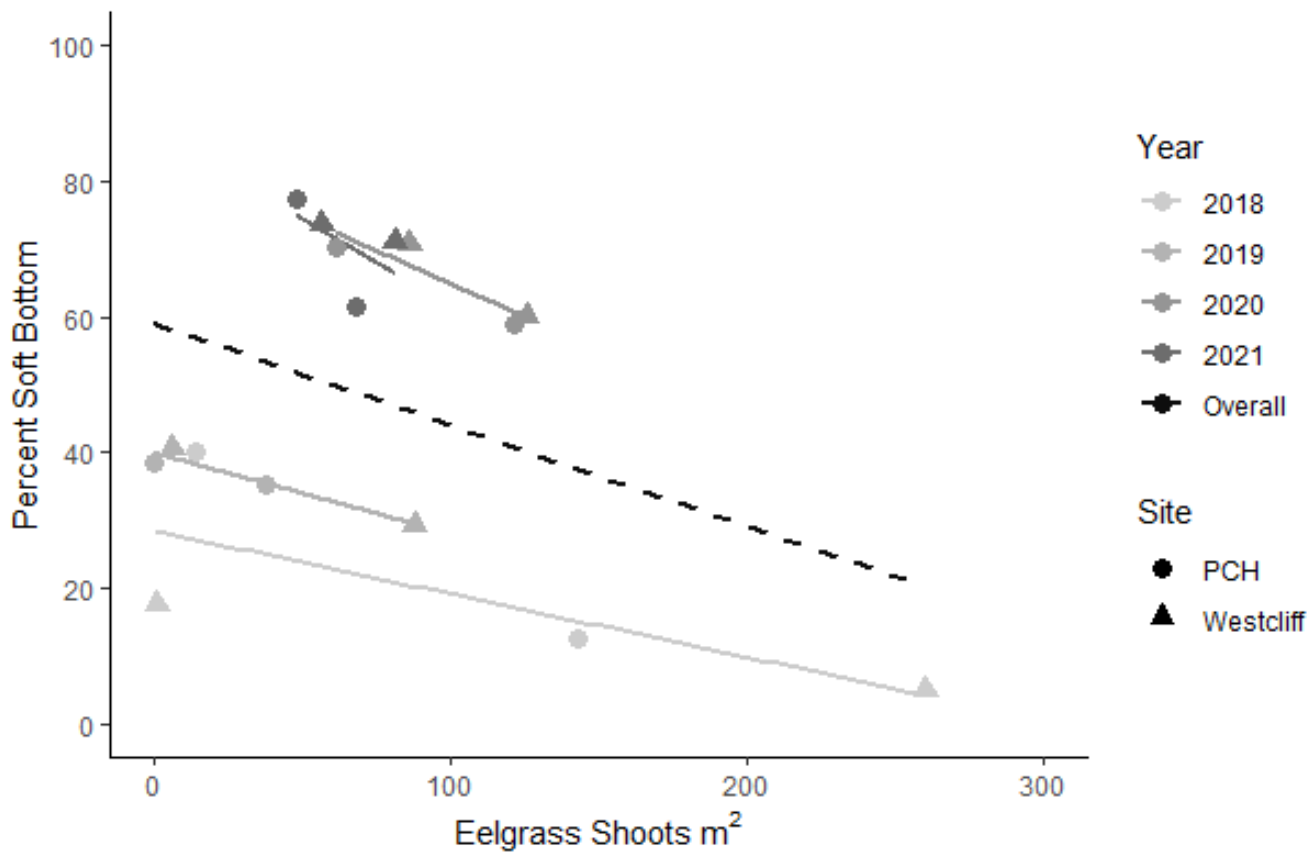


Figure 31. Predicted relationship between eelgrass density and percent soft bottom substrate during each year between 2018-2021 in Newport Bay, CA at high boat wake energy sites only, based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 4$ oyster beds per year). The overall predicted relationship is represented by a dashed line. Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point).

Effects of Annual Recruitment on Oyster Density and Bed Breakdown

The relationship between oyster density and prior year recruitment is shown in Figure 32.

Variation among years in slope did not significantly improve the model ($\chi^2 = 0.27$, $p = 0.87$) and I refit the model with only random intercepts. In this model, oyster density was positively correlated with prior year recruitment overall ($\chi^2 = 6.49$, $p = 0.01$).

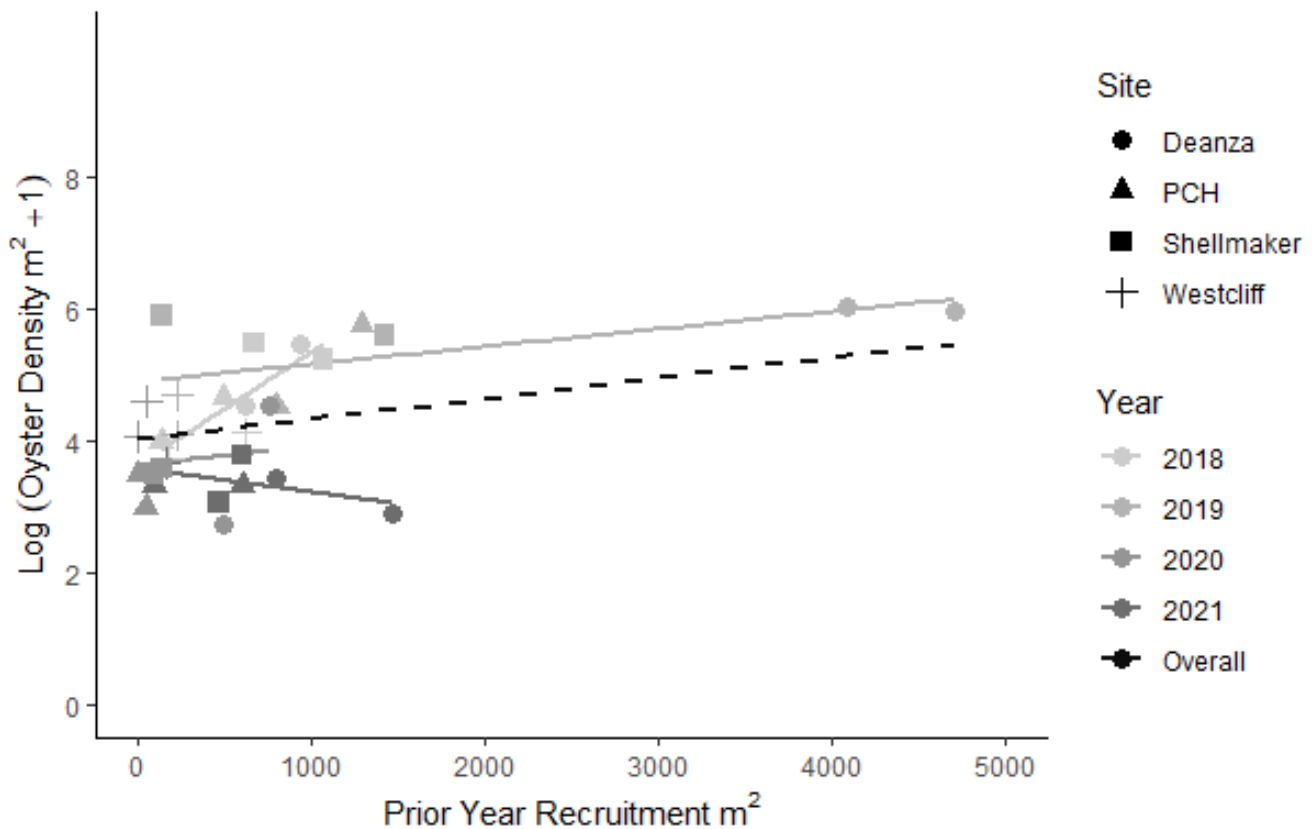


Figure 32. Predicted relationship between prior year recruitment and log-transformed oyster density during each year between 2018-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). The overall predicted relationship is represented by a dashed line. Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point).

The relationship between bed breakdown (represented by percent soft bottom substrate) and prior year recruitment is shown in Figure 33. Variation among years in slope did not significantly improve the model ($\chi^2 = 0.16$, $p = 0.92$) and I refit the model with only random intercepts. In this model, there was no correlation between bed breakdown and prior year recruitment ($\chi^2 = 1.78$, $p = 0.18$). Therefore, there was no detected relationship between bed breakdown and prior year recruitment.

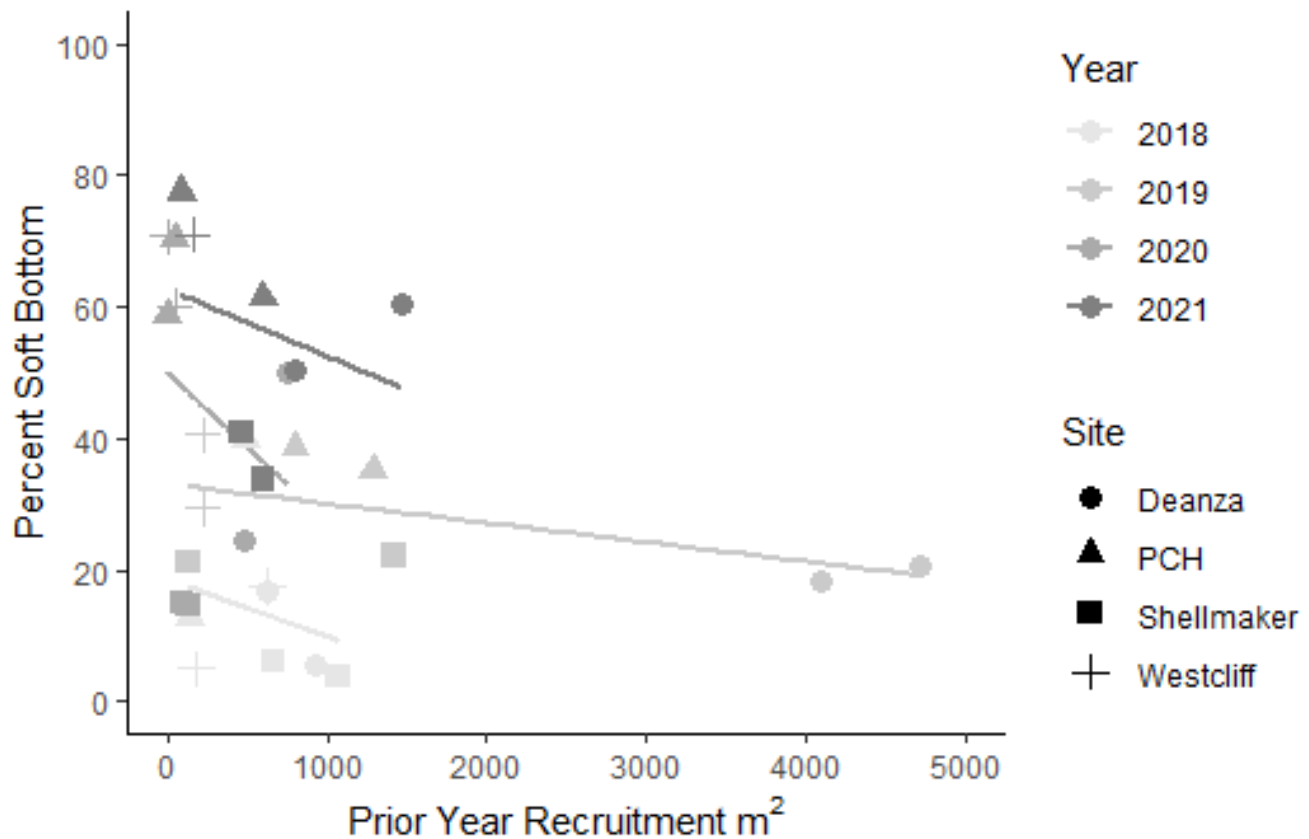


Figure 33. Predicted relationship between prior year recruitment and percent soft bottom substrate during each year between 2018-2021 in Newport Bay, CA based upon linear mixed model. Each solid line represents the predicted relationship during a given year ($N = 8$ oyster beds per year). Each point represents one oyster bed (two oyster beds per site; site is distinguished by shape of point). Absence of dashed line indicates no overall predicted relationship.

Multivariate Analysis: Environmental Variables and Oyster Bed Response

Site characteristics evaluated simultaneously differed among sites (Figure 34, Table 15, PERMANOVA, pseudo- $F = 16.003$, $p = 0.001$) and among years (Figure 34, Table 15, PERMANOVA, pseudo- $F = 12.094$, $p = 0.001$) with no interaction between site and year. Within groups, all years (pairwise test, Table 16) and sites (pairwise test, Table 17) differed from one another. The first two canonical correlations are $\delta_1 = 0.99$ and $\delta_2 = 0.99$, which indicated the strength of the relationship between the multivariate data cloud and the hypothesized groupings. Percent large boat wakes and onshore activity separated beds along the CAP1 axis by site, with “high boat wake energy sites” (PCH

and Westcliff) and “low boat wake energy sites” (Deanza and Shellmaker) forming distinct groups.

Oyster density separated beds along the CAP2 axis by year.

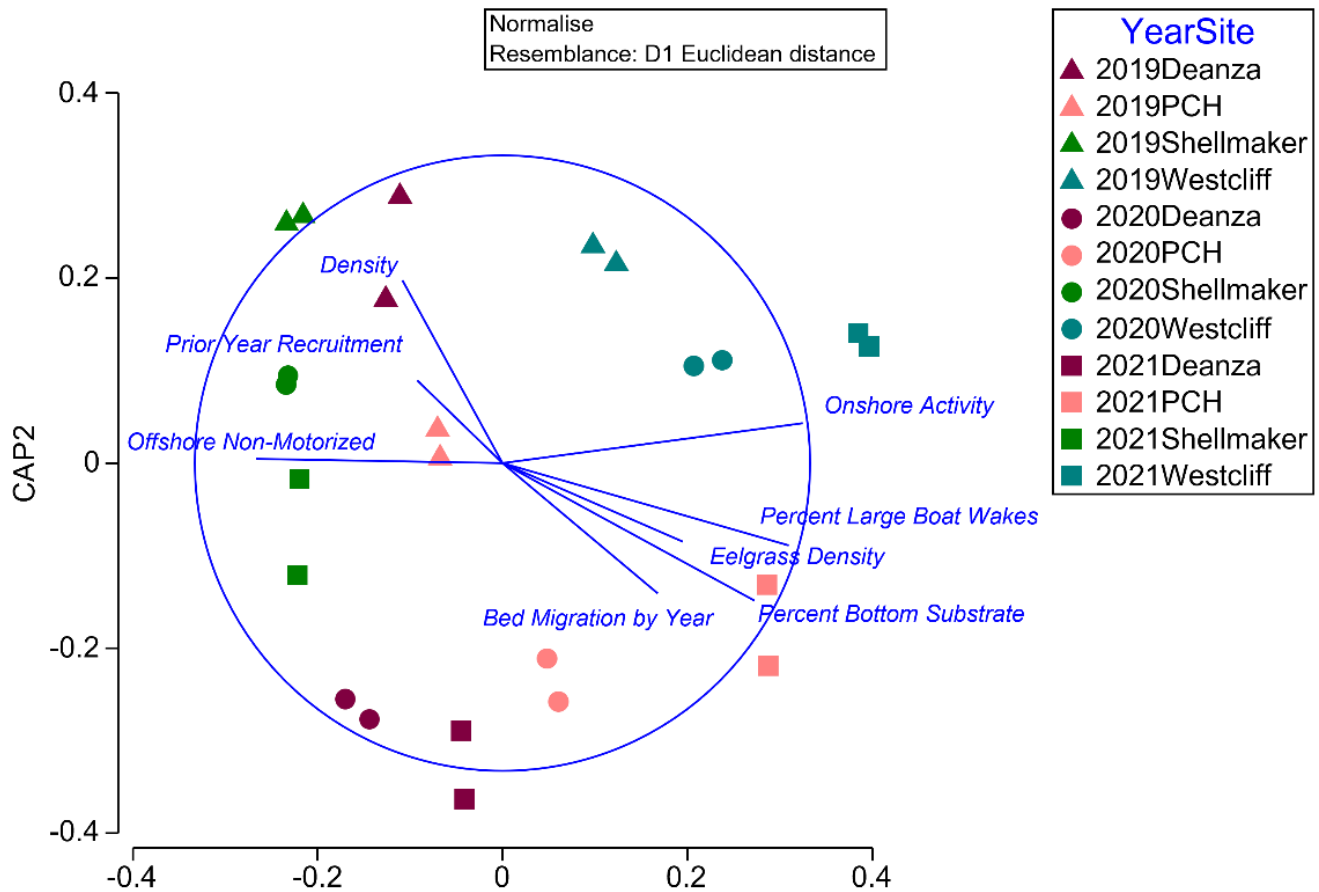


Figure 34. CAP analysis of site characteristics (prior year recruitment, human activity, eelgrass density) and oyster bed response variables (oyster density, percent bottom substrate, upshore bed migration) associated with individual oyster beds by year (point shape) and site (point color) during 2019-2021 in Newport Bay, CA.

Table 15. Two-way PERMANOVA results for effect of site and year on site characteristics and oyster bed response variables between 2019-2021 in Newport Bay, CA.

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	Pseudo- <i>F</i>	<i>P</i> (perm)
Year	2	47.991	23.995	12.094	0.001
Site	3	95.25	31.75	16.003	0.001
Year*Site	6	17.395	2.8991	1.4612	0.106
Residuals	12	23.809	1.9841		
Total	23	184.44			

Significant Values Displayed in Bold

Table 16. Two-way PERMANOVA pairwise test results for differences between years (2019-2021).

Groups	<i>t</i>	<i>P</i> (perm)
2019, 2020	3.4714	0.001
2019, 2021	4.8844	0.001
2020, 2021	2.1838	0.006

Significant Values Displayed in Bold

Table 17. Two-way PERMANOVA pairwise test results for differences between sites in Newport Bay, CA.

Groups	<i>t</i>	<i>P</i> (perm)
Deanza, PCH	2.7026	0.003
Deanza, Shellmaker	2.4863	0.006
Deanza, Westcliff	3.4096	0.001
PCH, Shellmaker	7.1914	0.004
PCH, Westcliff	2.1729	0.014
Shellmaker, Westcliff	7.4523	0.006

Significant Values Displayed in Bold

Ecosystem Service Response Variables

Upshore Grain Size

Four years post-restoration, changes in median grain size ranged from -6.15 to 19.83 standard deviations from mean starting conditions, with negative values indicating a shift towards finer grain sizes and positive values indicating a shift towards coarser grain sizes. There was no effect of site (Figure 35, Table 18, 1-way ANOVA, $p = 0.07$) or treatment (Figure 36, Table 19, 1-way ANOVA, $p = 0.6$) on change in median grain size.

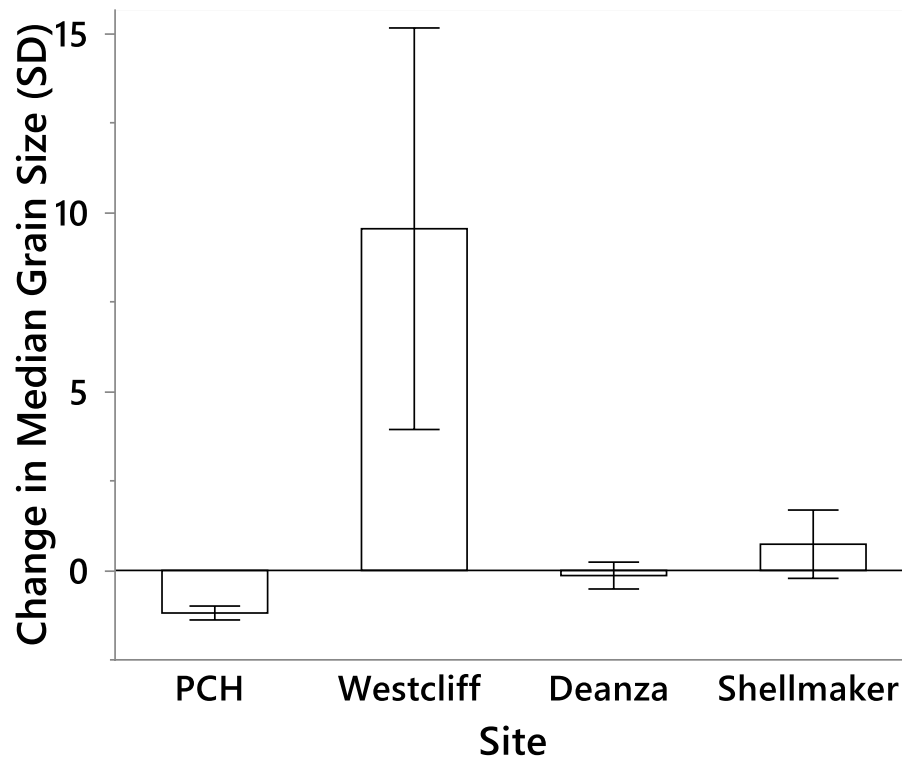


Figure 35. Differences in mean change in median grain size per site ($N = 4$ samples per site) in 2021, four years post-restoration, in Newport Bay, CA based upon one-way ANOVA. Error bars are ± 1 SE.

Table 18. One-way ANOVA results for effect of site on change in median grain size in 2021, four years post-restoration, in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	292.72544	2.9941	0.0731
Error	12	391.06953		
Total	15	683.79497		

Significant Values Displayed in Bold

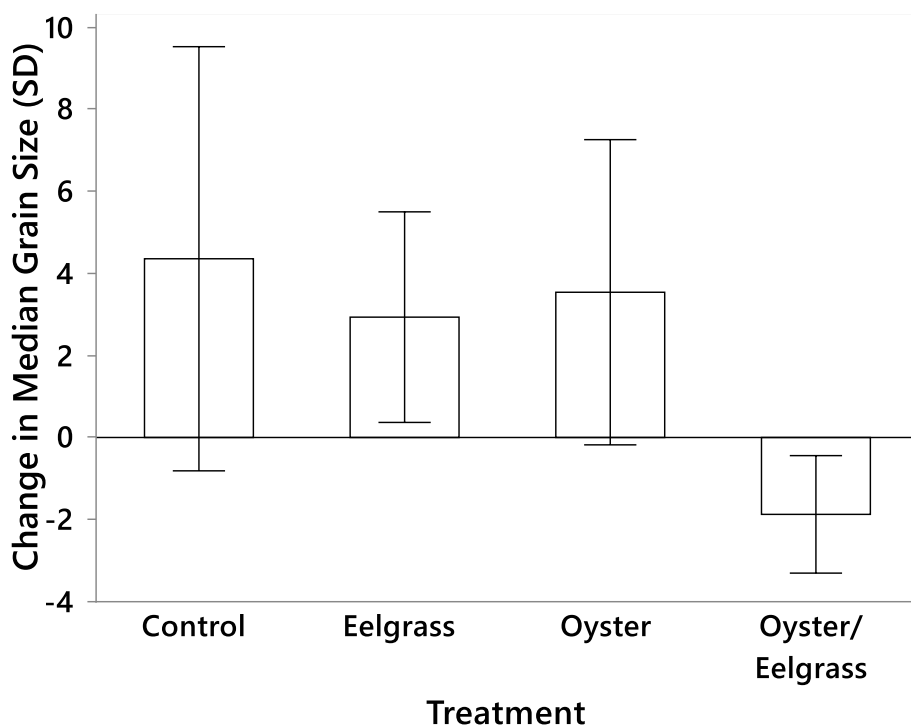


Figure 36. Differences in mean change in median grain size per treatment ($N = 4$ samples per treatment) in 2021, four years post-restoration, in Newport Bay, CA based upon one-way ANOVA. Error bars are ± 1 SE.

Table 19. One-way ANOVA results for effect of treatment on change in median grain size in 2021, four years post-restoration, in Newport Bay, CA.

	<i>DF</i>	Sum of Squares	<i>F</i> Ratio	Prob > <i>F</i>
Site	3	94.183086	0.6389	0.6043
Error	12	589.61188		
Total	15	683.79497		

Significant Values Displayed in Bold

When the relationship between change in median grain size and time since restoration was assessed for each individual treatment plot, only the eelgrass plot at PCH exhibited a statistically significant relationship (Figure 37, regression, $r^2 = 0.88$, $p = 0.02$), with median grain size decreasing (becoming finer) with time since restoration. There were no other significant relationships at any individual treatment plot (Figures 38-40).

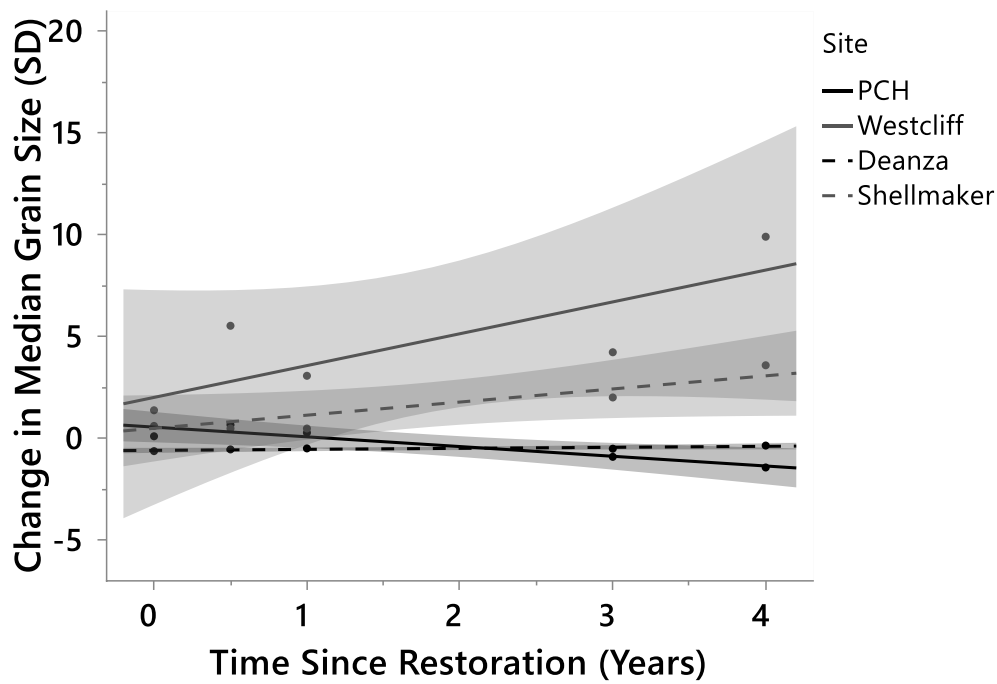


Figure 37. Change in median grain size between 2017-2021 at eelgrass treatment by site ($N = 5$ sampling events) in Newport Bay, CA based upon regression analysis. Shading indicates 95% confidence intervals.

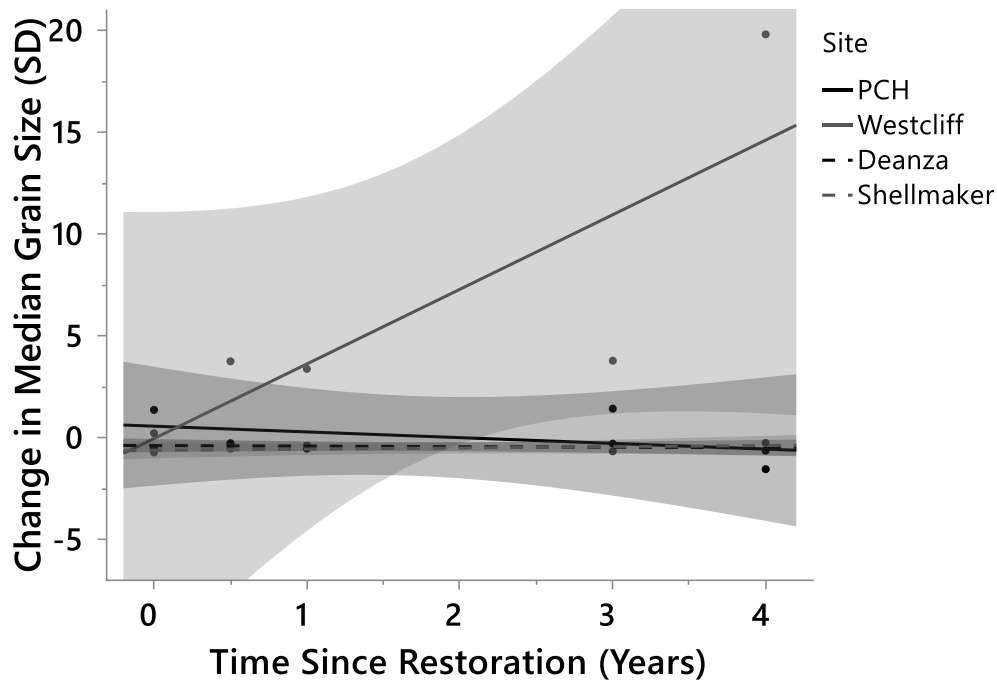


Figure 38. Change in median grain size between 2017-2021 at control treatment by site ($N = 5$ sampling events) in Newport Bay, CA based upon regression analysis. Shading indicates 95% confidence intervals.

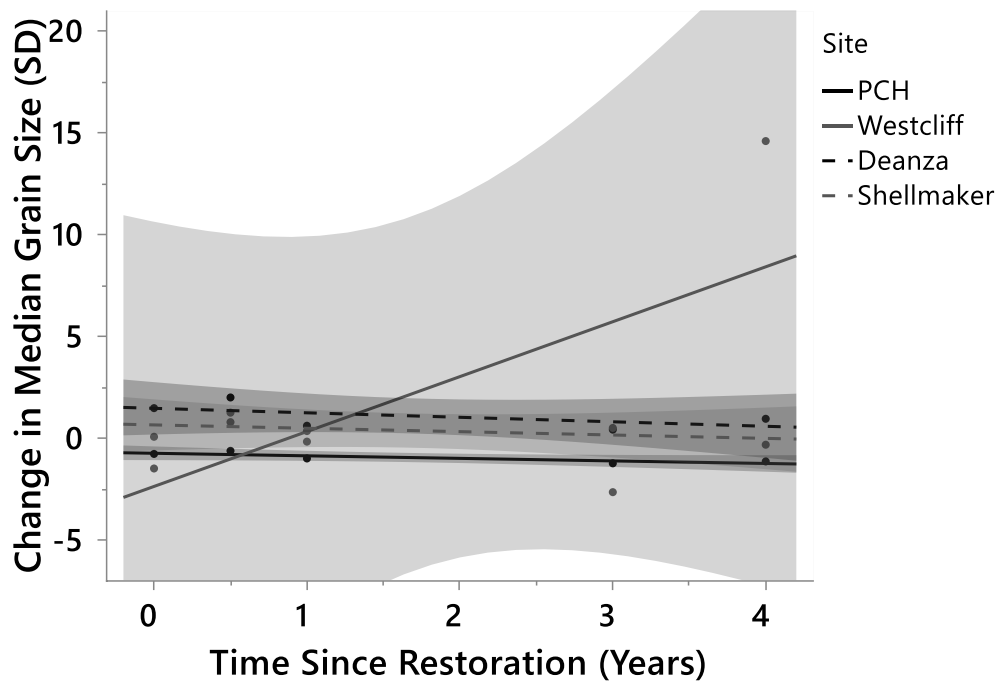


Figure 39. Change in median grain size between 2017-2021 at oyster treatment by site ($N = 5$ sampling events) in Newport Bay, CA based upon regression analysis. Shading indicates 95% confidence intervals.

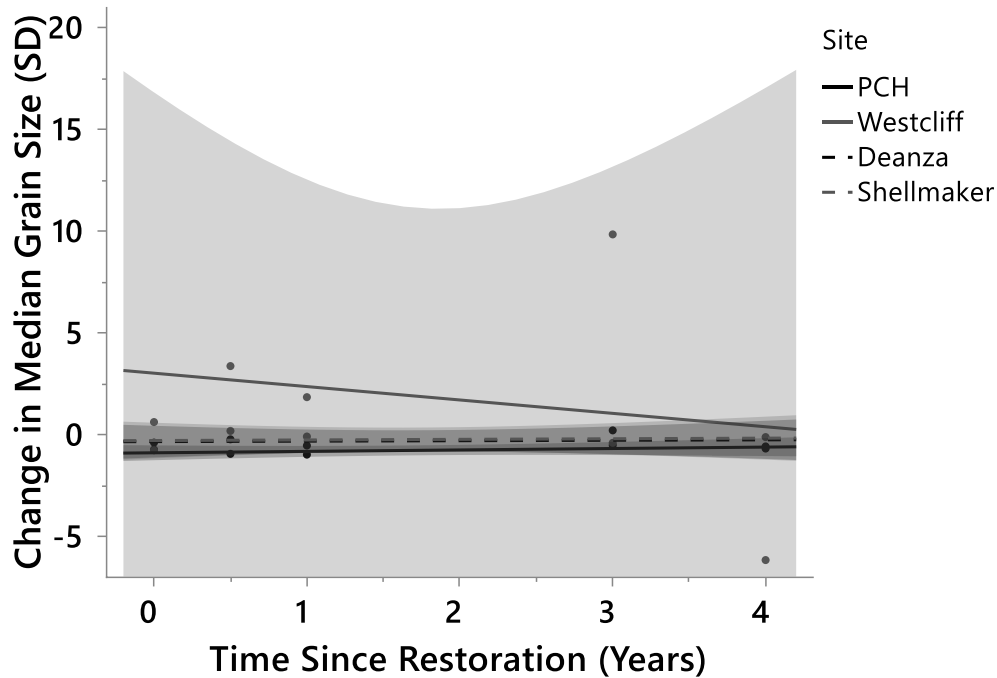


Figure 40. Change in median grain size between 2017-2021 at oyster/eelgrass treatment by site ($N = 5$ sampling events) in Newport Bay, CA based upon regression analysis. Shading indicates 95% confidence intervals.

Wave Attenuation

The peak spectral density (mBar^2/Hz) of passing boat wake sets was significantly higher at “Treatment” loggers than “Control” loggers (Figure 41, paired t -test, $t = 6.71$, $p < 0.0001$, $df = 57$). Therefore, a passing boat wake set transmitted higher energy within the wave set’s most prominent frequency band with an oyster bed present than without an oyster bed present. There was no difference between the “Treatment” and “Control” loggers in the total spectral density of passing boat wake sets (Figure 42, paired t -test, $t = 1.25$, $p = 0.11$, $df = 57$). Therefore, the presence of an oyster bed had no detectable effect on the total amount of energy transmitted by a passing boat wake set.

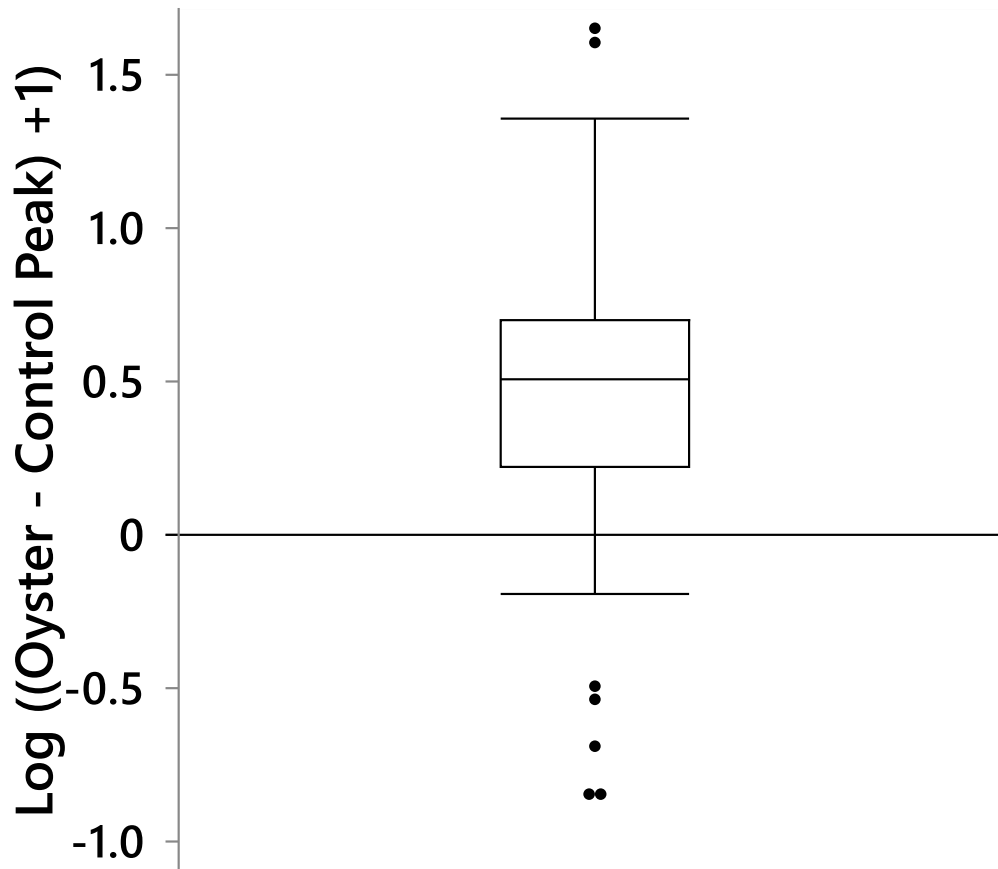


Figure 41. Log-transformed differences between “Treatment” (Oyster) and “Control” logger peak spectral density analyzed using paired t -test ($N = 58$). Wave logger trials took place between December 2021-February 2022 in Newport Bay, CA.

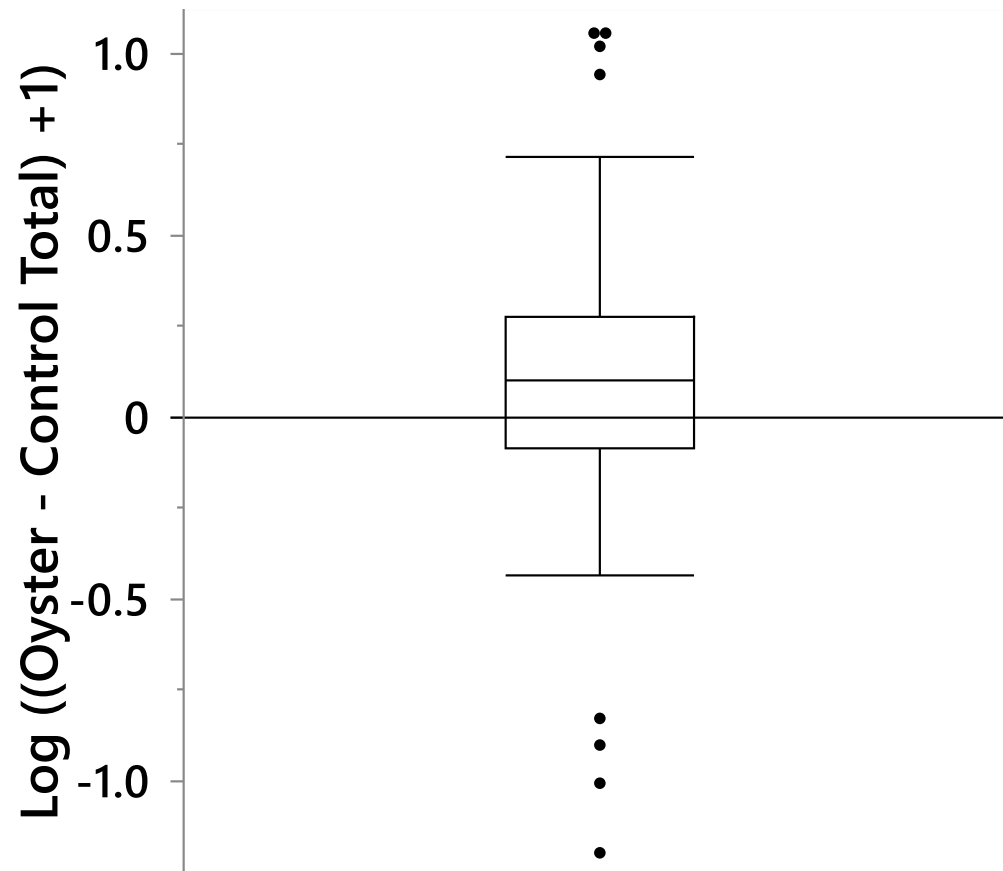


Figure 42. Log-transformed differences between “Treatment” (Oyster) and “Control” logger total spectral density analyzed using paired t -test ($N = 58$). Wave logger trials took place between December 2021-February 2022 in Newport Bay, CA.

CHAPTER 4

DISCUSSION

This is the first study to examine the effects of human activity on restored *Ostrea lurida* beds, and furthermore explored these effects within the context of additional site characteristics (eelgrass density and larval recruitment). Destructive human activity (e.g., boat wakes and human onshore activity) was associated with more-rapid breakdown of shell bag oyster restoration plots. This same human activity can be at least partially mitigated by placement of eelgrass beds directly down-shore of restored oyster plots; my data indicated that increased eelgrass density may attenuate wave energy associated with boating activity and reduce oyster bed breakdown. In addition, higher rates of larval recruitment were associated with higher oyster density on restoration plots in the following year, consistent with findings elsewhere (Livingston et al. 1999; Schulte et al. 2009; Teixeira Alves et al. 2021), but this positive effect could be limited when consolidated hard substrate falls below an undefined lower threshold.

In addition to studying the effects of various site characteristics on restoration of *Ostrea lurida* plots I measured wave attenuation by this species by directly measuring wave energy and changes in grain size directly up-shore of restoration plots. I did not find evidence of wave height reduction by restored beds or a trend towards finer grain sizes associated with sediment accumulation. In fact, surprisingly, I observed a trend of increased wave energy associated with restored beds (explained below). However, comparing wave patterns and frequency distributions of individual waves between control and treatment loggers indicate some evidence that oyster beds may be slowing wave velocity.

Increased Shell Bag Breakdown Associated with Human Activity

Increased levels of human activity were related to more rapid break down of the restored oyster beds, but were not related to oyster density on them. Furthermore, the specific type of human activity (in this case boating and onshore activity) mattered. More rapid bed breakdown was consistently associated with more frequent large wake-generating boat passes. In addition, there was a trend towards greater bed

migration at sites with more frequent large boat wake passes. This trend wasn't immediately clear, as unexpectedly high migration was observed at Deanza, which is usually characterized by fewer large wake boat passes. However, when the presence of an additional boating channel on the upbay end at Deanza was considered, it was evident that higher levels of boat wake energy contributed to higher migration than originally anticipated. Various studies have demonstrated the damaging effects of boat wake activity on oyster reefs by reducing juvenile survival (Wall et al. 2005) and causing disarticulation of clusters of live oyster shells from existing reefs (Walters et al. 2021). This study adds to this understanding by providing evidence of the negative effect of boat wakes on oyster beds via an additional possible mechanism: reduced substrate availability for new settlement. All oyster restoration projects involve deployment of some form of hard substrate for larval settlement. Oyster shell bags created with biodegradable coconut coir are a favorable method because the interstitial matrix created by oyster shells provides refuge from predation and physiological stress (Gutiérrez et al. 2003), and using biodegradable material prevents introduction of microplastics. However, biodegradable material breaks down more quickly which can result in substrate loss. Nitsch et al. (2021) deployed plastic (Vexar) and biodegradable (Biodegradable EcoSystem Engineering Elements or BESE) mats on live oyster reefs to track breakdown of these two potential restoration substrates over time. Within one year the biodegradable BESE material lost 8.57-11.06% of its mass compared to the plastic material which lost zero mass (and in some cases gained mass due to non-removable epiphytes). If the biodegradable material encasing the deployed shell breaks down before sufficient consolidation is achieved by oyster settlement and growth, there is a greater chance for high-energy boat wakes to disperse the shell and reduce substrate available for additional settlement. In addition, shell dispersal can reduce the overall relief of the oyster bed which may leave settled oysters vulnerable to burial. Therefore, shell bags may not be an appropriate restoration approach in high-energy areas unless they are somehow reinforced or shielded from damaging boat wakes. Safak et al. (2020) demonstrated the effectiveness of installing semi-permeable, brush-filled breakwalls downshore of oyster restoration substrate (shell-filled metal

cages and BESE material) at high-energy sites. Three years post-restoration all sites had oyster densities of nearly 4000/m² and significantly higher amounts of deposited fine sediment and organic material, indicating wave attenuation and sediment accretion (Safak et al. 2020). This study did not directly compare the stability of restored oyster plots with and without breakwalls present because their protective effect was demonstrated during a pilot study, wherein deployed oyster restoration elements were often removed by high-energy wakes and waves in the absence of breakwalls.

Bed breakdown was also associated with higher levels of onshore activity and this was likely due to trampling. Restored *Ostrea lurida* plots are deployed in the intertidal zone and are therefore vulnerable to trampling by beachgoers during low tide exposure. The negative effects of trampling on other marine species are well-studied. Experimental trampling on marine seaweed (*Sargassum*) beds resulted in lower chlorophyll a fluorescence and photosynthetic pigment concentrations, indicating reduced seaweed health (Barradas et al. 2018). Similar studies involving mussel beds demonstrated reduced mussel cover in beds exposed to experimental trampling (Micheli et al. 2018, Mendez et al. 2019). My study provides additional evidence of the negative effects of human activity on marine species that are likely associated with trampling. Nestlerode et al. (2002) examined different restoration substrates and found that *Crassostrea virginica* beds require large, complex substrate units with sufficient interstitial space to effectively recruit larvae. Trampling likely reduced the interstitial space available on the beds in Newport Beach via shell crushing, thereby limiting the amount of substrate available for larval recruitment. My findings also further suggest that shell bag oyster restoration may not be an appropriate method in areas with high human access without additional protection measures. While it is known that shell bag deployment can effectively recruit *Ostrea lurida*, additional work is needed to determine how to prevent premature breakdown at sites with high levels of human access and boat wake energy. Furthermore, experimental trampling studies involving restored oyster plots should be conducted to validate the relationship observed in this study.

Mediation of Human Impacts by Eelgrass

Eelgrass positively affected restored oyster bed integrity but had no effect on oyster density. However, the positive effects of eelgrass on oyster bed integrity were only observable at sites with greater boating activity (PCH and Westcliff). This suggests a possible protective effect of eelgrass, wherein the physical structure created by dense eelgrass meadows directly downshore of restored oyster beds attenuates destructive wave energy that would otherwise damage them. This relationship is supported by studies that have demonstrated wave attenuation by seagrass (Fonseca and Cahalan 1992; Reidenbach and Thomas 2018; Meysick et al. 2022), as well as studies that have demonstrated the damaging effects of boat wakes on oyster reefs (Garvis et al. 2015; Walters et al. 2020). Reusch and Chapman (1995) directly observed the protective effect of eelgrass on blue mussels (*Mytilus edulis*), another bed-forming bivalve as a result of an *in situ* mussel transplant experiment. Clumps of blue mussels experienced significantly less drift and over the course of the study when placed within eelgrass compared to clumps placed on bare substrate. In addition, mussel clumps placed in eelgrass experienced significantly less dislodgement during moderate storm events. Importantly, this observation provides support for co-restoration of seagrass and oysters in living shorelines projects, especially at sites with high amounts of boating activity (or other sources of strong wave action). There is ample evidence of beneficial effects of other seagrasses on bivalves. Some examples include mutual anchoring observed between eelgrass and Baltic clams (*Limecola balthica*) during high energy wave action (Meysick et al. 2022), and reduced predation of hard clams (*Mercinaria mercinaria*) by knobbed whelks (*Busycon carica*) in the presence of shoalgrass (*Halodule wrightii*) (Goshima and Peterson 2012). Little is currently known about the specific relationships between eelgrass and Olympia oysters and uncovering mutual beneficial effects of these two species may justify the added cost and effort associated with restoring them simultaneously in Living Shorelines projects, subsequently increasing the potential of returning ecosystem services by introducing a more complex habitat. Specifically in this case, co-restoration of these two species may increase the likelihood of oyster restoration success by providing

protection while the newly restored oyster plots are initially establishing. Oyster bed growth and consolidation is dependent on a high rate of shell accretion relative to shell loss and the rate of shell accretion is based on the number of disarticulated shell valves added to the bed as a result of adult oyster mortality (Powell et al. 2006). A newly-restored bed (in this context, bagged oyster shell) is initially devoid of live oysters and therefore is unable to immediately accrete additional shell, resulting in a disadvantageous rate of shell accretion to shell loss. A modeling study by Yurek et al. (2021) suggests that there is a 5-8 year lag between restoration and the ability of the restored bed to self-maintain. During this time period the restored bed is especially vulnerable and restoration success may be hindered by additional sources of shell loss (such as removal by boat wakes or excessive wave action). Investment in protective measures at the onset of restoration, such as by restoration of eelgrass, can reduce shell loss during this critical time period and increase the likelihood of bed consolidation. In addition, it may reduce long-term restoration costs by reducing the amount of shell that must be added to maintain sufficient shell cover at the restoration site.

It is worth noting that the proposed relationship between eelgrass and restored oyster beds is highly correlative in this context and additional work is necessary to directly test the role of eelgrass in preventing oyster bed breakdown. It will be valuable to experimentally test the effectiveness of eelgrass in preventing restored oyster bed breakdown. Wave tank studies are a common method used to experimentally test wave attenuation by various species and structures using artificially-produced waves of varying intensity (Fonseca and Cahalan 1992; Coops et al. 1996; Manis et al. 2015). This method could be utilized to track dispersal of unconsolidated oyster shell with and without eelgrass present under varying wave intensities.

Balancing Recruitment Rate and Substrate Availability

Several studies have demonstrated a relationship between larval recruitment and adult oyster density, wherein increased larval recruitment is related to higher oyster density (Schulte et al. 2009, Yurek et al. 2021). My data supported this relationship and, interestingly, demonstrated the breakdown

of this relationship as settlement substrate is reduced. For oyster bed growth (or accretion) to occur, shell addition must be greater than shell loss and recruitment must be greater than mortality (Mann and Powell 2007). These conditions necessary for oyster bed growth are guided by various positive feedback loops that, if interrupted, could lead towards oyster bed breakdown. For example, removal of large, long-lived oysters from the habitat reduces shell resources that would become available upon their death, which then reduces settlement substrate available for larvae, further limiting the addition of future shell (Walles et al. 2015a). At Newport, there was a positive relationship between prior-year recruitment and adult oyster density but that relationship appeared to lose strength over time (Figure 30), and this was likely due to the co-occurring progression of bed breakdown. In addition, I observed a pattern of alternating increases and decreases in oyster density based on recruitment during the prior year, though increases in recruitment appeared to no longer influence the following year's oyster density after 2019, during which time a significant reduction in recruitment coincided with 50% of the restored beds reaching a state of "significant breakdown". Several studies have identified a threshold of starting bed height that determines whether a restored bed will experience growth or degradation. Colden et al. (2017) tracked 24 *Crassostrea virginica* beds that were restored at varied starting heights and found that beds constructed below a starting height of 0.3m typically had lower oyster densities that tended to decrease over time, and the decrease in densities varied based on the amount of sedimentation experienced at a given site. Zacherl et al. (2015) compared starting bed height of *Ostrea lurida* beds and found that beds constructed at 0.14m experienced higher recruitment, reduced sedimentation, and lower breakdown compared to beds constructed at 0.04m. Beds at Newport had an approximate starting height of approximately 0.3m. This is more than twice the starting height of more successful beds restored in Zacherl et al. (2015) and matches the minimum height identified for a restored bed to experience growth rather than degradation in Colden et al. (2017). However, both of these studies only tracked bed metrics for two years compared to four years of monitoring data presented here. It is therefore possible that the starting height of restored *Ostrea lurida* beds must exceed 0.3m to experience persistence in systems

that experience variable recruitment. Shulte et al. (2009) found that the presence of multiple year classes can buffer against variable recruitment because larger, older oysters provide more settlement space. Newport experienced a steep decline in recruitment only two years after the beds were initially constructed. It is therefore also possible that, even if the starting bed height was above a beneficial threshold, the combination of poor recruitment and progression of bed breakdown during the early, vulnerable establishment period (Yurek et al. 2021) caused the beds to experience a phase shift towards degradation, which may have been exacerbated by damaging human activity at some sites (as described above). These results highlight the importance of long-term monitoring of dynamic systems (like oyster beds) that are dictated by a suite of positive and negative feedback loops that can cause dramatic year-to-year shifts based on changes in environmental conditions. These data also demonstrate a need to determine an accurate starting height threshold for restoring this species under various site conditions so that future restoration efforts will have a higher potential for achieving a trajectory towards growth rather than degradation. While the literature cited within this section suggest that a taller starting relief is necessary to increase the likelihood of oyster bed growth, it is important to note that an excessively high starting relief may expose the bed to increased wave action and subsequently increase breakdown. Therefore, rather than simply increasing the starting relief, future work should focus on determining a starting relief that balances the provision of sufficient substrate with the ability of a new bed to avoid additional damage during the early stages of restoration.

Ecosystem Services

I predicted that the restored Olympia oyster beds would attenuate wave energy and increase the relative proportion of finer sediments upshore, but my study did not find evidence to support this. However, no other studies have reported similar results and these contradicting findings may therefore be due to my study design and overall changes in the living shoreline blocks at the time of my study (relative to starting conditions).

I expected to see reduced wave height upshore of restored oyster beds relative to a control plot but instead found opposing results. Wave height was consistently higher in the presence of an oyster bed. As there is no physical mechanism for the restored beds to “add” energy (and therefore amplitude) to passing waves, there are several possible explanations for these results. First, the progression of breakdown of the original oyster beds and the low starting relief of the new “mini” beds may have prevented incoming waves from making contact with the beds at all. Multiple studies have found that the ratio of incoming wave height to the freeboard, or distance from the crest of the bed to the water line above it, determines the amount of wave attenuation achieved (Wilberg et al. 2019; Safak et al. 2020; Zhu et al. 2020; Leone and Tahvildari 2022). For example, Leone and Tahvildari (2022) found that two types of living shorelines structures, oyster reef balls and marsh sills, reduced wave height by 13% and 40% respectively when the freeboard was low (i.e. low tide, less submerged), and only reduced wave height by up to 7% when freeboard was high (i.e. high tide, more submerged). In order to induce shoaling, and thereby reduce wave energy, the wave must make contact with some form of substrate. The waves analyzed for this study did not exceed 6cm in height (and in fact were mostly 2cm or less) and the oyster beds at the time of this study did not exceed 15cm in height. In addition, the water depth during water logger deployment was never below 35cm. All these factors in combination may have resulted in too great of a freeboard to induce interaction between the waves and the oyster beds, preventing observation of wave attenuation. However, this still does not explain why waves were higher at the oyster beds relative to the control plots. If no attenuation was occurring, I would have expected to see no difference in wave height. An alternate explanation is that the water loggers were placed too close to the oyster beds and actually captured the *process* of wave attenuation, wherein wave height is initially increased due to shoaling *before* wave height is reduced (Longuet-Higgins and Stewart 1964). Jago et al. (2006) examined the progression of waves over a coral reef by tracking the height of individual waves passing the seaward end, the middle, and the shoreward end of the reef. During higher tides, wave height was slightly higher at the center of the reef compared to the seaward end, but was ultimately reduced

upon reaching the shoreward end. This increase in height occurred due to shoaling between the first two wave loggers, and it is likely that the same phenomenon was occurring in my study. However, I did not have a third logger placed further upshore to verify this. Therefore, this study should be repeated with loggers placed at varying distances from the restored oyster beds to capture a clearer picture of the progression of waves passing over them and determine whether the beds are in fact able to attenuate wave energy.

While statistical analysis did not provide evidence of wave attenuation by oyster beds, examination of differences in the real-time progression and frequency distribution of individual waves between control and treatment loggers indicate that the oyster beds may be reducing wave velocity (see Appendix A for all individual waves and FFT frequency distributions). In several cases, when a wave passed over the oyster bed it took longer to complete the same number of cycles as the wave passing over the control area (see figure A31 in Appendix A for example). In addition, while the FFT output for the same wave indicated a higher peak and total spectral density associated with the wave passing over the oyster bed, visual inspection indicated that the wave passing over the oyster bed exhibited a more narrow range of frequencies, further suggesting that the oyster bed may be “filtering” out higher frequency components of the wave via reduction of wave velocity (see figure A32 in Appendix A for example). Repeating this study with loggers at varying distances from the bed, as discussed above, will provide an opportunity to observe changes in wave velocity associated with restored oyster beds.

I found no consistent effect of Olympia oyster beds on changes in upshore grain size, which was also contradictory to my predictions. This may be due, again, to my study design or to inherent differences in physical processes at each site that are beyond the scope of this study. Grain size samples were taken once annually at the center of the bed, but as bed breakdown and shell migration progressed, samples had to be taken at greater distances upshore to keep the sampling distance from the bed (10cm) consistent. This, in combination with the low sample size, may have introduced too much noise to my statistical analysis that already suffered from very low power. Newport Bay experiences ebb-dominant

tides that cause a net seaward transport of sediments (Guo et al. 2018). It is understood that taller beds are more successful at attenuating wave energy (Manis et al. 2015) and retaining sediment (Wallis et al. 2015b), so it is therefore likely that the rapid progression of bed breakdown, and associated reduction in bed height, in this system did not create conditions that would retain fine sediment. A former grad student found a trend towards fining at PCH and coarsening at Westcliff one year post-restoration (Wood 2018). My data reveal a similar, though non-significant, trend which suggests that site-specific processes are still dominating. As discussed before, an appropriate starting relief may have prevented pre-mature breakdown and increased the likelihood of bed growth, which may have created conditions that increased fine sediment accumulation. Additionally, the starting bed orientation may have prevented deposition of fine sediment. Colden et al. (2016) found significantly more sediment fining adjacent to rectangular oyster beds were restored perpendicular to the shoreline rather than parallel (such as those constructed in Newport Bay). Finally, it is alternatively possible that fine sediment was being accumulated, but not directly upshore of the oyster beds. Wood (2018) found that there was less sediment deposition directly onto the oyster beds if eelgrass was present. When I began my sampling in 2020 the restored eelgrass had expanded beyond its initial treatment boundaries and grown into many of the plots that were intended to serve as “no eelgrass” treatments. Eelgrass is also known to attenuate wave energy (Lacy and Stevens 2011; Hansen and Reidenbach 2012), and it is therefore possible that sediment was being deposited between the eelgrass and oyster plots, on the eelgrass beds, or directly onto the oyster beds themselves. Colden et al. (2016) collected grain size samples at varied locations around the perimeter of the bed, and at increasing distances from the bed. This approach would have likely produced a more refined understanding of sediment dynamics associated with the restored beds in Newport Bay.

Conclusions

Oyster beds and reefs are dynamic habitats that rely on a complex balance of internal and environmental interactions to remain in a state of self-propagated growth. Due to the early decline and

relatively nascent state of research on *Ostrea lurida* restoration, existing studies are typically limited to examination of a single factor that affects successful restoration of this species. This is the first study that has attempted to contextualize multiple environmental factors in an effort to tease apart the dense network of interactions that work together to determine the trajectory of a newly-restored Olympia oyster bed and, furthermore, connect these interactions to the ecosystem services that may be achieved based on the success or failure of a restored bed. I found evidence of an interactive effect of human activity, eelgrass, and larval recruitment on restored oyster beds, wherein human activity contributes to early breakdown of the bed, but this early breakdown can be mediated by eelgrass density and sustained larval recruitment. However, if early breakdown still proceeds past an undefined threshold and larval recruitment is unreliable year-to-year, subsequent years of high larval recruitment can no longer push the restored bed into a state of growth because substrate (shell) is too limited to establish a robust, connected adult population. The progression of breakdown four years post-restoration likely prevented me from finding evidence of wave attenuation and upshore sediment accretion because these ecosystem services rely on sufficient bed height to reduce water velocity. Incidentally, in addition to enhancing the provision of potential ecosystem services, higher bed height may push restored beds toward a trajectory of growth by providing additional settlement substrate, which provides a buffer against shell loss during early low-recruitment years and in areas with destructive human activity, and by increasing the size of the wake volume, which is an area of recirculating flow adjacent to the bed that traps nutrients, thereby enhancing oyster growth and survival (Kim et al. 2023). However, an excessively high starting relief may result in premature breakdown as well. Therefore, much work is necessary to determine the starting height threshold necessary to restore a self-propagating Olympia oyster bed that will carry the greatest likelihood of restoration success and the return of economically-valuable ecosystem services. Overall, this study highlights the importance of long-term monitoring of a suite of variables in restoration projects so that a holistic view of the restoration “story” can be examined.

APPENDIX A

WAVE HEIGHT LOGGER ASSEMBLY AND INSTRUCTIONS

The following instruction and assembly guide was writing by the logger developer, Jon Pompa (Daring Engineering LLC.). As stated below, the model design was based on loggers developed by Dr. Luke Miller (San Diego State University).

Pressure Logger Instructions

Overview

This pressure logger is intended for high rate, short duration pressure logging in water (ocean and fresh). Examples of typical use include wave height monitoring, coordinated tide and temperature observations, and storm surge observation.

Specifications

Value	Range	Resolution
Depth Rating	300m (limited by sensor)	
Data Parameters		
Temperature	2-40 degrees C	0.01 Deg C (accuracy +/- 1.5C)
Pressure	0-30 Bar absolute	0.2 mBar (accuracy +/- 200 mBar)
Battery Voltage	0-5 Volts	0.01V
Sampling Frequency	0.5 to 20 Hz	1 ms timing interval
Battery Capacity	4500 mAh @ 3.7V (~14 days run time)	



Pressure Logger fully assembled

Electronics

The logger is made using an adafruit 32u4 data logger board (<https://learn.adafruit.com/adafruit-feather-32u4-adalogger>) and an adafruit RTC clock unit (<https://learn.adafruit.com/ds3231-precision-rtc-featherwing>)

The pressure sensor is from Blue Robotics (<https://bluerobotics.com/store/sensors-sonars-cameras/sensors/bar30-sensor-r1>). It includes an MS5837 absolute pressure sensor housed in a pass-through that fits into the pressure housing endcap. This sensor is rated to 300m and has a pressure resolution of 0.2 millibar. (equivalent to 2mm water depth).

Tests have shown the system maintains a noise level below 0.5 mBar in a static environment. Drift over long periods (hours) has not been well characterized yet as it needs to be compared against well-calibrated barometric pressure sensors.

The pressure sensor is not rated for continuous contact with water (readings drift), so it is protected from water by operating in a mineral-oil filled chamber. The oil is kept in the chamber by a

membrane (made of a nitrile glove finger) which transmits pressure from the external water to the interior oil without influencing the pressure. This nitrile membrane is protected from damage by a rubber cap with a small hole to allow water flow.



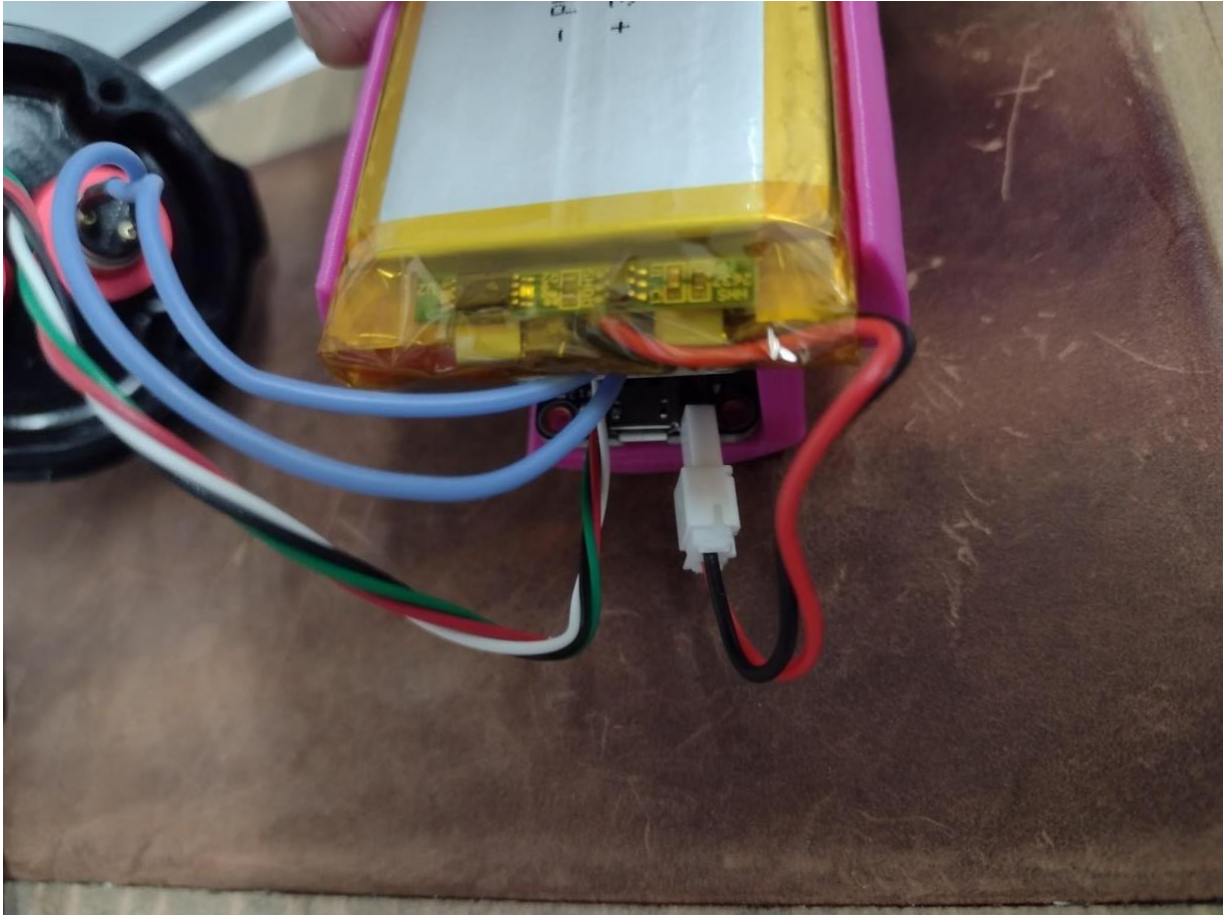
The pressure sensor is covered in a protective tube filled with mineral oil and covered with a nitrile membrane.

Battery

The logger is provided with a 4500mAh battery. It is a single cell battery providing an average 3.7V with a working range from 3.2V to 4.2V. The adafruit logger board automatically turns off when the voltage reaches a minimum to avoid damaging the battery.

***NOTE ON POLARITY:** The batteries provided with the loggers are wired in a “normal” direction with pin 1 of the connector negative and pin 2 positive. The Adafruit logger has a connector polarity reversed from almost all other devices that use the same connectors and battery types so it is provided with a short extension cable to reverse the polarity. When plugging in a battery, always make sure this cable is in place in the logger. When charging, always plug the battery directly into a charger without the extension cable.

There is a lithium button cell battery in the Clock board which provides constant backup power to retain the clock's date and time reference when the main battery is removed. This is a lithium CR2012 size button cell.



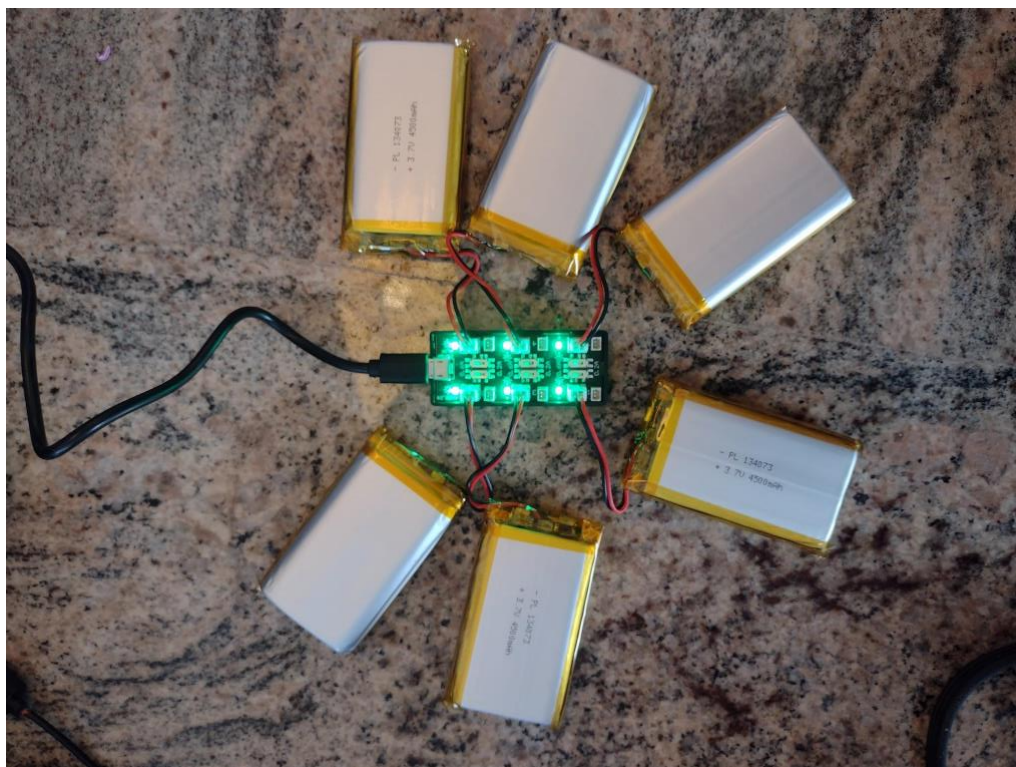
Battery connector: Always disconnect the battery here, not at the side of the board. The battery connector polarity is correct for the charger directly from the battery. The extension cable hidden between the circuit boards reverses the polarity for the adafruit board and should never be plugged into a charger.

Charging

When the logger is plugged into a USB port, an internal battery charging circuit will charge the LiPo battery at a rate of 0.1A. A yellow light next to the USB port on the logger board will indicate charging is active. The light will turn off when the battery is fully charged at 4.2V. This charge rate is

very low for the capacity of battery provided (4500mAh) and charging this way will take approximately 45 hours.

Using an external charger is recommended. A charger should be provided with the loggers which is capable of charging 6 batteries simultaneously at 0.6A rate.



6 batteries attached to the external charger

Software

Assembled loggers are pre-programmed when shipped and do not need to be programmed to record data. As of this writing, they are shipped with 4Hz sampling rate. If you prefer to change the logging parameters (such as sampling interval) you should follow the instructions below to reprogram them.

It may be helpful to reprogram the loggers occasionally to update the clock time if it has drifted or if the clock battery needs to be replaced.

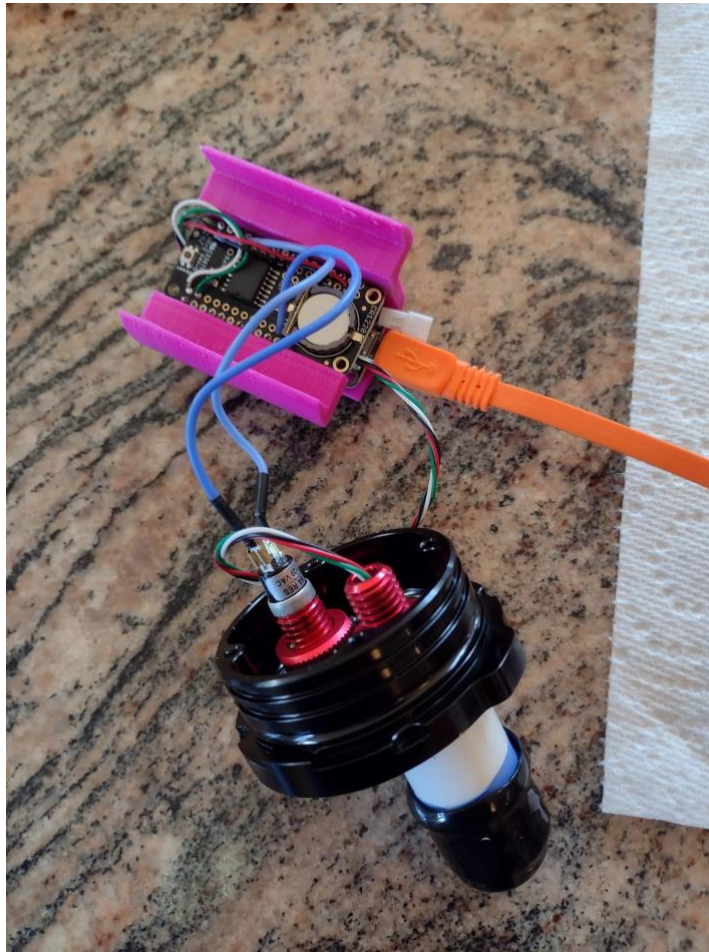
The logger is programmed in the Arduino environment: Arduino IDE (download at <https://www.arduino.cc/en/software>)

Instructions for connecting a logger and installing are here (<https://learn.adafruit.com/adafruit-feather-32u4-adalogger/setup>). This gives instructions for adding the required libraries to the Arduino environment to compile this code.

The loggers should be distributed with the Arduino code sketches needed to run them,

Wavelogger2.ino and ds3231.ino, both available at <https://github.com/JonPompa/Wavelogger2>

The logger board has a USB port on it and can be connected with a USB cable to a computer running the Arduino IDE for programming.



The logger can be connected to a computer to program it using a USB cable attached to the USB port on the logger board. This port also charges the battery (slowly) from the USB port.

Arduino sketch Ds3231.ino is used to set the RTC clock on the logger and should only need to be used once when the logger is first powered or when the button cell backup battery is replaced.

DS3231.ino should be uploaded to the logger through the Arduino IDE. You can verify success by opening a serial terminal and seeing confirmation of the current time and date. (ctrl+shift+m opens a terminal window in a windows environment) The baud rate of the terminal window should be set to 56700 or whatever rate is specified in the version of ds3231.ino that you are using)

Wavelogger2 is the main program running the data collection. It should be compiled and uploaded to the logger after the ds3231.ino clock setting sketch is run. In this program, there is a set of user parameters to set for the interval between data pushes to the log file and also for frequency of sampling. The sampling interval is given in milliseconds. Know that there is also a 50ms sampling duration added to the period you specify, for example, an interval of 200ms will mean a total time between samples of 250ms, leading to a 4Hz actual sample rate.

Code example:

```
//User settings//
int logInterval = 4000; //milliseconds between data saves to the SD
card *note max of 32000 allowed with an int data type
int senseInterval = 200; //milliseconds between data read attempts for
pressure and temp sensor.
//Data reading +overhead takes about 50ms so
a value of 200 here gives ~4Hz,
//Fastest achievable is about 18Hz by setting
senseInterval low (5ms)
bool recordBatVolts = true; //record or don't record battery voltage
```

Log files are started when power is turned on. The log files are named for the date on which they start, using year, month, day format. i.e. 20210131.txt

Assembly

The logger housing must be opened to access the data port and card reader. Once the logger has been appropriately programmed, it is not necessary to plug it into a computer to restart logging. Inserting a data card and turning on power will always initiate logging.

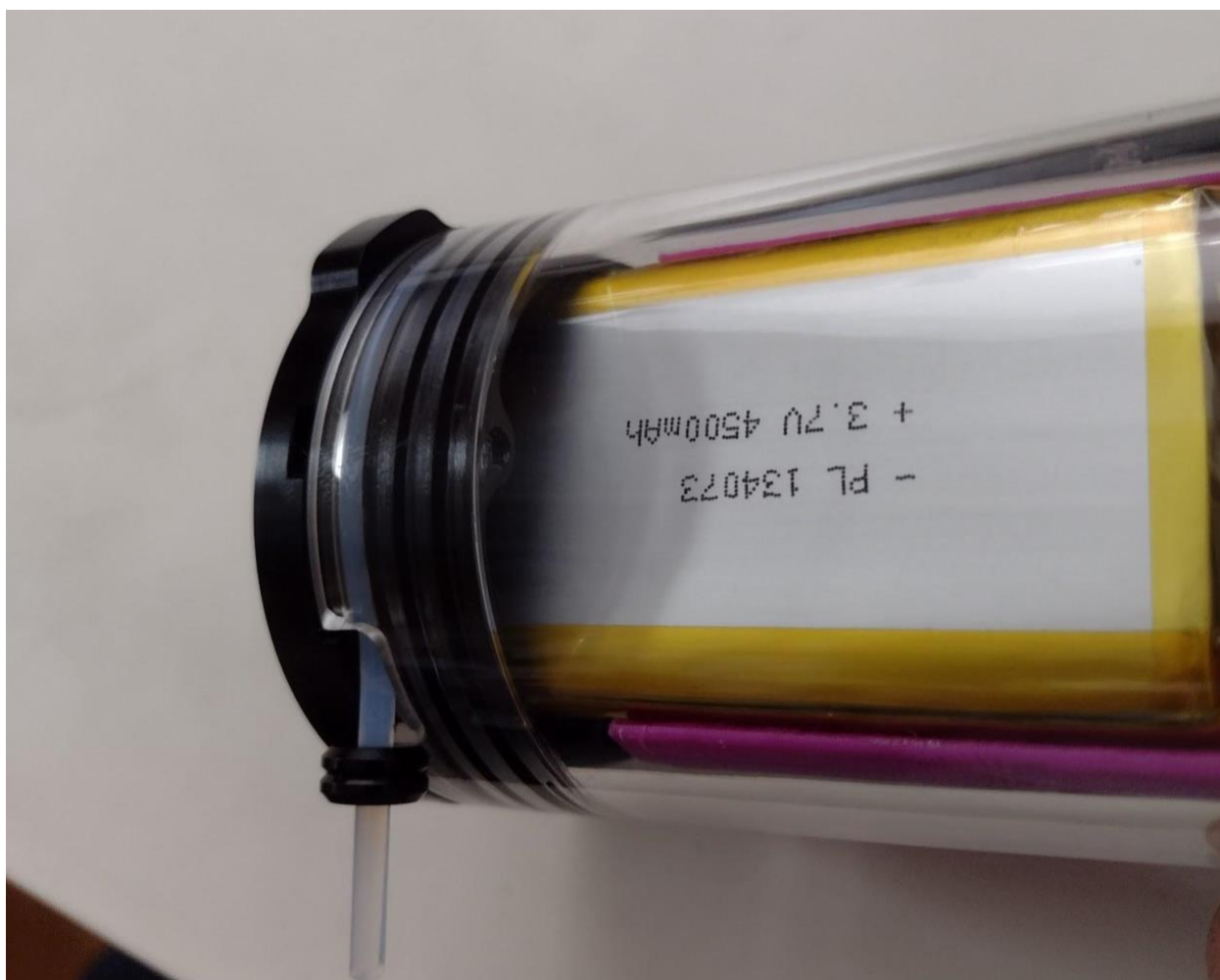
It is recommended to open the logger from the sensor endcap end.



Opening an endcap is achieved by pulling the white plastic cord then gently sliding the endcap out by hand. Before closing an endcap, always clean and inspect orings. The orings should be lubricated with silicone grease.

To assemble the logger, slide the electronics tray (with battery) into the housing, being careful to seat the battery into the blank endcap and to align the switch and battery so that they don't interfere. The end cap with the sensors must be rotated so that its tab aligns with the notch in the housing body for it to seat fully. See images below for important alignment notes.

The following images show some important details of how the parts fit together.



The battery fits down into the blank endcap when the battery and electronics tray are inserted fully into the pressure housing as shown here. This is only possible at some angles because of the shape of the endcap interior.



This image shows mirrored versions of the logger endcap. Unfortunately, some loggers were built in each configuration and the configurations require attention to assemble correctly. The notch in the housing that allows insertion of the locking cord must align with a small tab on the endcap. That alignment sets the position of the switch in the endcap. Because the switch terminals extend downward far enough to interfere with the battery, the electronics tray must be rotated to place the battery under the sensor side of the endcap, not the switch. Please pay attention to this when assembling the loggers!

The housing is sealed with o-rings on the circumference of the end caps. When the housing is assembled, the rubber o-rings must be inspected, cleaned (very carefully look for threads, fibers, and hair on the rings), and lightly greased with silicone grease.

When the end caps are pushed in, it may be helpful to remove the top of the power switch completely. This allows air to vent from the housing through a small hole (this also turns the logger on). Once the end caps are seated, they should be fastened by sliding the plastic lock cords around the

circumference of the housing in the locking groove. The power switch top may then be re-inserted, being careful to note whether it is set in the on or off state. It is also helpful to inspect and grease the o-rings of the switch at this time.

Power Switch

The logger housing can be assembled with the switch in the off position. This is when the switch top is fully screwed into the base.

At deployment time, the logger can be turned on by twisting the switch approximately one half turn in the unscrewing direction (counterclockwise).

Verify that the logger is recording by watching for an intermittent flashing of a red LED on the processor board next to the USB port. The red light flashes when data is written to the SD card, so if you have a short data writing interval, it flashes often and if you have a long data writing interval, it flashes seldom.

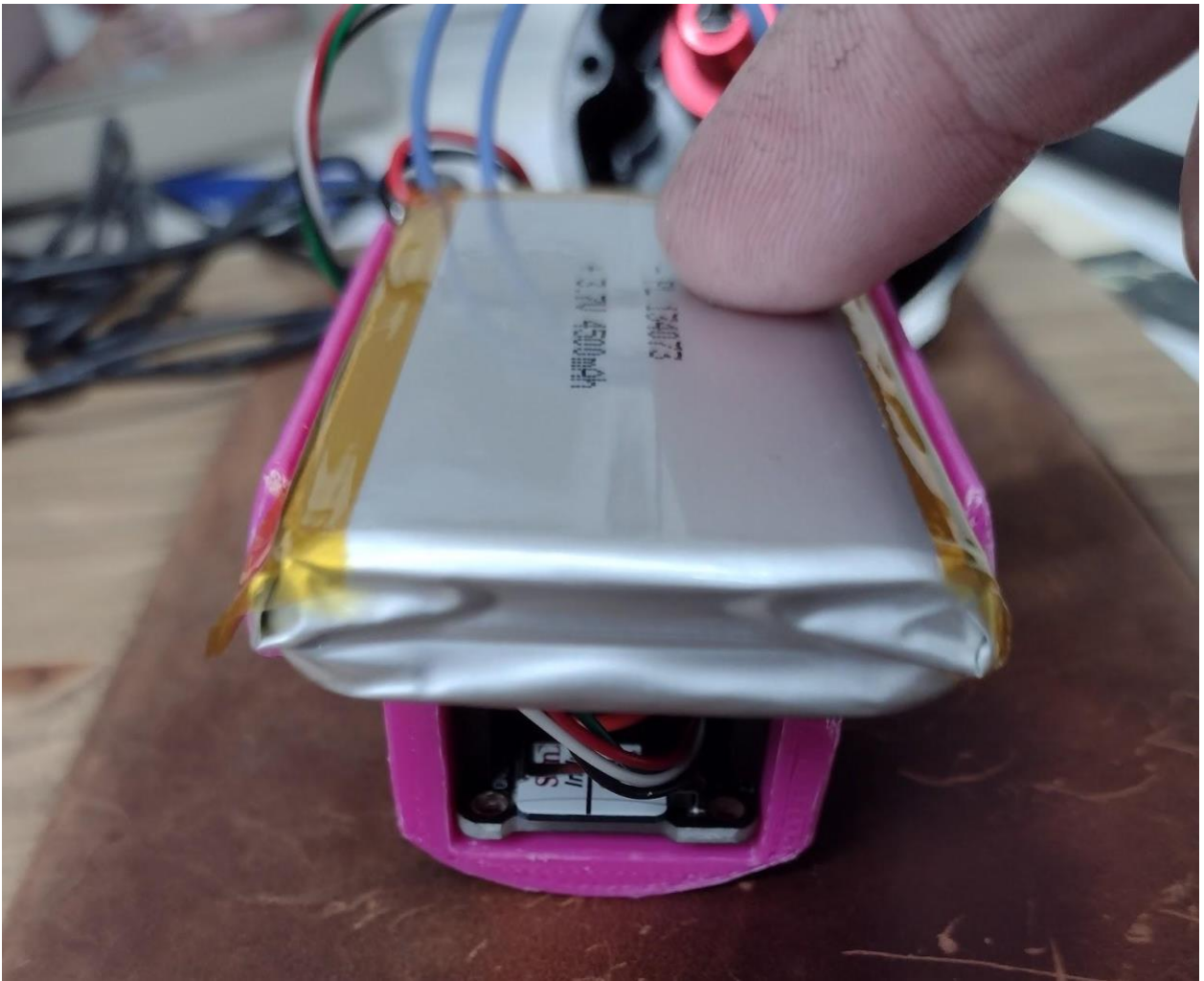


Here the power switch is shown on the end cap next to the bare pressure sensor. On finished loggers, the pressure sensor is protected by a cover.

Data

Whenever the logger is turned on, it immediately starts recording data. Data is appended to an existing file if the logger has been started more than once in a day. It will start a new file if it is turned on during a new day.

Data is stored on a micro SD card which is inserted into the logger board (at the end opposite from the sensors and USB port). This card should be formatted in FAT32 format to work with the software.



The SD card can be seen in its slot under the battery in this image of the disassembled logger.

Data is recorded in ASCII text format. The data fields include a header line explaining the columns. The data includes time in year, month, day, hour, min, sec, and milliseconds. The millisecond value is not referenced to the seconds value, and so may roll over independently from the count of seconds.

The data columns are:

Year Month Day Hour Minute Second Milliseconds Pressure Temperature BatteryVolts

Data for temperature is recorded in degrees C.

Data for pressure is provided in absolute millibars.

Battery voltage is recorded in volts.

*Note that as battery voltage drops for the last few hours of recording, before the low voltage cutoff shuts off the logger, the pressure reading will drift upward by several millibar.

At the time of this writing, there is no provision for retrieving data from the logger other than manually extracting the microSD card and reading it in another device. Future improvements include implementing a set of commands to retrieve the data via the USB connection and to add a USB connection through a connector on the pressure housing to prevent the need to open the loggers after each deployment.

Data Processing

This logger records data files that become large quickly – i.e. hundreds of megabytes over a few days. Typically processing the data is best done in a scientific programming language set up for such data. Examples would be the R language, Matlab, or Python with NumPy.

A few notes on importing data follow

- 1) The files have a header row. This header row gives column names. If the logging was restarted within a 24 hour period, there will be an extra copy of this header line in the data for each restart instance. This may challenge your data importing script!
- 2) The pressure data is in absolute pressure. The sensor is sensitive enough to track barometric pressure very well, so your pressure data processing may need to include an effort to obtain a local barometric pressure record and subtract that pressure from the recorded data. You may be able to use an on-shore logger to serve as a reference pressure recorder if you have a spare logger available.
- 3) Battery voltage is included as a debugging and convenience feature. You can reduce the data file size by turning off battery voltage logging (set the battery logging parameter value to “false” in the wavelogger2.ino file).
- 4) Battery voltage will influence the pressure reading when the battery is very low. Do not use the last few hours of the pressure record before the logger shuts down due to low battery state. The pressure reading will drift upward during that time.

Mounting

The logger can be attached to a mounting location with cable ties, hose clamps, or other purpose-made clamps around the housing body. If using hose clamps, you may want to cover the clamp in a rubber tube such as a bicycle tire inner tube to prevent scratching the housing. If using cable-ties, it is

suggested to avoid nylon cable ties which lose a significant amount of their strength when submerged in water over time.

Credits

This manual is a living document and is subject to change.

This logger has been designed by Jon Pompa using readily available parts and code as referenced above.

Major inspiration was taken from Luke Miller's Open Wave Height Logger project (which provides a much higher level of documentation, testing, and a longer-duration logger design).

Much of this project is also built on the Adalogger family of devices from Adafruit which provide nearly complete hardware and software out of the box.

The underwater housings and sensors are stock items from Blue Robotics.

Contact

Please direct questions or ideas to Jon Pompa - jon@reefgen.io

Plans for incremental upgrades at the moment include data access and battery charging by connector, better wire management, and mounting brackets.

If anyone wants a construction manual for building these loggers, please make a request.

Bill of Materials

Part		Qty
Pressure housing		
	Blue robotics 2" x 100mm housing	1
	Blue robotics 2" blank endcap with flange	1
	Blue robotics 2" endcap 2 hole with flange	1
	BR switch / vent penetrator (modified to vent)	1
	BR Bar30 pressure sensor	1
	BR sealing cord (included with endcaps)	2
	BR sealing orings (included with endcaps)	4
Electronics		
	Adafruit Adalogger 32u4	1
	Adafruit precision RTC featherwing	1
	SD card	1
	stacking header pins	2
	header pins (included with adalogger)	1
	Lipo single cell 4500mAh 13x40x72mm	1
	CR1220 button cell (3V lithium)	1
	Mounting bracket (parts holder_R2.sldprt)	1
Sensor protection		
	PVC 1/2 pipe bored out for sensor plus oring groove	1
	5min epoxy (gorilla) to seal pvc to sensor	1
	Nitrile glove finger	1
	mineral oil	1
	Rubber cap (with hole) to go over pvc pipe	1
	oring m2x17.5	1

APPENDIX B

LINEAR MIXED MODEL R SCRIPT AND OUTPUT

The following R script was developed by Dr. Sean Walker. Model outputs will follow the order they are presented in above in “Results”.

R Script (example input for relationship between prior year recruitment and oyster density)

```
##library stuff to load
library(ggplot2)
library(ggeffects)
library(lme4)
library(lmerTest)
library(sjPlot)
library(sjmisc)
library(sjlabelled)
library(RColorBrewer)

#set working directory and upload data
setwd("C:/Users/Valerie/Dropbox (CSU Fullerton)/Valerie's Master's File/Thesis/MAIN WORKING FOLDER/R")
data <- read.csv("eelgrass and oysters noNA.csv")

#Change year from "numeric" to "factor"
data$Year = as.factor(data$Year)
str(data)

##regular linear regression
alm<-lm(log.oyster~Prior.year.recruitment, data=data)
summary(alm)

##regular linear regression with interaction
alm<-lm(log.oyster~Prior.year.recruitment+Year+Prior.year.recruitment*Year, data=data)
summary(alm)
anova(alm)

##mixed model
re.lm <- lmer(Percent.bottom ~ Prior.year.recruitment + (Prior.year.recruitment|Year), data = data,
REML = FALSE)
summary(re.lm)

#mixed model simplified (year as intercept instead of slope)
re.lm <- lmer(Percent.bottom ~ Prior.year.recruitment + (1|Year), data = data, REML = FALSE)
summary(re.lm)

##hypothesis test for fixed effects
drop1(re.lm, ddf="lme4", test="Chi")
```

```
##hypothesis tests for random effects
ranova(re.lm, reduce.terms=TRUE)
#residual by fit plot
plot(re.lm)
#normal quantile plot
qqnorm(residuals(re.lm))
qqline(residuals(re.lm))
#predicted values for
data$predict1<-predict(re.lm, re.form=NA)
##plotting the monster
### single plot
##ggplot prediction
predp<-ggpredict(re.lm,type="fixed",terms="Prior.year.recruitment")
bb<-ggplot(predp, aes(x,predicted))+geom_line(aes(y=predicted))+geom_ribbon(aes(ymin=conf.low,
ymax=conf.high, alpha=0.2))
##sjplot prediction plot
plot_model(re.lm, type="pred", terms=c("Prior.year.recruitment"))

#make some expressions for axis labels
x1 <- expression(Oyster ~ Density ~ m^2)
x2 <- expression(Prior ~ Year ~ Recruitment ~ m^2)
x3 <- expression(Log ~ (Oyster ~ Density ~ m^2 ~ + 1))

#ggplot by group
plot2 <- ggplot(data, aes(x=Prior.year.recruitment, y=Percent.bottom)) +
  labs(y = "Percent Soft Bottom", x = x2) +
  scale_y_continuous(limits = c(0, 100), breaks = c(0, 20, 40, 60, 80, 100)) +
  scale_x_continuous(limits = c(0, 5000)) +
  geom_smooth(method = 'lm', se = F, aes(group = Year, col= Year))+
  geom_point(size = 3, aes(col=Year,shape=Site)) +
  geom_line(aes(y=predict1, color="Overall"), size=1, linetype="dashed") +
  theme_bw() +
  theme(panel.border = element_blank(), panel.grid.major = element_blank(),
panel.grid.minor = element_blank(), axis.line = element_line(colour = "black"))+
  scale_color_grey(start = 0.8, end = 0.05)
plot2
#to add confidence intervals to lines change se=F to se=TRUE in
#geom_smooth and add ", fill=Year" afer col=Year
```

Model Outputs

Relationship between onshore activity and oyster density (see Figure 23)

```
> ##mixed model
> re.lm <- lmer(Log.density ~ average.onshore.activity + (average.onshore.activity|
Year), data = data, REML = FALSE)
boundary (singular) fit: see help('isSingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula:
Log.density ~ average.onshore.activity + (average.onshore.activity |
```

```

Year)
Data: data

      AIC      BIC   logLik deviance df.resid
 57.9    65.0   -23.0    45.9      18

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.7403 -0.7220 -0.0728  0.6021  1.8442

Random effects:
 Groups   Name                Variance Std.Dev. Corr
  Year    (Intercept)          1.32808  1.1524
         average.onshore.activity 0.05372  0.2318  -1.00
  Residual                    0.27091  0.5205
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)      4.21435    0.68380  3.00916   6.163  0.00852
average.onshore.activity -0.08172    0.14798  2.68476  -0.552  0.62341

(Intercept)      **
average.onshore.activity
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
avrg.nshr.c -0.952
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
Log.density ~ average.onshore.activity + (average.onshore.activity | Year)
              npar
<none>                6
average.onshore.activity in (average.onshore.activity | Year)  4
              logLik
<none>                -22.952
average.onshore.activity in (average.onshore.activity | Year) -26.757
              AIC
<none>                57.903
average.onshore.activity in (average.onshore.activity | Year) 61.514
              LRT Df
<none>
average.onshore.activity in (average.onshore.activity | Year) 7.6104 2
              Pr(>Chisq)
<none>
average.onshore.activity in (average.onshore.activity | Year)  0.02226

<none>
average.onshore.activity in (average.onshore.activity | Year) *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(Log.density ~ average.onshore.activity + (1|Year), data = data, REM
L = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: Log.density ~ average.onshore.activity + (1 | Year)
Data: data

```

```

      AIC      BIC    logLik deviance df.resid
    61.5     66.2    -26.8     53.5      20

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.8331 -0.7286 -0.1579  0.8400  1.4099

Random effects:
 Groups   Name      Variance Std.Dev.
  Year    (Intercept)  0.6417   0.8011
  Residual              0.3909   0.6253
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error      df t value
(Intercept)    4.159e+00  5.010e-01  3.525e+00   8.302
average.onshore.activity -2.463e-05  7.904e-02  2.126e+01   0.000
              Pr(>|t|)
(Intercept)    0.00195 **
average.onshore.activity  0.99975
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
avrg.nshr.c -0.288

```

Relationship between onshore activity and percent soft bottom (see Figure 24)

```

> ##mixed model
> re.lm <- lmer(percent.soft.bottom ~ average.onshore.activity + (average.onshore.a
ctivity|Year), data = data, REML = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula:
percent.soft.bottom ~ average.onshore.activity + (average.onshore.activity |
  Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    203.2     210.3    -95.6     191.2      18

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.6644 -0.6138 -0.1191  0.7200  1.7443

Random effects:
 Groups   Name      Variance Std.Dev. Corr
  Year    (Intercept)    55.017   7.417
         average.onshore.activity  5.381   2.320  -0.02
  Residual              128.380  11.330
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    30.129     5.540    2.947   5.439   0.0128 *
average.onshore.activity  7.599     2.025    1.776   3.753   0.0769 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
avrg.nshr.c -0.362
> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)

```

ANOVA-like table for random-effects: Single term deletions

```

Model:
percent.soft.bottom ~ average.onshore.activity + (average.onshore.activity | Year)
                                npar
<none>                                6
average.onshore.activity in (average.onshore.activity | Year)      4
                                logLik
<none>                                -95.623
average.onshore.activity in (average.onshore.activity | Year) -95.771
                                AIC
<none>                                203.25
average.onshore.activity in (average.onshore.activity | Year) 199.54
                                LRT
<none>
average.onshore.activity in (average.onshore.activity | Year) 0.29637
                                Df
<none>
average.onshore.activity in (average.onshore.activity | Year) 2
                                Pr(>Chisq)
<none>
average.onshore.activity in (average.onshore.activity | Year) 0.8623
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(percent.soft.bottom ~ average.onshore.activity + (1|Year), data = d
ata, REML = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: percent.soft.bottom ~ average.onshore.activity + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
199.5    204.3    -95.8    191.5      20

Scaled residuals:
      Min       1Q   Median       3Q      Max
-1.73351 -0.61861 -0.01229  0.76556  1.80336

Random effects:
Groups   Name             Variance Std.Dev.
Year     (Intercept)    59.25     7.698
Residual              142.60    11.941
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    30.227     5.759  4.706   5.249  0.00398
average.onshore.activity  7.657     1.498 21.796   5.112 4.12e-05

(Intercept)      **
average.onshore.activity ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
avrg.nshr.c -0.475
> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
percent.soft.bottom ~ average.onshore.activity + (1 | Year)
                                npar    AIC    LRT    Pr(Chi)
<none>                                199.54
average.onshore.activity      1 215.22 17.679 2.615e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Relationship between large boat wake passes and oyster density (see Figure 25)

```
> ##mixed model
> re.lm <- lmer(Log.density ~ Mean.large.boat.wakes + (Mean.large.boat.wakes|Year),
  data = data, REML = FALSE)
boundary (singular) fit: see help('issingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula:
Log.density ~ Mean.large.boat.wakes + (Mean.large.boat.wakes |
  Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    61.9     69.0     -24.9     49.9       18

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.5322 -0.5128 -0.1732  0.6848  1.7054

Random effects:
Groups           Name                Variance Std.Dev. Corr
Year              (Intercept)         1.13151  1.0637
                  Mean.large.boat.wakes 0.06496  0.2549  -1.00
Residual                                0.33888  0.5821
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    4.2446     0.6399  2.9842   6.633   0.0071 **
Mean.large.boat.wakes -0.1529     0.1613  1.4897  -0.948   0.4710
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr)
Mn.lrg.bt.w -0.955
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('issingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
Log.density ~ Mean.large.boat.wakes + (Mean.large.boat.wakes | Year)
              npar    logLik
<none>                6 -24.948
Mean.large.boat.wakes in (Mean.large.boat.wakes | Year)    4 -26.706
              AIC      LRT
<none>                61.897
Mean.large.boat.wakes in (Mean.large.boat.wakes | Year)    61.412 3.5152
              Df Pr(>Chisq)
<none>
Mean.large.boat.wakes in (Mean.large.boat.wakes | Year)    2    0.1725
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(Log.density ~ Mean.large.boat.wakes + (1|Year), data = data, REM
  L = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: Log.density ~ Mean.large.boat.wakes + (1 | Year)
Data: data
```

```

      AIC      BIC    logLik deviance df.resid
    61.4     66.1    -26.7     53.4      20

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.8834 -0.6249 -0.1186  0.7991  1.3557

Random effects:
 Groups   Name      Variance Std.Dev.
 Year     (Intercept) 0.6851   0.8277
 Residual                0.3857   0.6211
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    4.10384    0.52189  3.50973   7.863  0.00239 **
Mean.large.boat.wakes 0.02878    0.08718 22.41056   0.330  0.74437
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Mn.lrg.bt.w -0.320
> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
Log.density ~ Mean.large.boat.wakes + (1 | Year)
              npar    AIC      LRT Pr(Chi)
<none>                61.412
Mean.large.boat.wakes    1 59.514 0.10181  0.7497

```

Relationship between large boat wake passes and percent soft bottom (see Figure 26)

```

> ##mixed model
> re.lm <- lmer(percent.soft.bottom ~ Mean.large.boat.wakes + (Mean.large.boat.wake
s|Year), data = data, REML = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula:
percent.soft.bottom ~ Mean.large.boat.wakes + (Mean.large.boat.wakes |
  Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    196.1     203.2    -92.1     184.1      18

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.58965 -0.62915 -0.06968  0.58598  2.32582

Random effects:
 Groups   Name      Variance Std.Dev. Corr
 Year     (Intercept)  32.88    5.734
        Mean.large.boat.wakes 18.87    4.344 -0.92
 Residual                101.77   10.088
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    23.968    4.676    2.086   5.126  0.033 *
Mean.large.boat.wakes 12.009    3.134    2.815   3.832  0.035 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

Correlation of Fixed Effects:
      (Intr)
Mn.lrg.bt.w -0.817
> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
percent.soft.bottom ~ Mean.large.boat.wakes + (Mean.large.boat.wakes | Year)
              npar    logLik
<none>                6 -92.061
Mean.large.boat.wakes in (Mean.large.boat.wakes | Year)    4 -93.383
              AIC      LRT
<none>                196.12
Mean.large.boat.wakes in (Mean.large.boat.wakes | Year) 194.77 2.6451
              Df Pr(>Chisq)
<none>
Mean.large.boat.wakes in (Mean.large.boat.wakes | Year)  2      0.2665
> ##mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(percent.soft.bottom ~ Mean.large.boat.wakes + (1|Year), data = data
, REML = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: percent.soft.bottom ~ Mean.large.boat.wakes + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
194.8    199.5    -93.4    186.8      20

Scaled residuals:
      Min       1Q   Median       3Q      Max
-1.40144 -0.84451 -0.08967  0.59333  2.33731

Random effects:
Groups   Name             Variance Std.Dev.
Year     (Intercept)      4.122     2.03
Residual                  136.595    11.69
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)      26.834      3.731   6.046   7.192 0.000353 ***
Mean.large.boat.wakes    9.057      1.366  16.721   6.633 4.6e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Mn.lrg.bt.w -0.702
> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
percent.soft.bottom ~ Mean.large.boat.wakes + (1 | Year)
              npar    AIC      LRT    Pr(Chi)
<none>                194.77
Mean.large.boat.wakes    1 215.22 22.455 2.151e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Relationship between percent large boat wake passes and oyster density (see Figure 27)

```
> ##mixed model
```

```

> re.lm <- lmer(Log.density ~ percent.large.boat.wakes + (percent.large.boat.wakes |
Year), data = data, REML = FALSE)
boundary (singular) fit: see help('isSingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula:
Log.density ~ percent.large.boat.wakes + (percent.large.boat.wakes |
Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    58.4     65.5    -23.2     46.4       18

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.58220 -0.62498 -0.06528  0.78442  1.86412

Random effects:
Groups      Name                Variance Std.Dev. Corr
Year      (Intercept)           1.316993  1.1476
          percent.large.boat.wakes 0.001529  0.0391  -1.00
Residual                    0.289890  0.5384
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    4.31042    0.68767   2.98928   6.268   0.00828
percent.large.boat.wakes -0.02405    0.02406   1.78798  -1.000   0.43332

(Intercept)      **
percent.large.boat.wakes
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
prcnt.lrg.. -0.974
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
Log.density ~ percent.large.boat.wakes + (percent.large.boat.wakes | Year)
      npar
<none>          6
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 4
      logLik
<none>      -23.219
percent.large.boat.wakes in (percent.large.boat.wakes | Year) -26.735
      AIC
<none>     58.437
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 61.469
      LRT Df
<none>
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 7.0316 2
      Pr(>Chisq)
<none>
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 0.02972
<none>
percent.large.boat.wakes in (percent.large.boat.wakes | Year) *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #mixed model simplified (year as intercept instead of slope)

```

```

> re.lm <- lmer(Log.density ~ percent.large.boat.wakes + (1|Year), data = data, REML = FALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method [lmerModLmerTest]
Formula: Log.density ~ percent.large.boat.wakes + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    61.5     66.2    -26.7     53.5      20

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.7910 -0.7942 -0.1637  0.8562  1.4486

Random effects:
 Groups   Name      Variance Std.Dev.
 Year      (Intercept) 0.6122   0.7824
 Residual              0.3925   0.6265
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value
(Intercept)  4.200971   0.507182  3.786390   8.283
percent.large.boat.wakes -0.002404  0.011000 22.341950  -0.219
              Pr(>|t|)
(Intercept)    0.00147 **
percent.large.boat.wakes 0.82896
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr)
prcnt.lrg.. -0.378

```

Relationship between percent large boat wake passes and percent soft bottom (see Figure 28)

```

> ##mixed model
> re.lm <- lmer(percent.soft.bottom ~ percent.large.boat.wakes + (percent.large.boat.wakes|Year), data = data, REML = FALSE)
boundary (singular) fit: see help('isSingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method [lmerModLmerTest]
Formula:
percent.soft.bottom ~ percent.large.boat.wakes + (percent.large.boat.wakes | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    189.5     196.6    -88.8     177.5      18

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.7906 -0.7768  0.1654  0.6856  2.1357

Random effects:
 Groups   Name      Variance Std.Dev. Corr
 Year      (Intercept) 89.9022  9.4817
          percent.large.boat.wakes 0.2555  0.5055  -1.00
 Residual              77.0536  8.7780
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)  19.8784     6.2734  2.4945   3.169  0.0649 .

```

```

percent.large.boat.wakes 1.5282 0.3305 2.7171 4.624 0.0236 *
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
prcnt.lrg.. -0.941
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('issingular')

> ##hypothesis tests for random effects
> anova(re.lm, reduce.terms=TRUE)
boundary (singular) fit: see help('issingular')
ANOVA-like table for random-effects: Single term deletions

Model:
percent.soft.bottom ~ percent.large.boat.wakes + (percent.large.boat.wakes | Year)
                                npar
<none>                                6
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 4
                                logLik
<none>                                -88.757
percent.large.boat.wakes in (percent.large.boat.wakes | Year) -90.546
                                AIC
<none>                                189.51
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 189.09
                                LRT Df
<none>                                3.5776 2
                                Pr(>Chisq)
percent.large.boat.wakes in (percent.large.boat.wakes | Year) 0.1672
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(percent.soft.bottom ~ percent.large.boat.wakes + (1|Year), data = d
ata, REML = FALSE)
boundary (singular) fit: see help('issingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: percent.soft.bottom ~ percent.large.boat.wakes + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
189.1    193.8    -90.5    181.1      20

Scaled residuals:
      Min       1Q   Median       3Q      Max
-1.38772 -0.95231 -0.07975  0.69733  2.15617

Random effects:
Groups   Name             Variance Std.Dev.
Year     (Intercept)      0.0      0.00
Residual                  110.8    10.53
Number of obs: 24, groups: Year, 3

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    22.5741     3.4150 24.0000   6.610 7.75e-07
percent.large.boat.wakes 1.2396     0.1522 24.0000   8.147 2.28e-08

(Intercept) ***
percent.large.boat.wakes ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
prcnt.lrg.. -0.777

```

```
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')

> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
percent.soft.bottom ~ percent.large.boat.wakes + (1 | Year)
              npar      AIC      LRT    Pr(Chi)
<none>                189.09
percent.large.boat.wakes    1 215.22 28.129 1.135e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Relationship between eelgrass density and oyster density (see Figure 29)

```
> ##mixed model
> re.lm <- lmer(log.oyster ~ Eelgrass.density + (Eelgrass.density|Year), data = dat
a, REML = FALSE)
boundary (singular) fit: see help('isSingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: log.oyster ~ Eelgrass.density + (Eelgrass.density | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
  76.3    85.1    -32.2     64.3       26

Scaled residuals:
    Min       1Q   Median       3Q      Max
-2.2557 -0.5572  0.1809  0.8068  1.2326

Random effects:
Groups      Name                Variance Std.Dev. Corr
Year              (Intercept)  9.150e-01 0.956538
              Eelgrass.density  3.358e-05 0.005795 -1.00
Residual              3.099e-01 0.556696
Number of obs: 32, groups: Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    4.2687842  0.4955293  3.9888655   8.615  0.00101 **
Eelgrass.density -0.0005666  0.0033571  3.6510442  -0.169  0.87490
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Elgrss.dnst -0.918
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
log.oyster ~ Eelgrass.density + (Eelgrass.density | Year)
              npar    logLik      AIC
<none>                6 -32.155 76.311
Eelgrass.density in (Eelgrass.density | Year)    4 -35.349 78.698
              LRT Df Pr(>Chisq)
<none>
Eelgrass.density in (Eelgrass.density | Year) 6.3871  2    0.04103 *
```

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(log.oyster ~ Eelgrass.density + (1|Year), data = data, REML = FALSE
)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: log.oyster ~ Eelgrass.density + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    78.7     84.6    -35.3     70.7       28

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.8487 -0.7624 -0.1635  0.8903  1.5691

Random effects:
Groups   Name              Variance Std.Dev.
Year     (Intercept)    0.4881     0.6986
Residual                   0.3958     0.6292
Number of obs: 32, groups: Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    4.380081   0.378877   4.536204  11.561 0.000155 ***
Eelgrass.density -0.002014   0.001963  28.643522  -1.026 0.313371
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr)
Elgrss.dnst -0.253

```

Relationship between eelgrass density and percent soft bottom (see Figure 30)

```

> ##mixed model
> re.lm <- lmer(Percent.bottom ~ Eelgrass.density + (Eelgrass.density|Year), dat
a = data, REML = FALSE)
boundary (singular) fit: see help('issingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: Percent.bottom ~ Eelgrass.density + (Eelgrass.density | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
    273.2     282.0    -130.6     261.2       26

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.4283 -0.6117 -0.2409  0.5344  2.0295

Random effects:
Groups   Name              Variance Std.Dev. Corr
Year     (Intercept)    79.62599   8.9233
        Eelgrass.density  0.02494   0.1579  1.00
Residual                   141.48151 11.8946
Number of obs: 32, groups: Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    28.26112   5.29380   4.22499   5.339 0.00508 **
Eelgrass.density  0.18742   0.09055   4.28124   2.070 0.10267
---

```

```

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Elgrss.dnst 0.561
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('issingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
Percent.bottom ~ Eelgrass.density + (Eelgrass.density | Year)
              npar    logLik      AIC      LRT
<none>                6 -130.59  273.17
Eelgrass.density in (Eelgrass.density | Year)    4 -137.21  282.42  13.25
              Df Pr(>Chisq)
<none>
Eelgrass.density in (Eelgrass.density | Year)    2   0.001327 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(Percent.bottom ~ Eelgrass.density + (1|Year), data = data, REML = F
ALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: Percent.bottom ~ Eelgrass.density + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
 282.4    288.3   -137.2    274.4        28

Scaled residuals:
      Min       1Q   Median       3Q      Max
-1.7966 -0.5653 -0.1759  0.6722  1.9243

Random effects:
Groups   Name             Variance Std.Dev.
Year     (Intercept)    279.9      16.73
Residual                230.8      15.19
Number of obs: 32, groups: Year, 4

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)   32.22675    9.08453  4.55250   3.547   0.0192 *
Eelgrass.density  0.08781    0.04740 28.65919   1.853   0.0743 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Elgrss.dnst -0.254

```

Relationship between eelgrass density and percent soft bottom at high-energy sites only (see Figure 31)

```

> ##mixed model
> re.lm <- lmer(Percent.bottom ~ Eelgrass.density + (Eelgrass.density|Year), dat
a = data, REML = FALSE)
boundary (singular) fit: see help('issingular')
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]

```

```

Formula: Percent.bottom ~ Eelgrass.density + (Eelgrass.density | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
  130.0    134.6    -59.0    118.0      10

Scaled residuals:
      Min       1Q   Median       3Q      Max
-1.97460 -0.23934  0.00273  0.37813  2.08076

Random effects:
Groups      Name      Variance Std.Dev. Corr
Year      (Intercept)  6.174e+02 24.84717
          Eelgrass.density 2.023e-03 0.04498 -1.00
Residual              3.408e+01 5.83811
Number of obs: 16, groups: Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    58.9054    12.6480   3.5311   4.657   0.0129 *
Eelgrass.density -0.1482     0.0333   2.1616  -4.452   0.0406 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Elgrss.dnst -0.772
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
Percent.bottom ~ Eelgrass.density + (Eelgrass.density | Year)
              npar    logLik      AIC
<none>                6 -58.979 129.96
Eelgrass.density in (Eelgrass.density | Year)    4 -59.446 126.89
              LRT Df Pr(>Chisq)
<none>
Eelgrass.density in (Eelgrass.density | Year) 0.93511 2    0.6265
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(Percent.bottom ~ Eelgrass.density + (1|Year), data = data, REML = F
ALSE)
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: Percent.bottom ~ Eelgrass.density + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
  126.9    130.0    -59.4    118.9      12

Scaled residuals:
      Min       1Q   Median       3Q      Max
-2.03122 -0.32235  0.08036  0.38611  1.85261

Random effects:
Groups      Name      Variance Std.Dev.
Year      (Intercept)  442.1    21.026
Residual              37.5     6.123
Number of obs: 16, groups: Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    55.38727    10.80775   4.28051   5.125   0.00571 **
Eelgrass.density -0.10255     0.02655  12.12491  -3.862   0.00222 **

```

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Elgrss.dnst -0.184
> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
Percent.bottom ~ Eelgrass.density + (1 | Year)
      npar      AIC      LRT   Pr(Chi)
<none>          126.89
Eelgrass.density    1 134.60  9.7057 0.001837 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Relationship between prior year recruitment and oyster density (see Figure 32)

```

> ##mixed model
> re.lm <- lmer(log.oyster ~ Prior.year.recruitment + (Prior.year.recruitment|Year), data = data, REML = FALSE)
boundary (singular) fit: see help('issingular')
warning messages:
1: Some predictor variables are on very different scales: consider rescaling
2: Some predictor variables are on very different scales: consider rescaling
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula:
log.oyster ~ Prior.year.recruitment + (Prior.year.recruitment |
  Year)
Data: data

      AIC      BIC    logLik deviance df.resid
  75.1    83.7    -31.5     63.1      25

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.8065 -0.6687 -0.1741  0.6781  2.0395

Random effects:
 Groups   Name                Variance Std.Dev.  Corr
  Year    (Intercept)          2.597e-01 0.5095703
        Prior.year.recruitment 1.596e-08 0.0001263  1.00
  Residual                    3.349e-01 0.5786845
Number of obs: 31, groups:  Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    4.0734238   0.2899335  4.3478532  14.050 8.68e-05
Prior.year.recruitment 0.0001915   0.0001471  1.7573230   1.302  0.338

(Intercept)          ***
Prior.year.recruitment
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Prr.yr.rcrt 0.095
fit warnings:
Some predictor variables are on very different scales: consider rescaling
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('issingular')

```

```

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
log.oyster ~ Prior.year.recruitment + (Prior.year.recruitment | Year)
                                npar  logLik
<none>                          6  -31.549
Prior.year.recruitment in (Prior.year.recruitment | Year)  4  -31.684
                                AIC
<none>                          75.098
Prior.year.recruitment in (Prior.year.recruitment | Year) 71.367
                                LRT Df
<none>
Prior.year.recruitment in (Prior.year.recruitment | Year) 0.26951  2
                                Pr(>Chisq)
<none>
Prior.year.recruitment in (Prior.year.recruitment | Year)  0.8739
Warning messages:
1: Some predictor variables are on very different scales: consider rescaling
2: Some predictor variables are on very different scales: consider rescaling
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(log.oyster ~ Prior.year.recruitment + (1|Year), data = data, REM
L = FALSE)
Warning messages:
1: Some predictor variables are on very different scales: consider rescaling
2: Some predictor variables are on very different scales: consider rescaling
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: log.oyster ~ Prior.year.recruitment + (1 | Year)
Data: data

            AIC      BIC    logLik deviance df.resid
       71.4      77.1     -31.7     63.4       27

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.8750 -0.6891 -0.1606  0.6947  1.9028

Random effects:
Groups   Name             Variance Std.Dev.
Year     (Intercept)  0.3804     0.6167
Residual              0.3371     0.5806
Number of obs: 31, groups: Year, 4

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    4.033e+00  3.365e-01 4.369e+00  11.985 0.000166
Prior.year.recruitment 3.071e-04  1.138e-04 2.859e+01   2.698 0.011577

(Intercept)      ***
Prior.year.recruitment *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr)
Prr.yr.rcrt -0.253
fit warnings:
Some predictor variables are on very different scales: consider rescaling
> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
log.oyster ~ Prior.year.recruitment + (1 | Year)

```

```

      npar      AIC      LRT Pr(Chi)
<none>          71.367
Prior.year.recruitment 1 75.861 6.4938 0.01083 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Relationship between prior year recruitment and percent soft bottom (see Figure 33)

```

> ##mixed model
> re.lm <- lmer(Percent.bottom ~ Prior.year.recruitment + (Prior.year.recruitment |
Year), data = data, REML = FALSE)
boundary (singular) fit: see help('issingular')
warning messages:
1: Some predictor variables are on very different scales: consider rescaling
2: Some predictor variables are on very different scales: consider rescaling
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula:
Percent.bottom ~ Prior.year.recruitment + (Prior.year.recruitment |
Year)
Data: data

      AIC      BIC    logLik deviance df.resid
 278.8    287.4   -133.4    266.8      25

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.89744 -0.75392 -0.02646  0.68834  1.56888

Random effects:
Groups   Name              Variance Std.Dev.  Corr
Year     (Intercept)      1.955e+02 13.980782
        Prior.year.recruitment 4.819e-06 0.002195 -1.00
Residual                2.559e+02 15.998403
Number of obs: 31, groups: Year, 4

Fixed effects:
              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)   39.031717   7.879329   5.039048   4.954   0.00418
Prior.year.recruitment -0.004594   0.003054  10.963648  -1.504   0.16079

(Intercept)      **
Prior.year.recruitment
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Prr.yr.rcrt -0.581
fit warnings:
Some predictor variables are on very different scales: consider rescaling
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('issingular')

> ##hypothesis tests for random effects
> ranova(re.lm, reduce.terms=TRUE)
ANOVA-like table for random-effects: Single term deletions

Model:
Percent.bottom ~ Prior.year.recruitment + (Prior.year.recruitment | Year)
      npar  logLik
<none>         6 -133.42
Prior.year.recruitment in (Prior.year.recruitment | Year)  4 -133.50
      AIC
<none>      278.84

```

```

Prior.year.recruitment in (Prior.year.recruitment | Year) 275.00
                                LRT Df
<none>
Prior.year.recruitment in (Prior.year.recruitment | Year) 0.16264 2
                                Pr(>ChiSq)
<none>
Prior.year.recruitment in (Prior.year.recruitment | Year) 0.9219
Warning messages:
1: Some predictor variables are on very different scales: consider rescaling
2: Some predictor variables are on very different scales: consider rescaling
> #mixed model simplified (year as intercept instead of slope)
> re.lm <- lmer(Percent.bottom ~ Prior.year.recruitment + (1|Year), data = data, R
EML = FALSE)
Warning messages:
1: Some predictor variables are on very different scales: consider rescaling
2: Some predictor variables are on very different scales: consider rescaling
> summary(re.lm)
Linear mixed model fit by maximum likelihood . t-tests use
Satterthwaite's method [lmerModLmerTest]
Formula: Percent.bottom ~ Prior.year.recruitment + (1 | Year)
Data: data

      AIC      BIC    logLik deviance df.resid
 275.0    280.7   -133.5    267.0      27

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.92791 -0.64492  0.03114  0.57480  1.61349

Random effects:
Groups   Name             Variance Std.Dev.
Year     (Intercept)    218.7      14.79
Residual                  247.0      15.72
Number of obs: 31, groups: Year, 4

Fixed effects:
              Estimate Std. Error    df t value Pr(>|t|)
(Intercept)    38.994122   8.242882  4.626441   4.731  0.00633
Prior.year.recruitment -0.004157   0.003069 29.009126  -1.354  0.18603

(Intercept)      **
Prior.year.recruitment
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr)
Prr.yr.rcrt -0.279
fit warnings:
Some predictor variables are on very different scales: consider rescaling
> ##hypothesis test for fixed effects
> drop1(re.lm, ddf="lme4", test="Chi")
Single term deletions

Model:
Percent.bottom ~ Prior.year.recruitment + (1 | Year)
      npar      AIC      LRT Pr(Chi)
<none>      275.00
Prior.year.recruitment  1 274.79 1.7819  0.1819

```

APPENDIX C
SINGLE WAVE ANALYSIS RESULTS
Deployment 1

Deanza: January 1, 2022

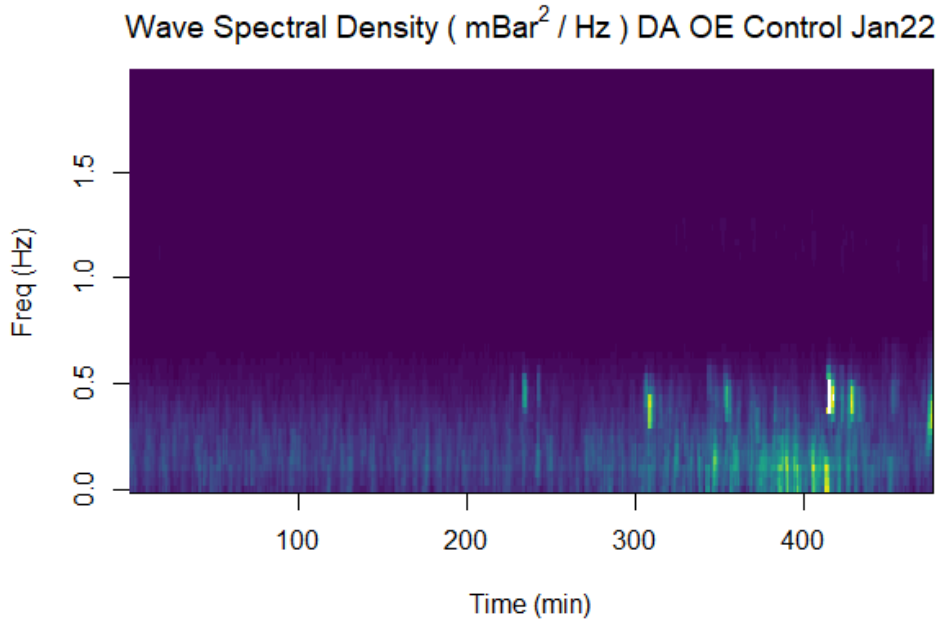


Figure C1. Wave spectral density over duration of full deployment at Deanza Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

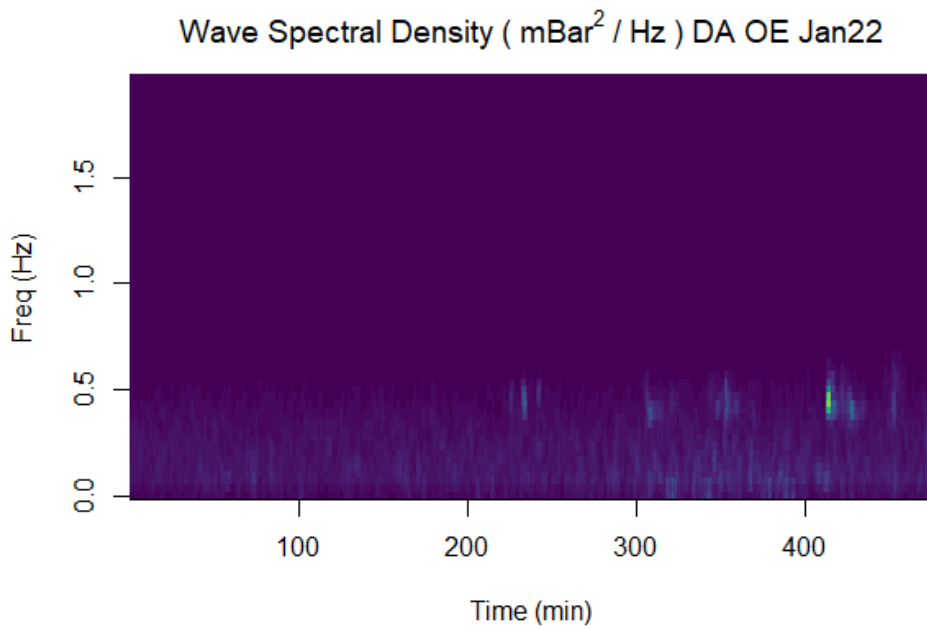


Figure C2. Wave spectral density over duration of full deployment at Deanza Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz

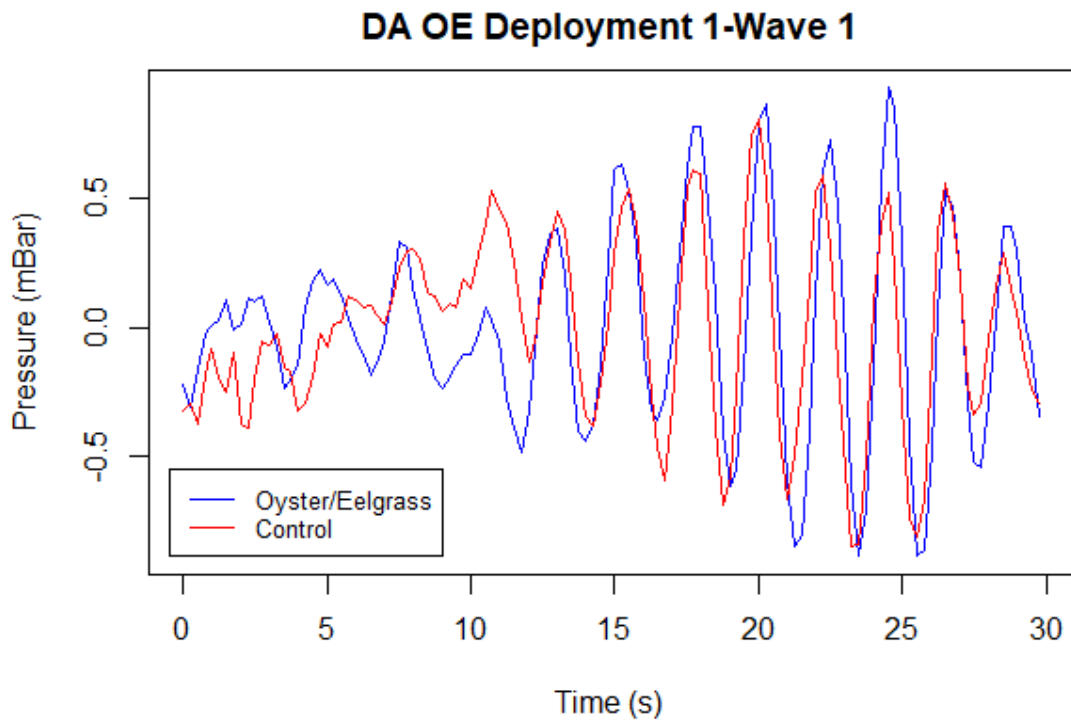


Figure C3. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

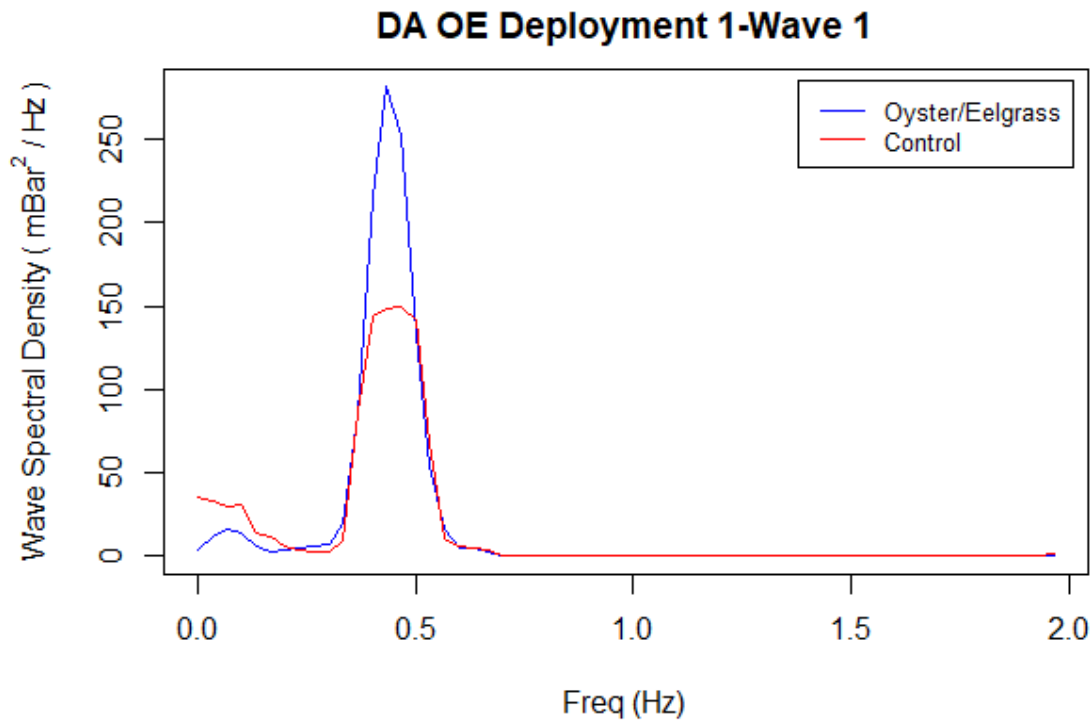


Figure C4. FFT of wave 1 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

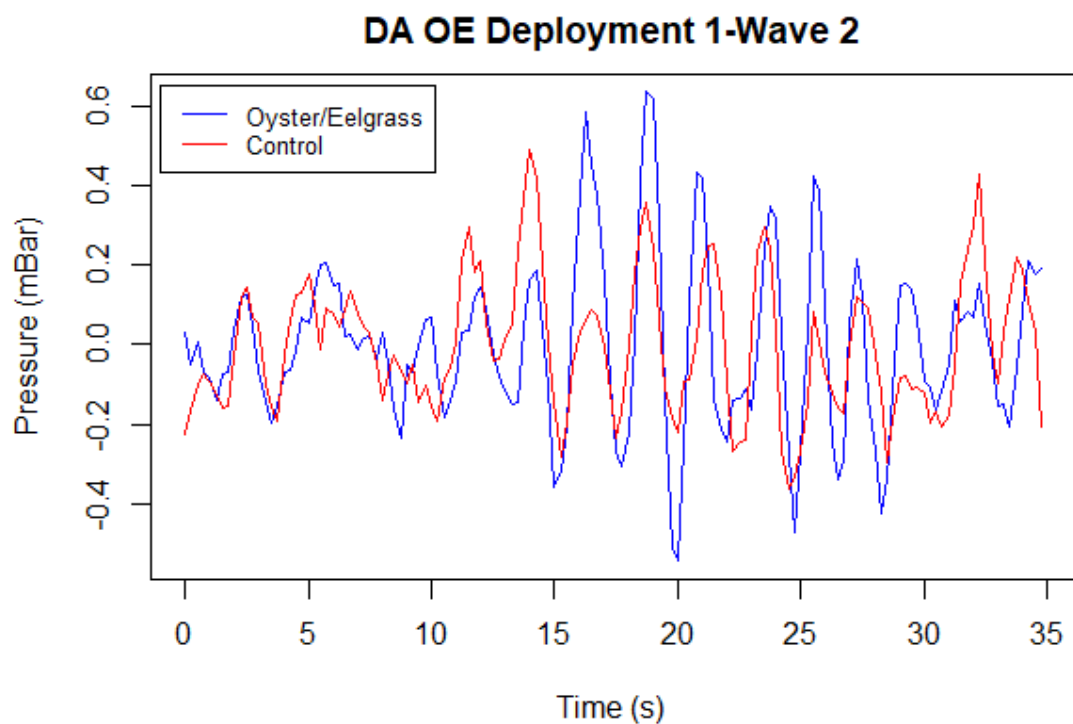


Figure C5. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

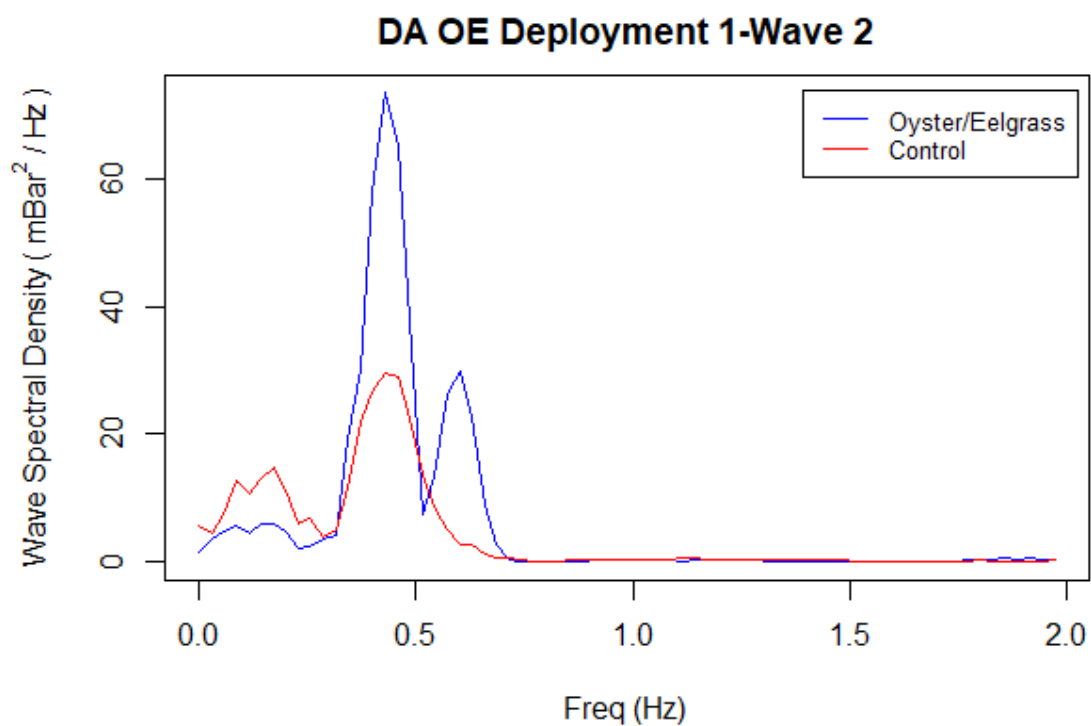


Figure C6. FFT of wave 2 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

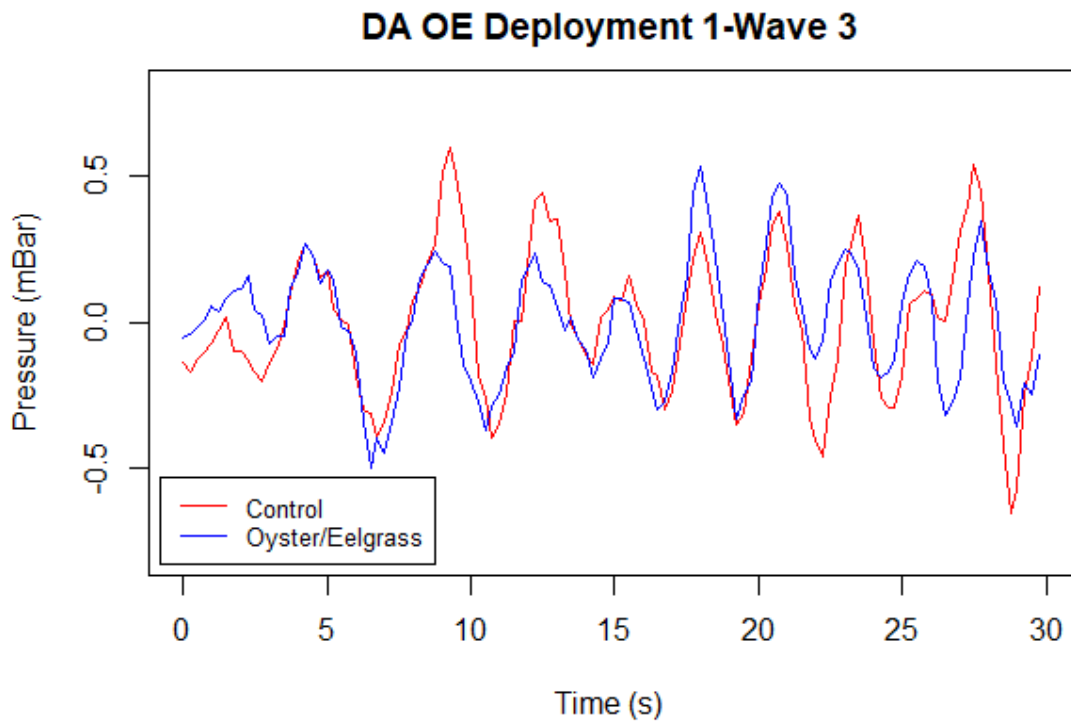


Figure C7. Progression of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

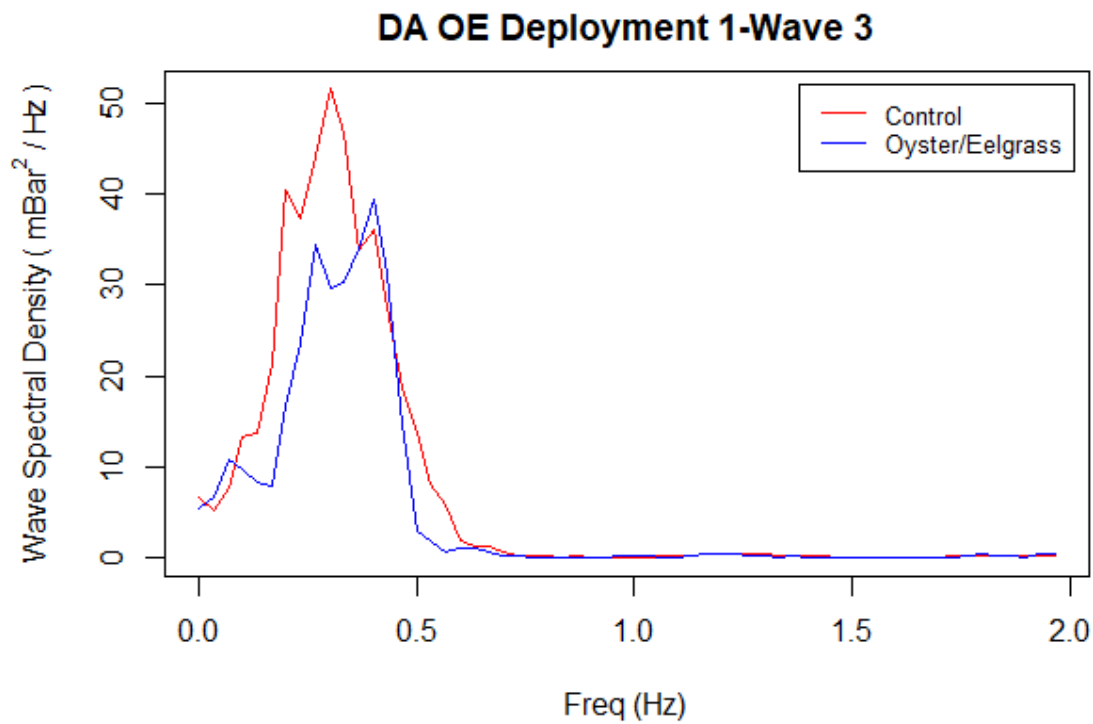


Figure C8. FFT of wave 3 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

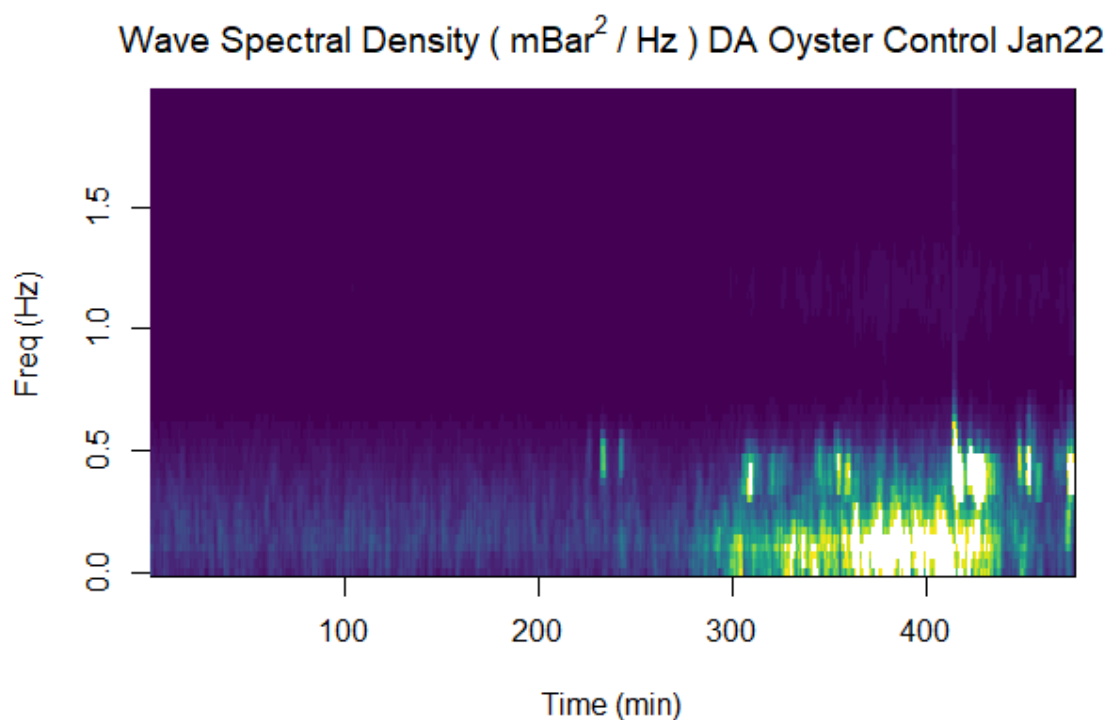


Figure C9. Wave spectral density over duration of full deployment at Deanza Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

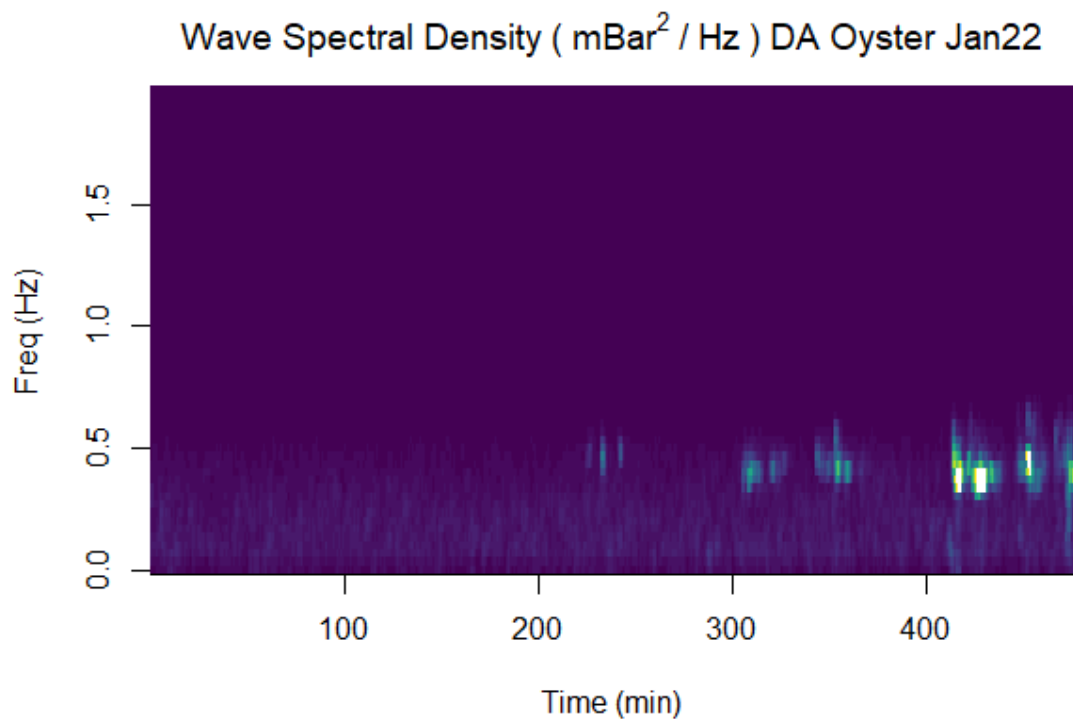


Figure C10. Wave spectral density over duration of full deployment at Deanza Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

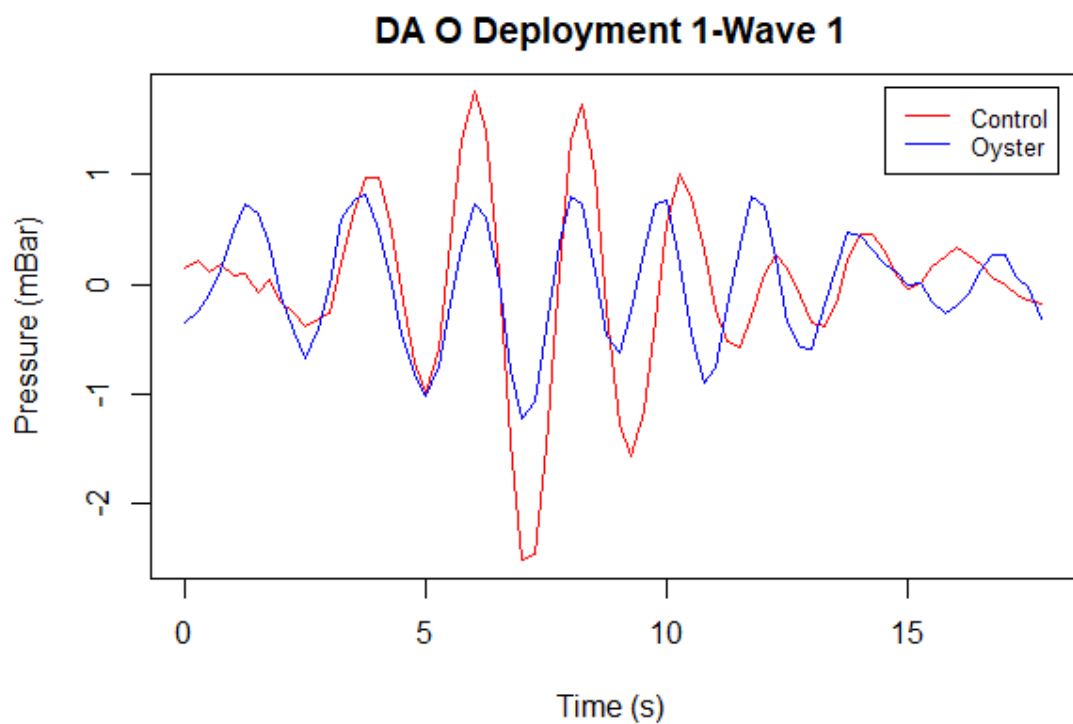


Figure C11. Progression of wave 1 over time at Oyster and Oyster control logger.

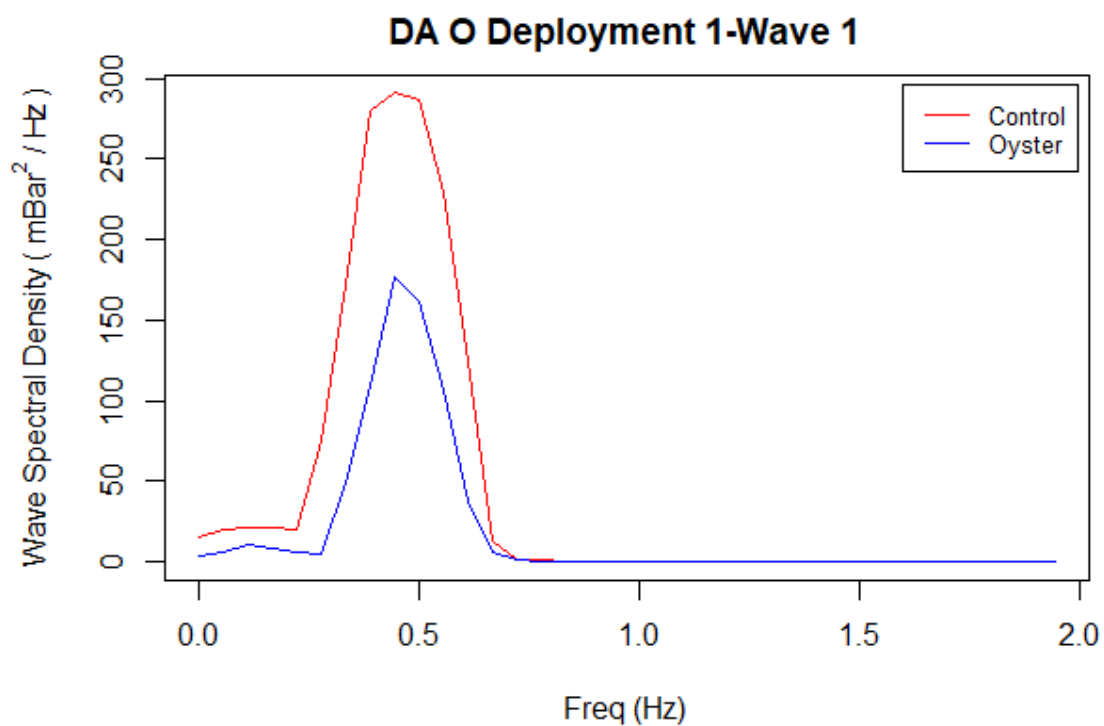


Figure C12. FFT of wave 1 at Oyster and Oyster control logger.

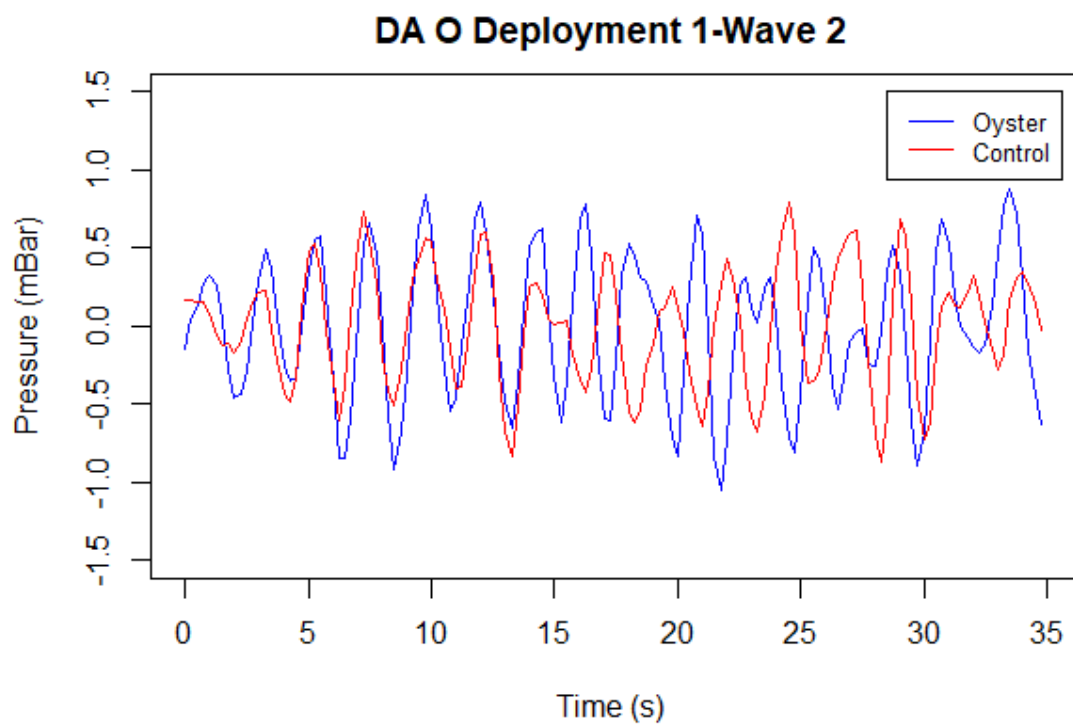


Figure C13. Progression of wave 2 over time at Oyster and Oyster control logger.

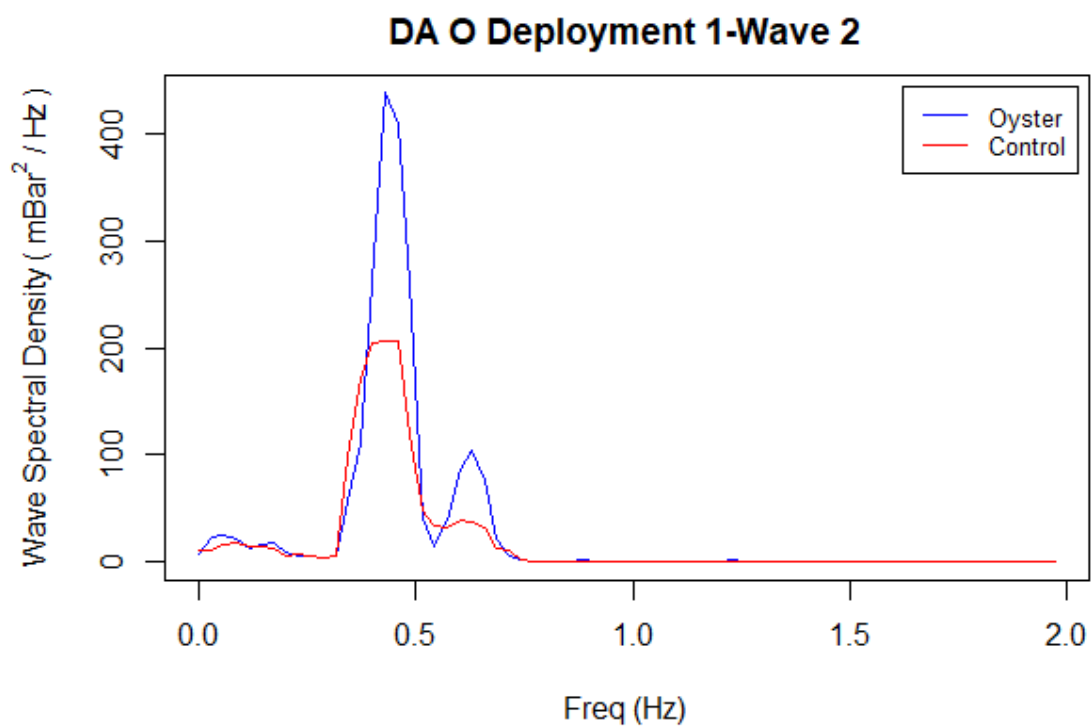


Figure C14. FFT of wave 2 at Oyster and Oyster control logger.

PCH: January 2, 2022

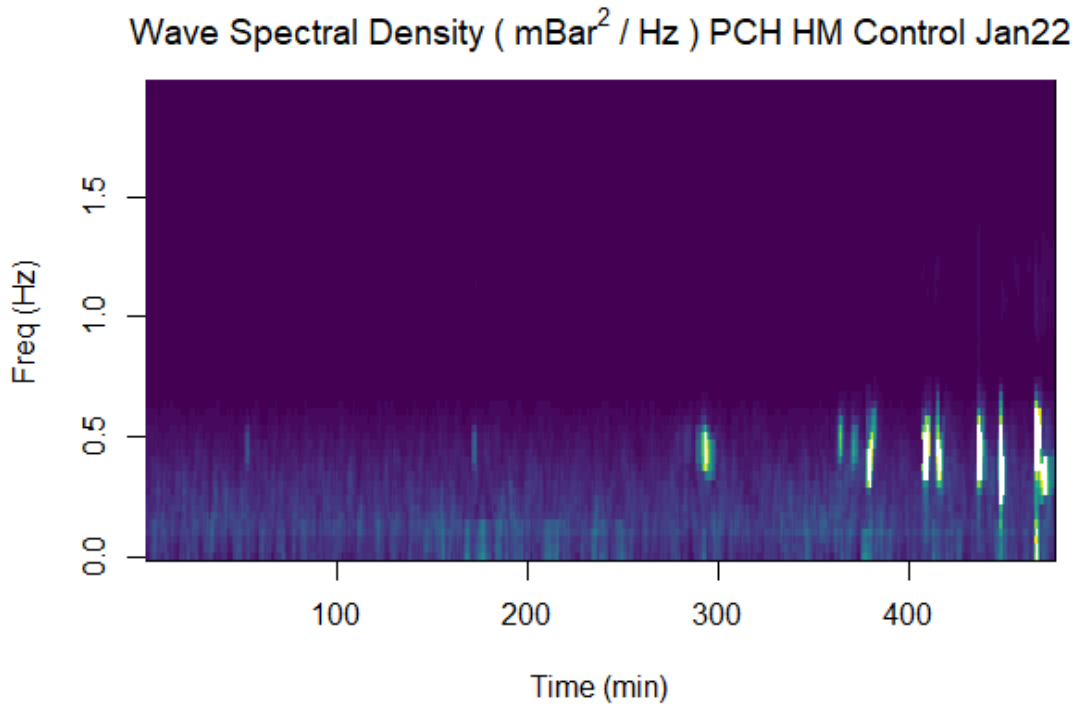


Figure C15. Wave spectral density over duration of full deployment at PCH High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

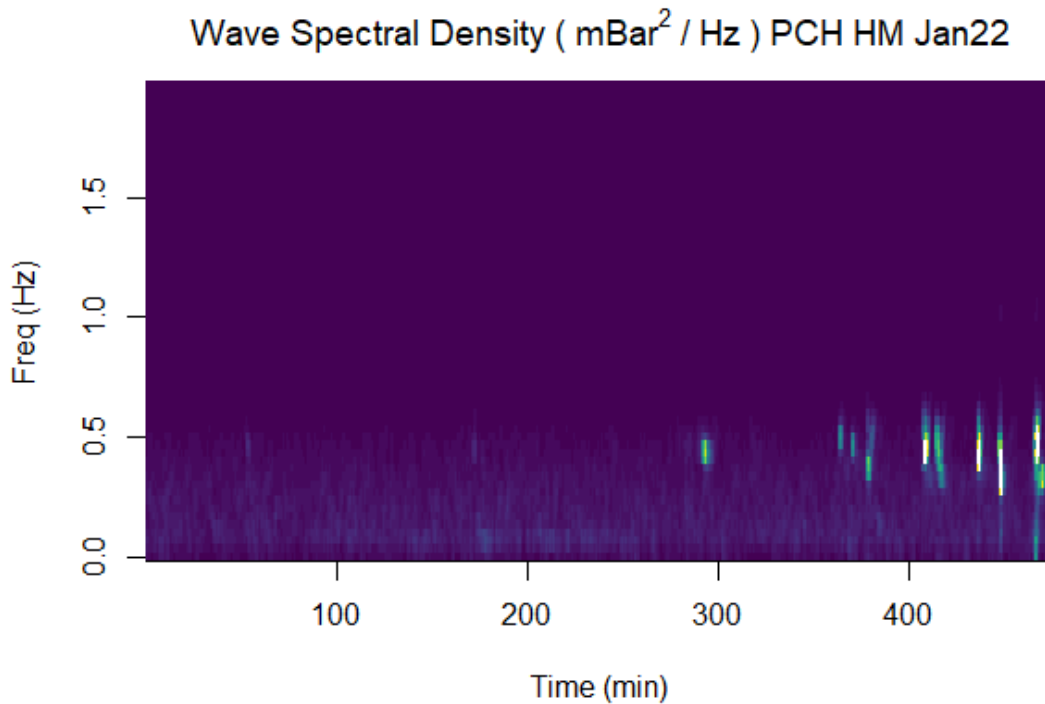


Figure C16. Wave spectral density over duration of full deployment at PCH High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

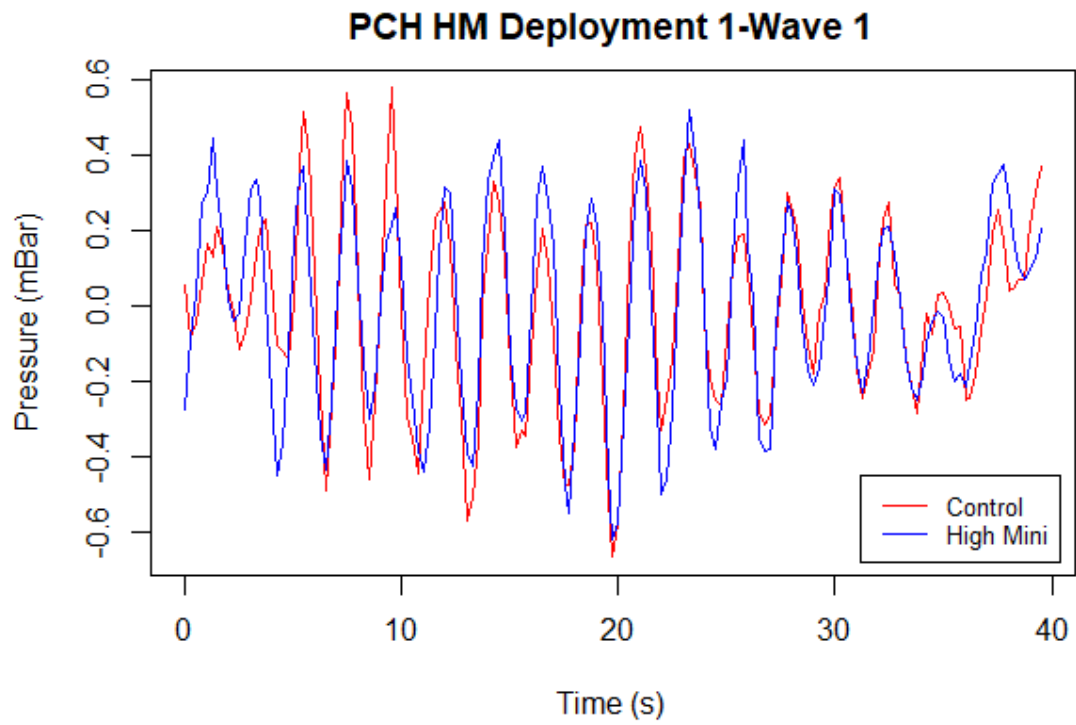


Figure C17. Progression of wave 1 over time at High Mini and High Mini control logger.

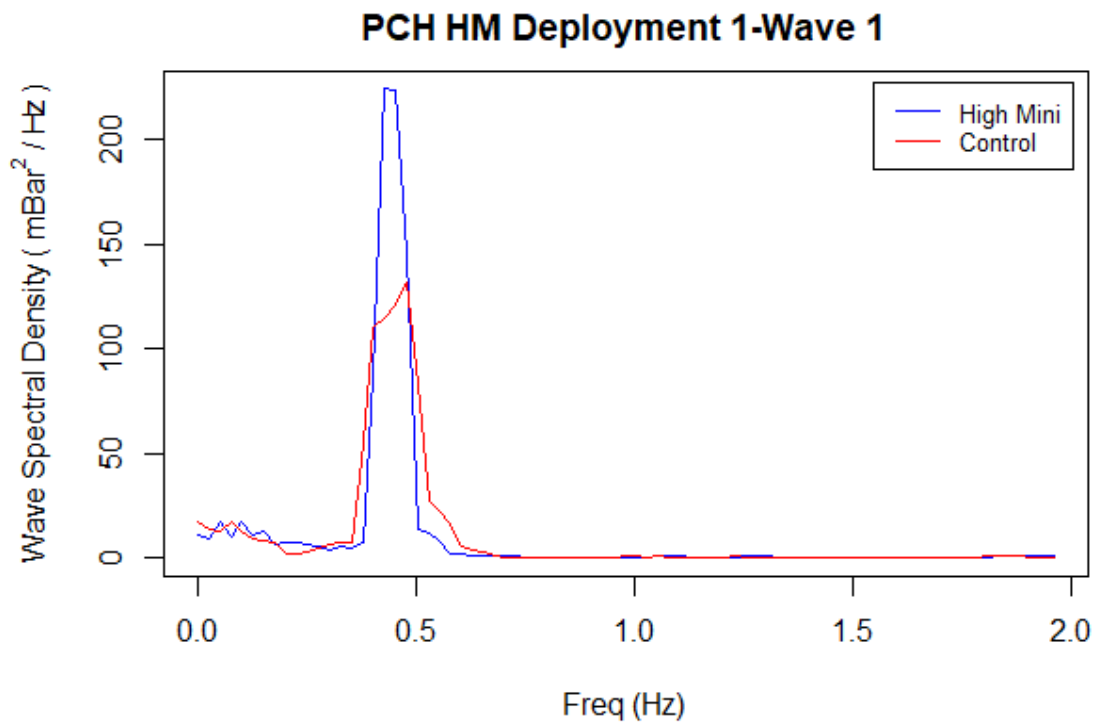


Figure C18. FFT of wave 1 at High Mini and High Mini control logger.

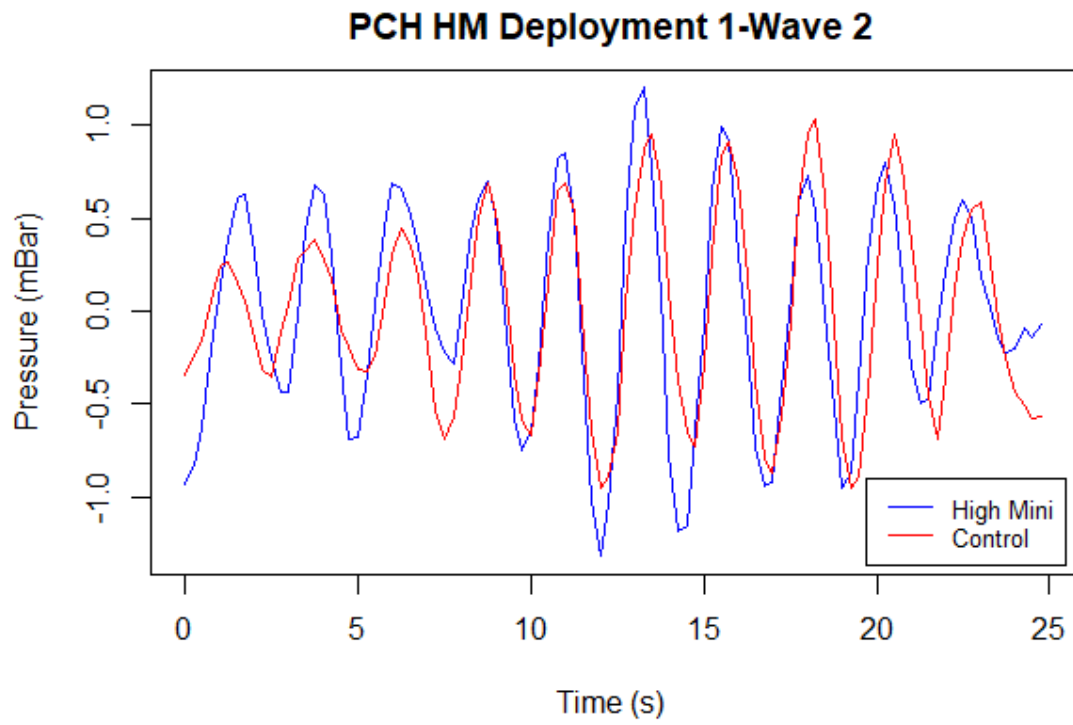


Figure C19. Progression of wave 2 over time at High Mini and High Mini control logger.

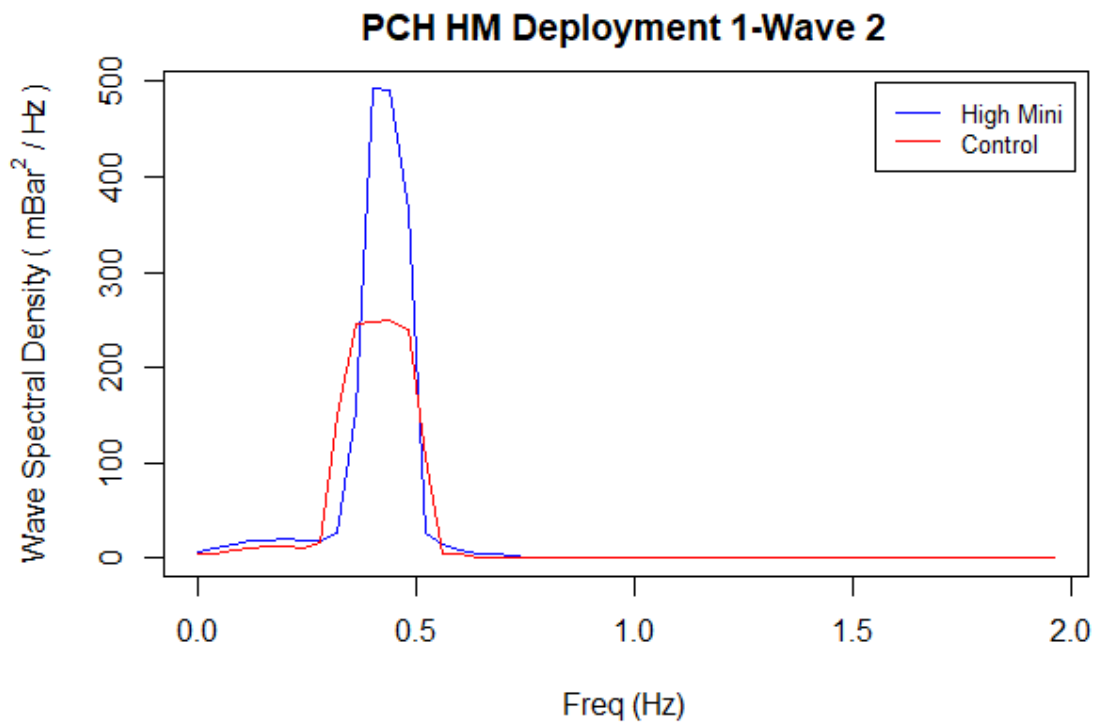


Figure C20. FFT of wave 2 at High Mini and High Mini control logger.

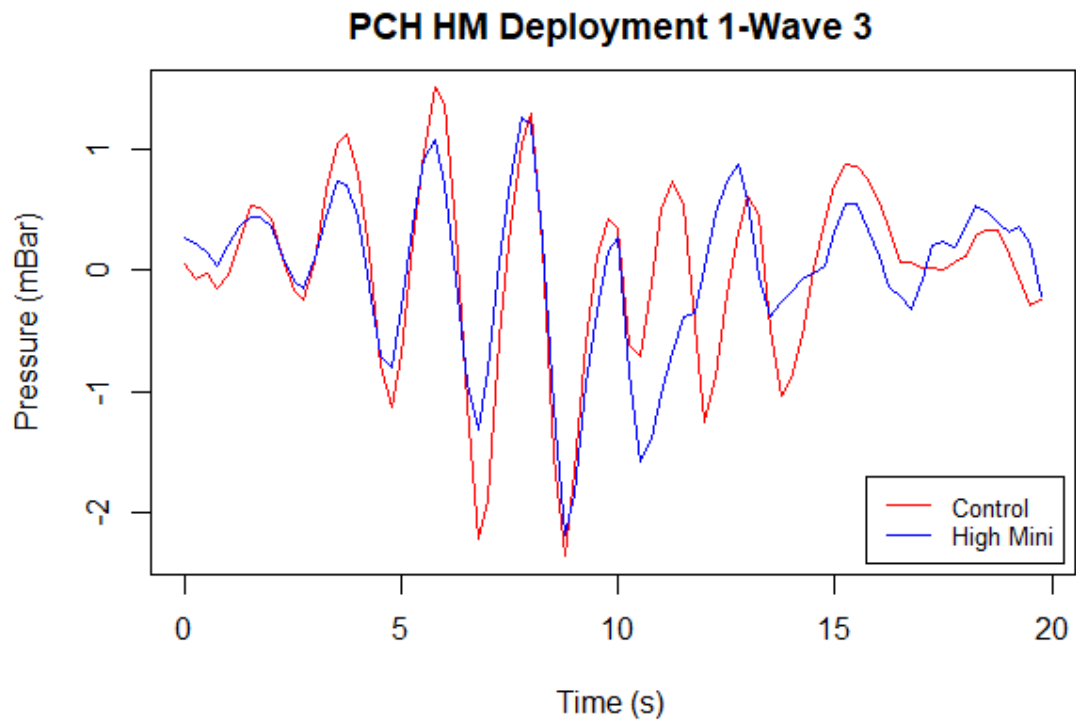


Figure C21. Progression of wave 3 over time at High Mini and High Mini control logger.

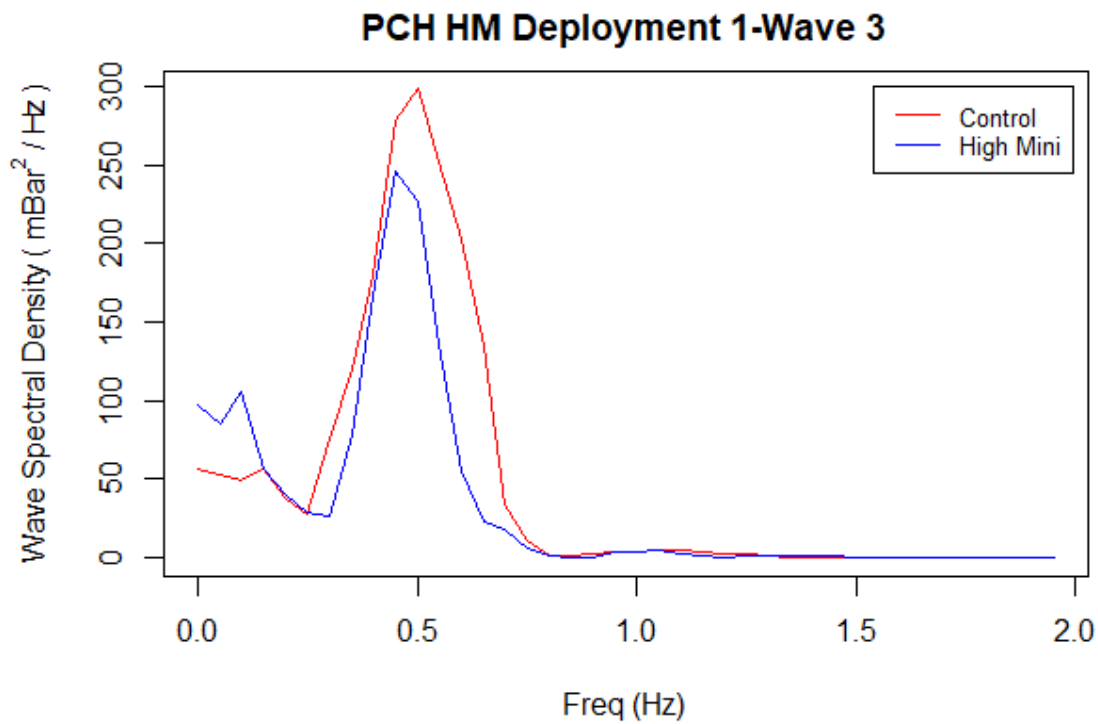


Figure C22. FFT of wave 3 at High Mini and High Mini control logger.

Westcliff: January 4, 2022

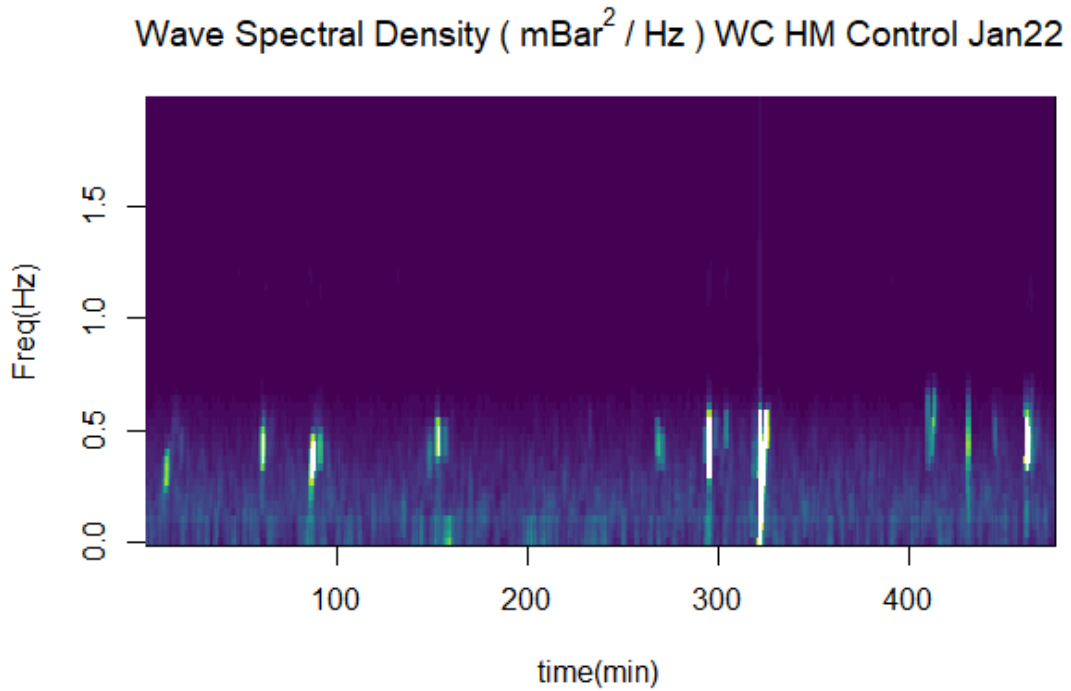


Figure C23. Wave spectral density over duration of full deployment at Westcliff High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

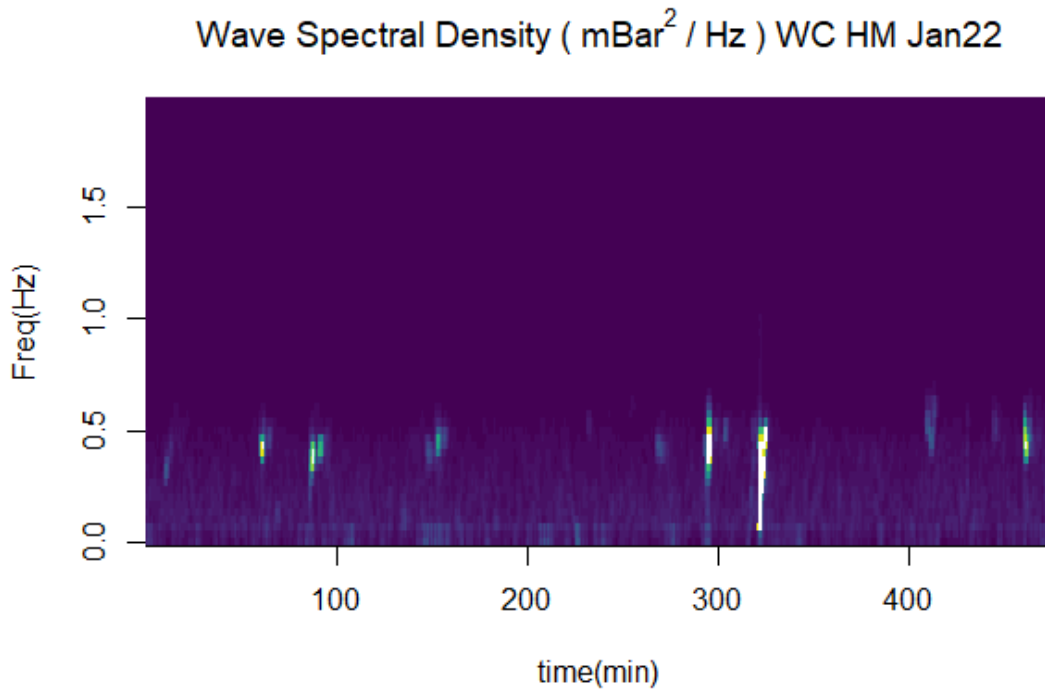


Figure C24. Wave spectral density over duration of full deployment at Westcliff High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

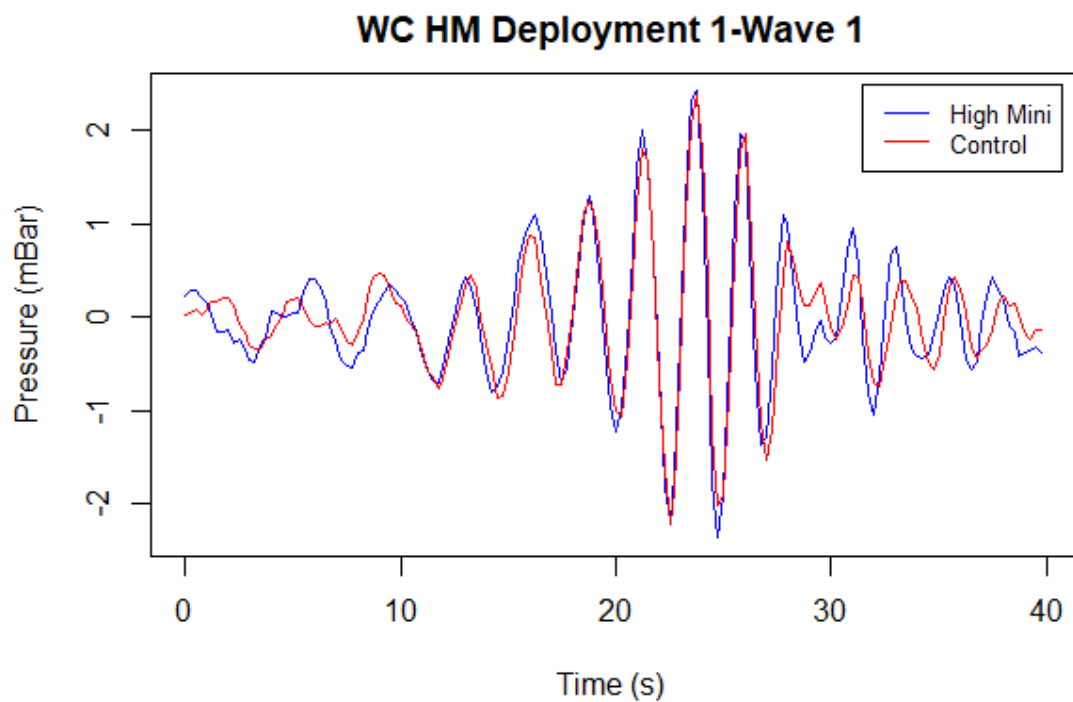


Figure C25. Progression of wave 1 over time at High Mini and High Mini control logger.

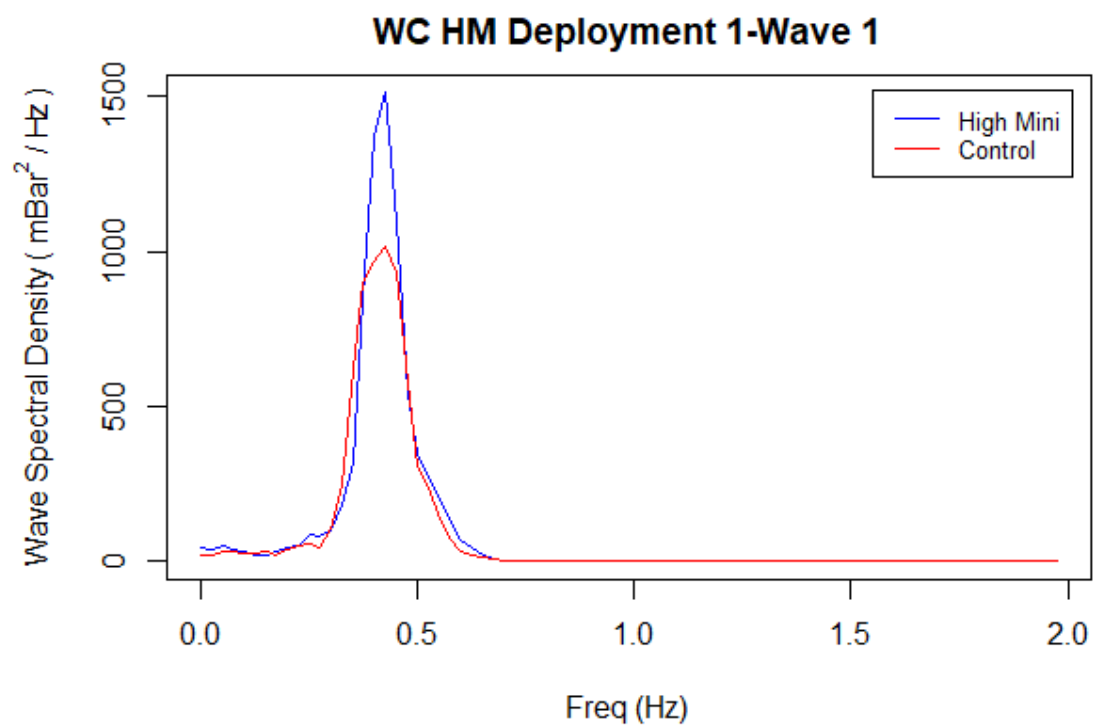


Figure C26. FFT of wave 1 at High Mini and High Mini control logger.

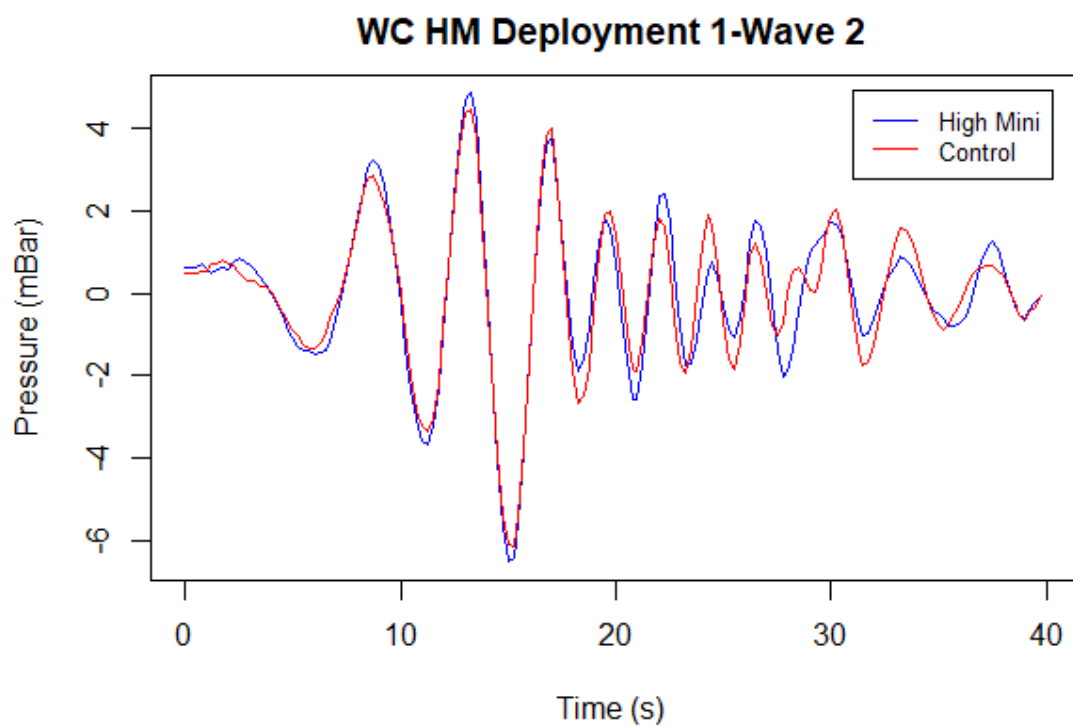


Figure C27. Progression of wave 2 over time at High Mini and High Mini control logger.

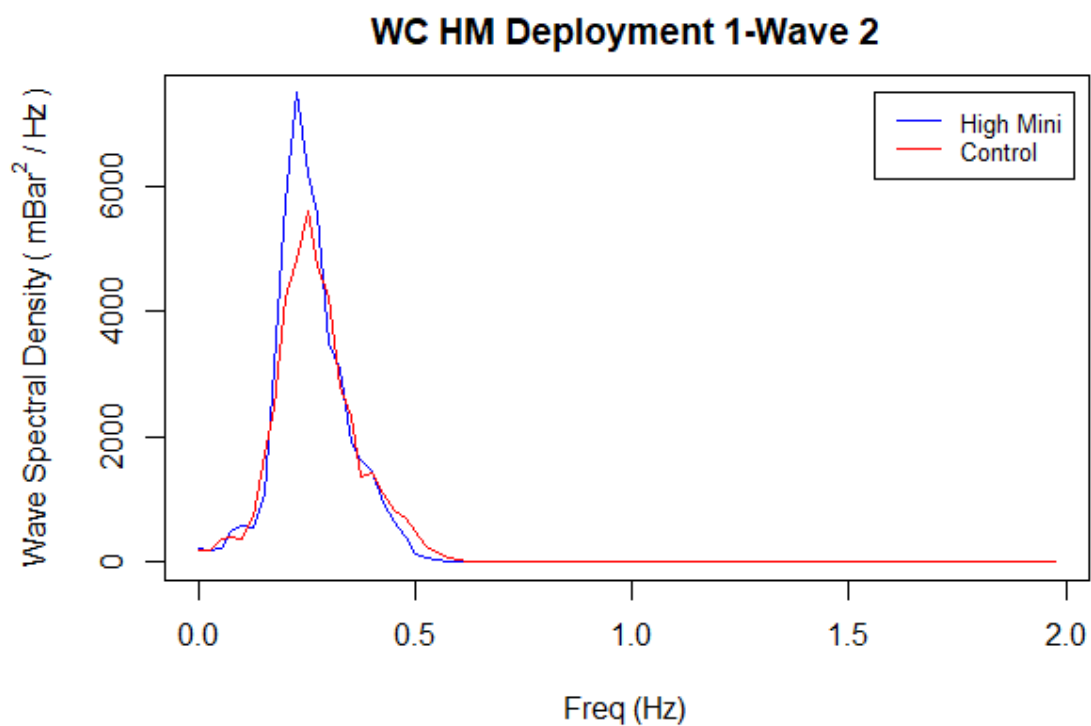


Figure C28. FFT of wave 2 at High Mini and High Mini control logger.

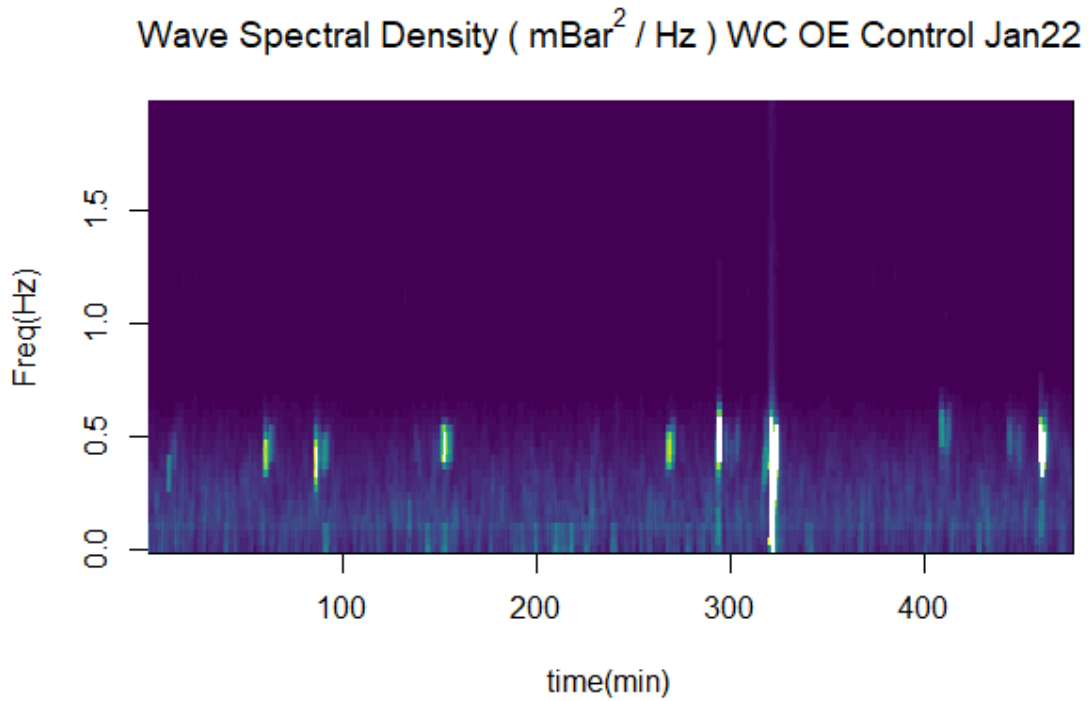


Figure C29. Wave spectral density over duration of full deployment at Westcliff Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

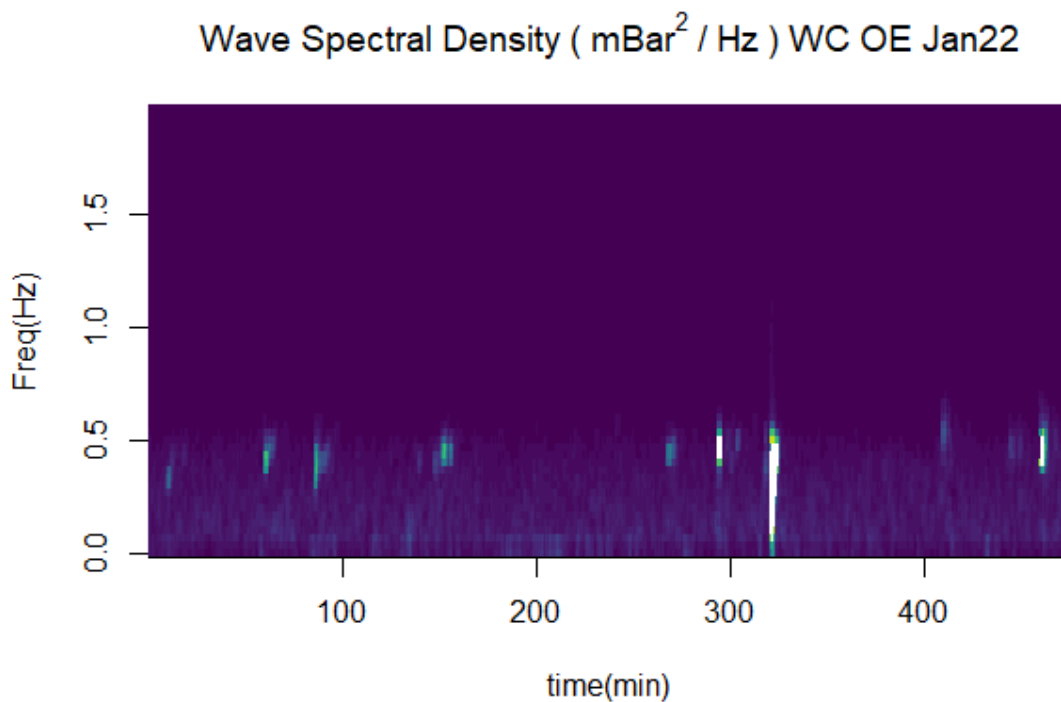


Figure C30. Wave spectral density over duration of full deployment at Westcliff Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

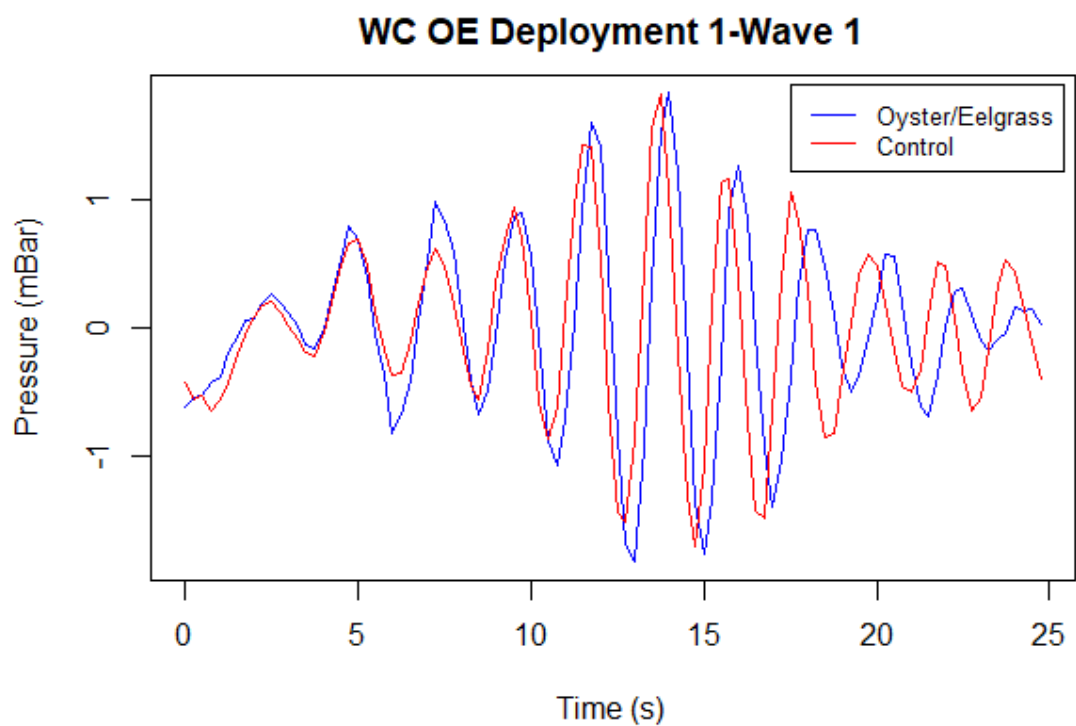


Figure C31. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

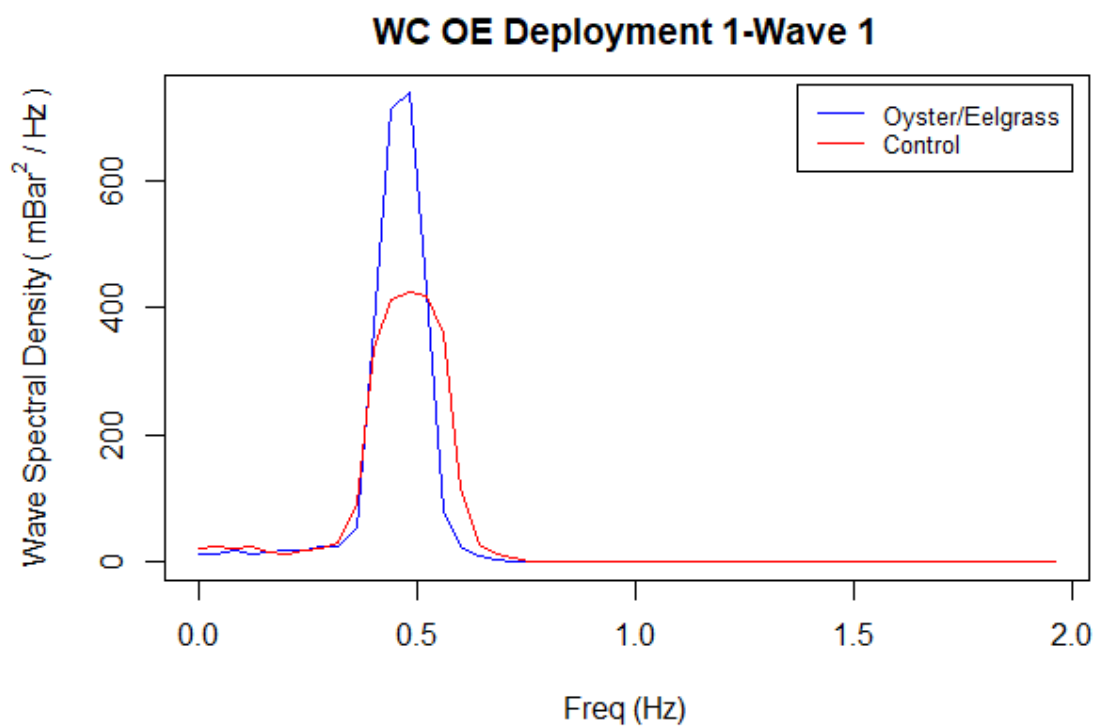


Figure C32. FFT of wave 1 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

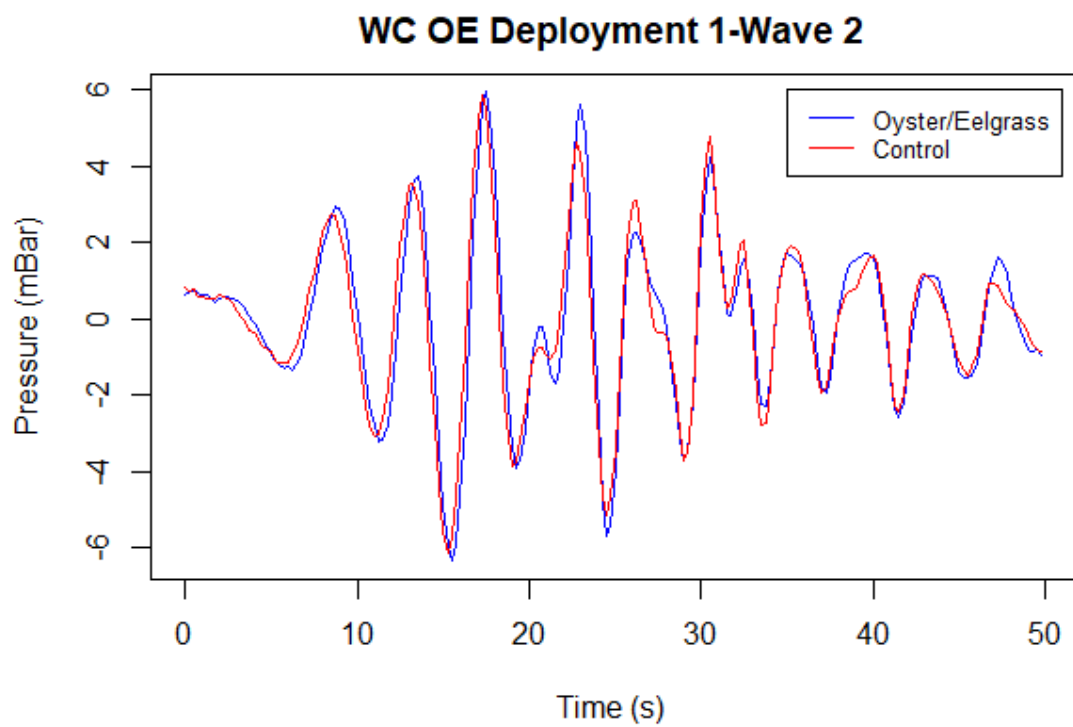


Figure C33. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

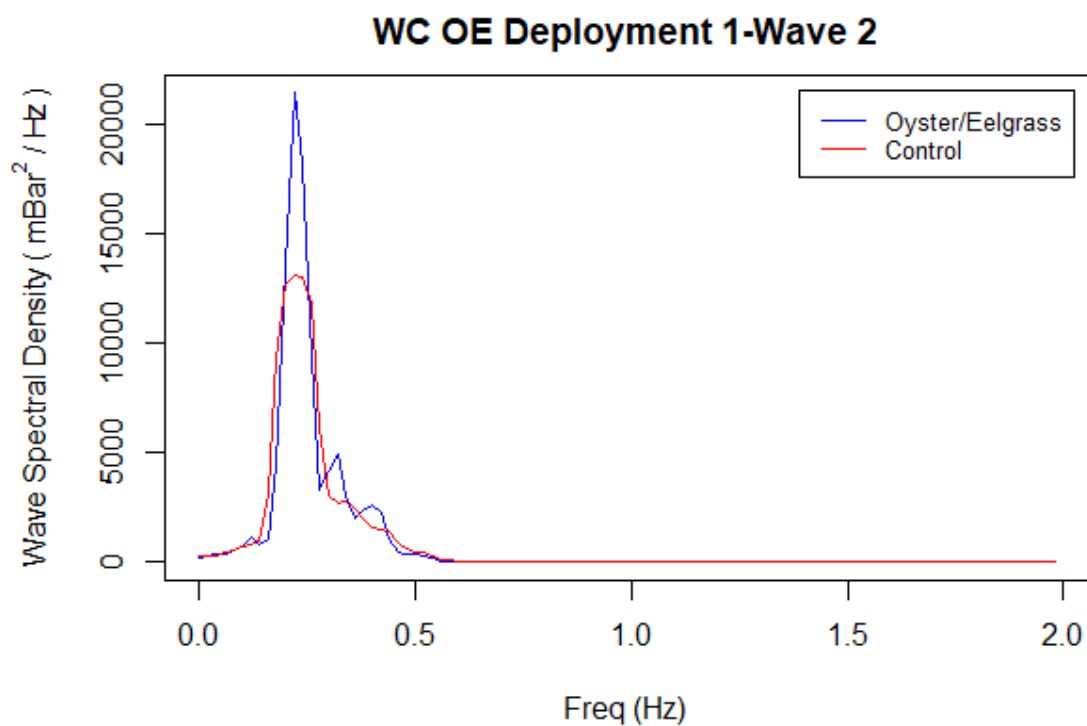


Figure C34. FFT of wave 2 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

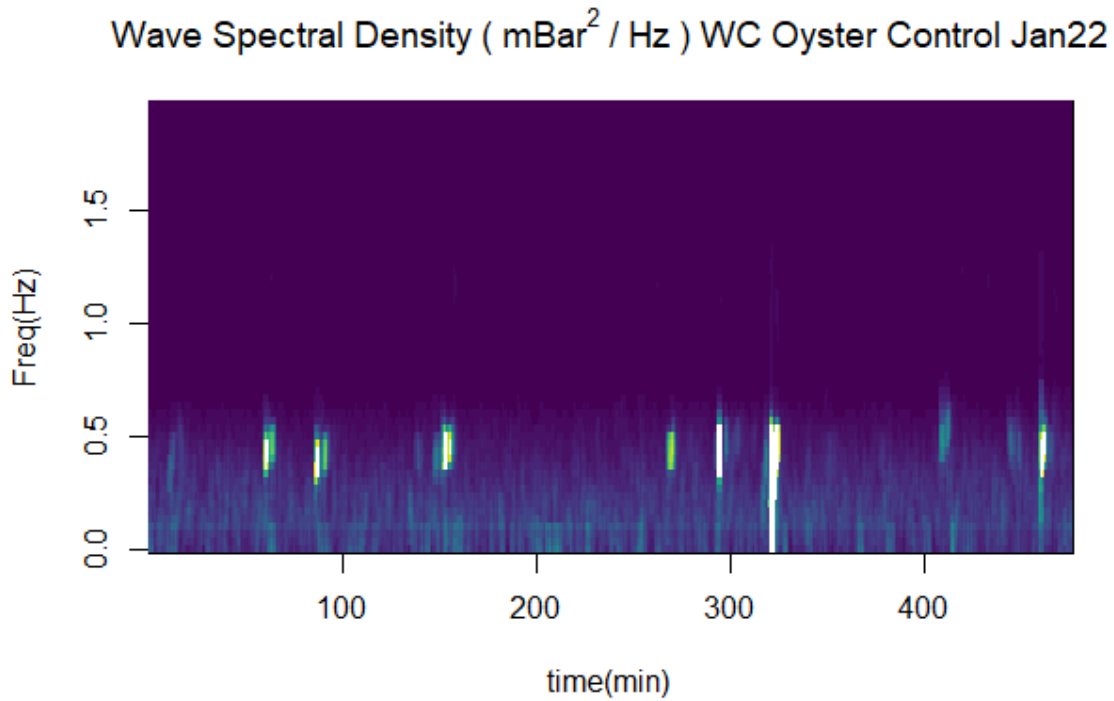


Figure C35. Wave spectral density over duration of full deployment at Westcliff Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

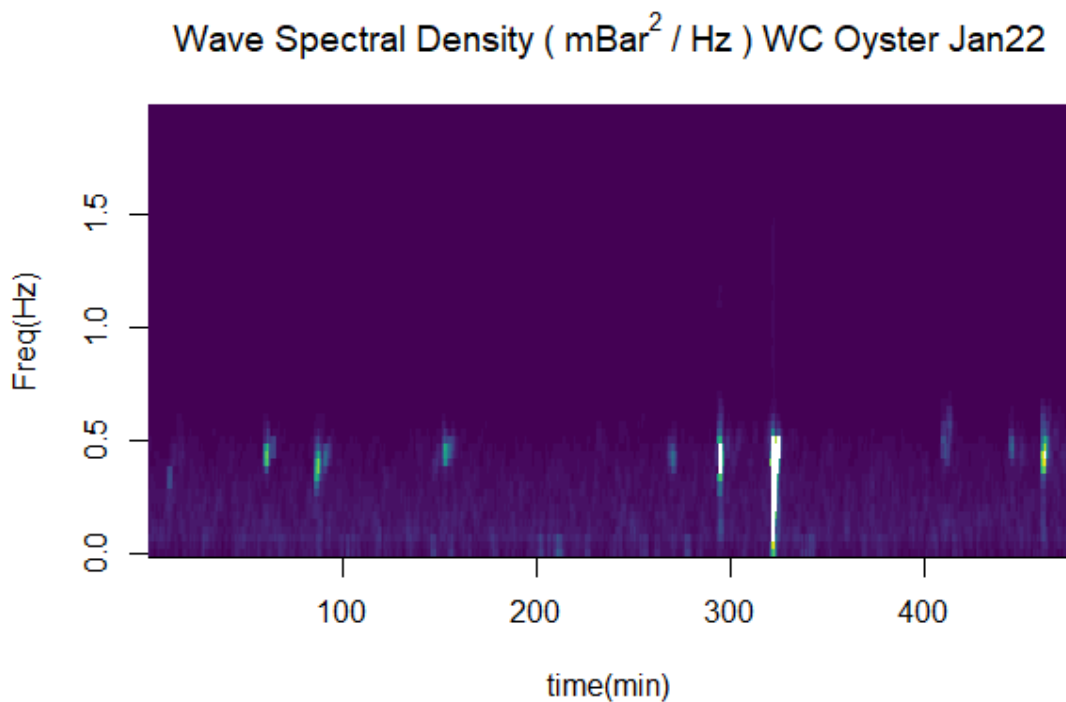


Figure C36. Wave spectral density over duration of full deployment at Westcliff Oyster logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

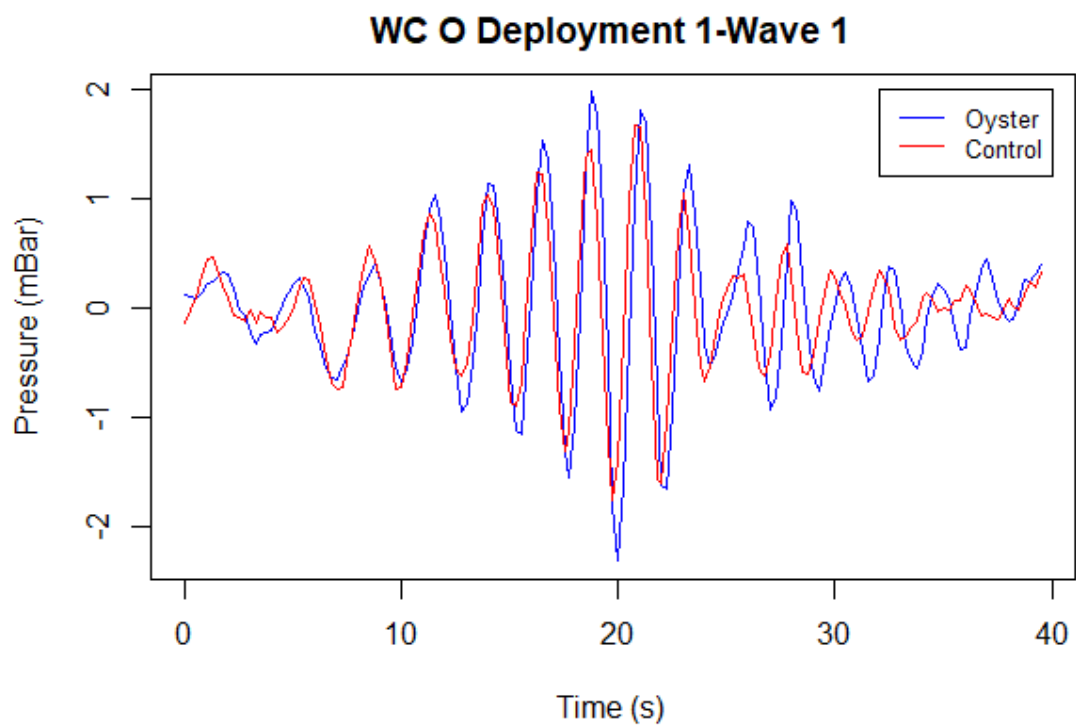


Figure C37. Progression of wave 1 over time at Oyster and Oyster control logger.

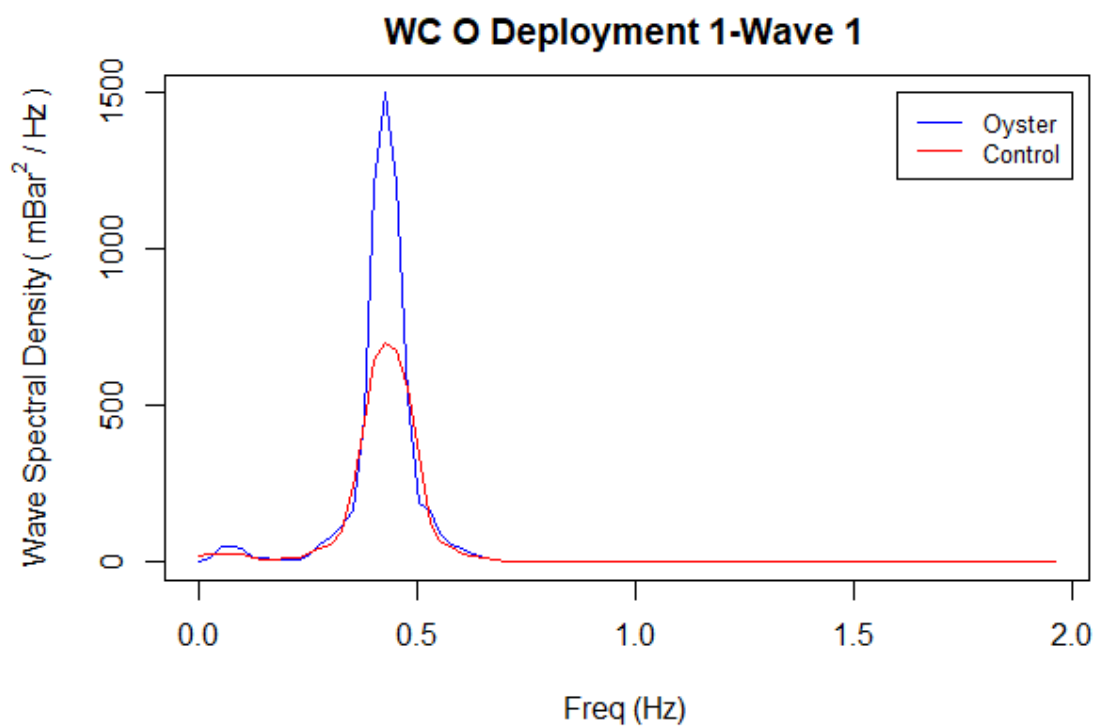


Figure C38. FFT of wave 1 at Oyster and Oyster control logger.

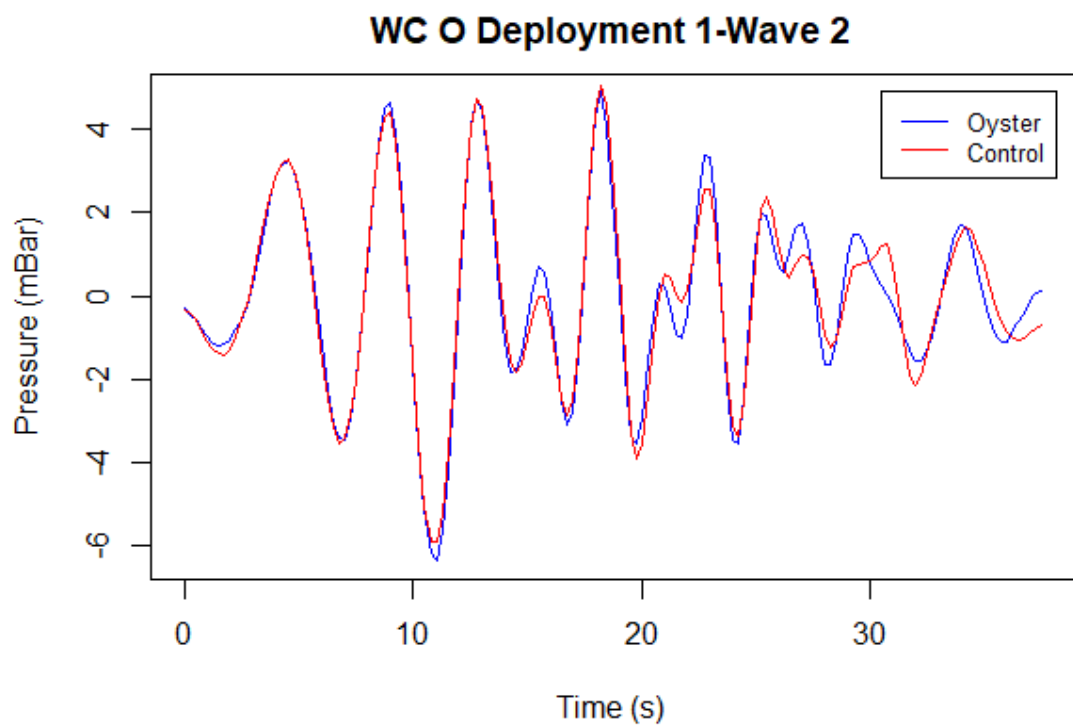


Figure C39. Progression of wave 2 over time at Oyster and Oyster control logger.

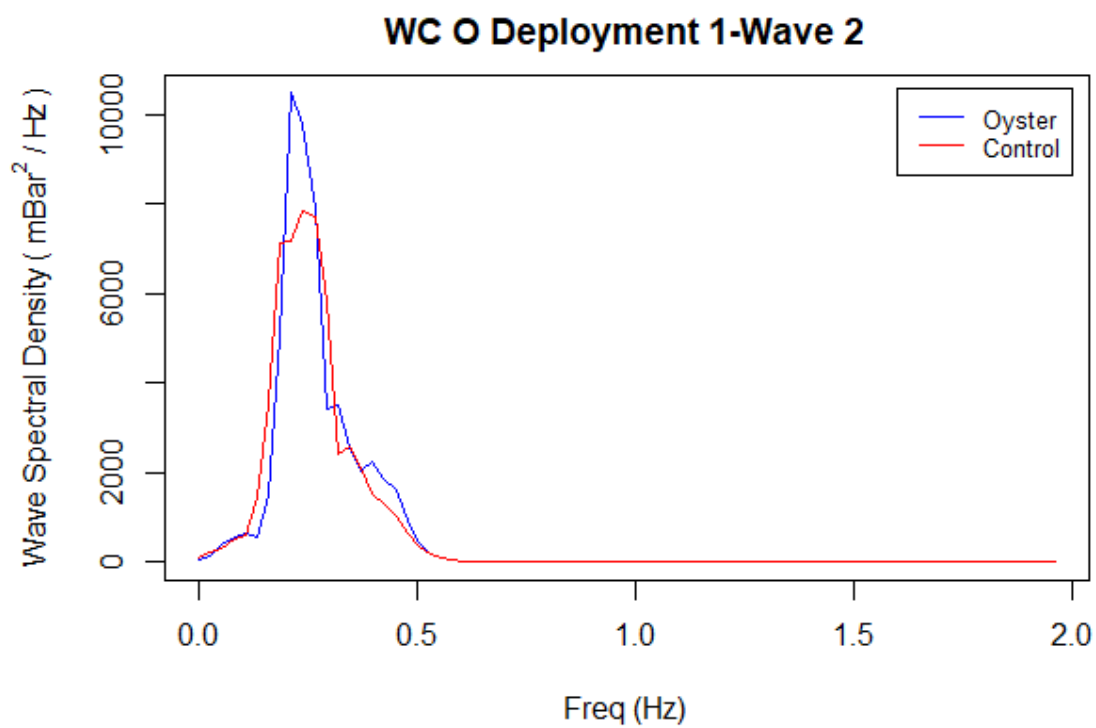


Figure C40. FFT of wave 2 at Oyster and Oyster control logger.

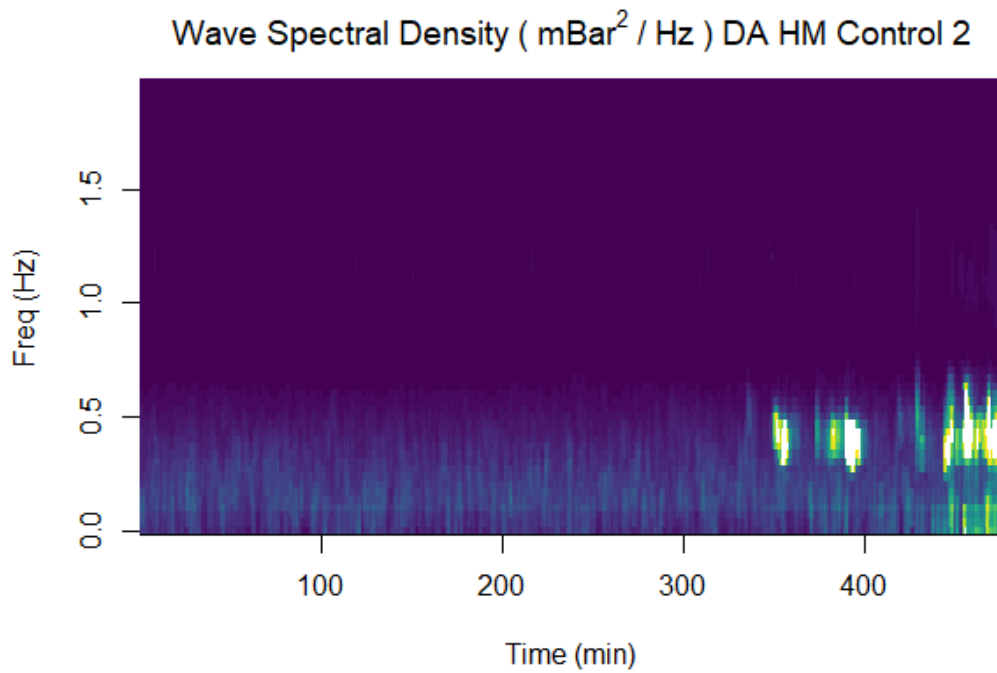
Deployment 1**Deanza: January 29, 2022**

Figure C41. Wave spectral density over duration of full deployment at Deanza High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

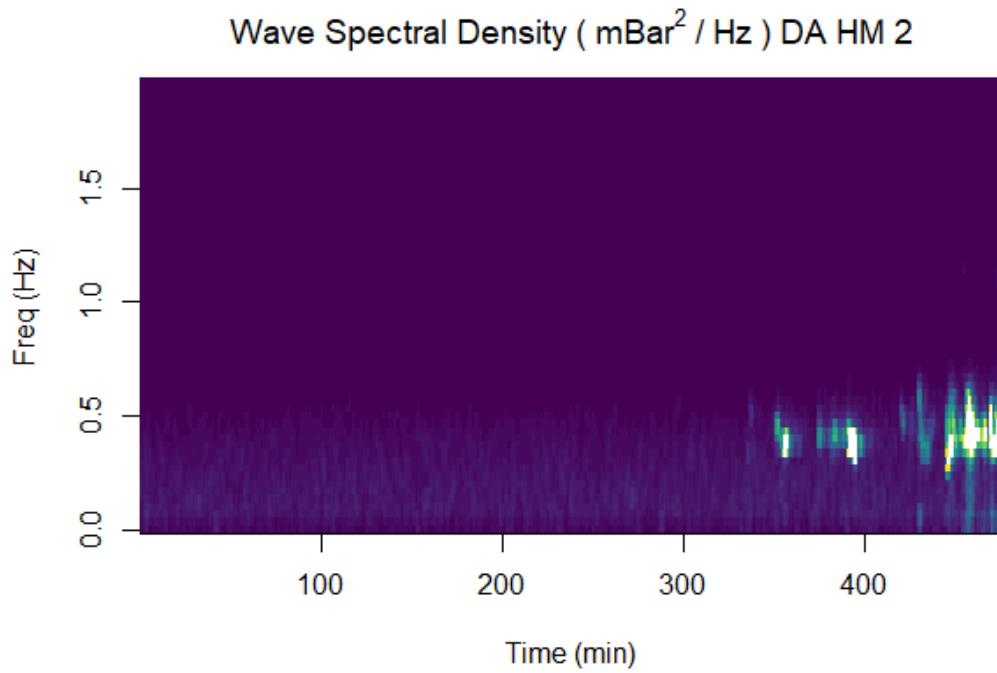


Figure C42. Wave spectral density over duration of full deployment at Deanza High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

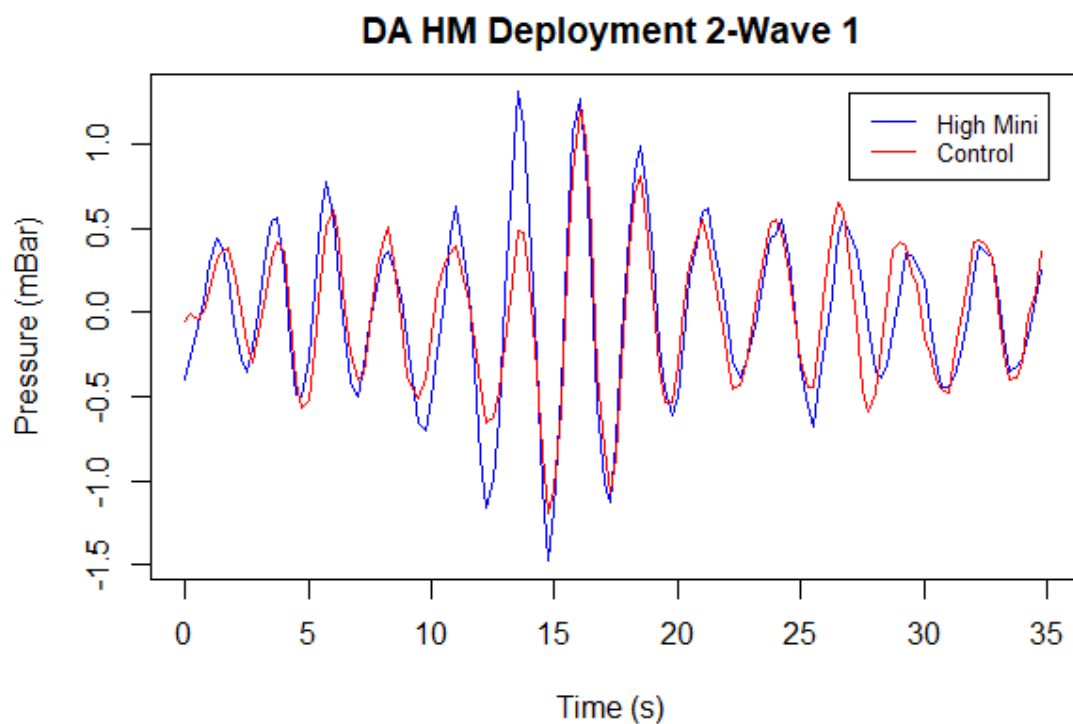


Figure C43. Progression of wave 1 over time at High Mini and High Mini control logger.

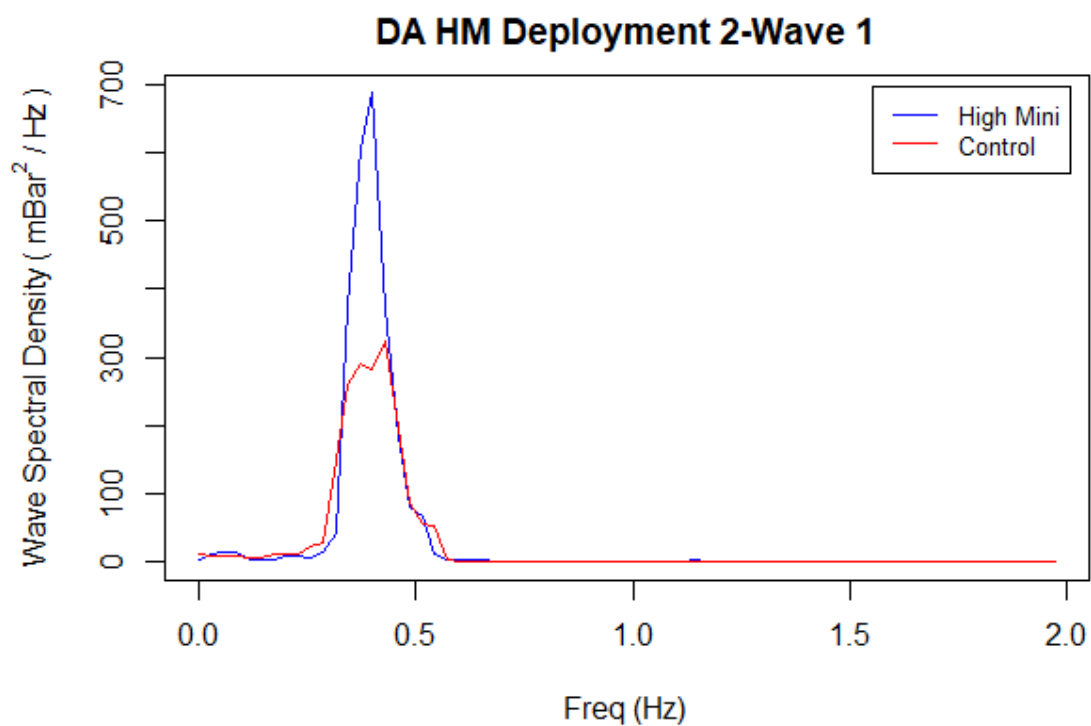


Figure C44. FFT of wave 1 at High Mini and High Mini control logger.



Figure C45. Progression of wave 2 over time at High Mini and High Mini control logger.

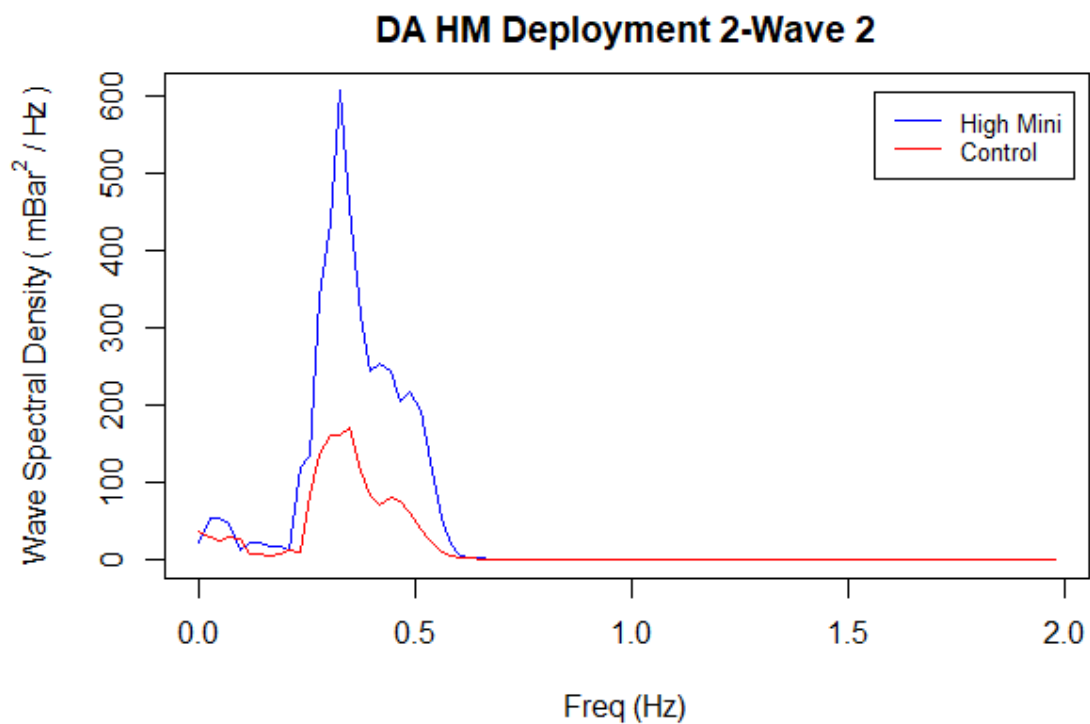


Figure C46. FFT of wave 2 at High Mini and High Mini control logger.

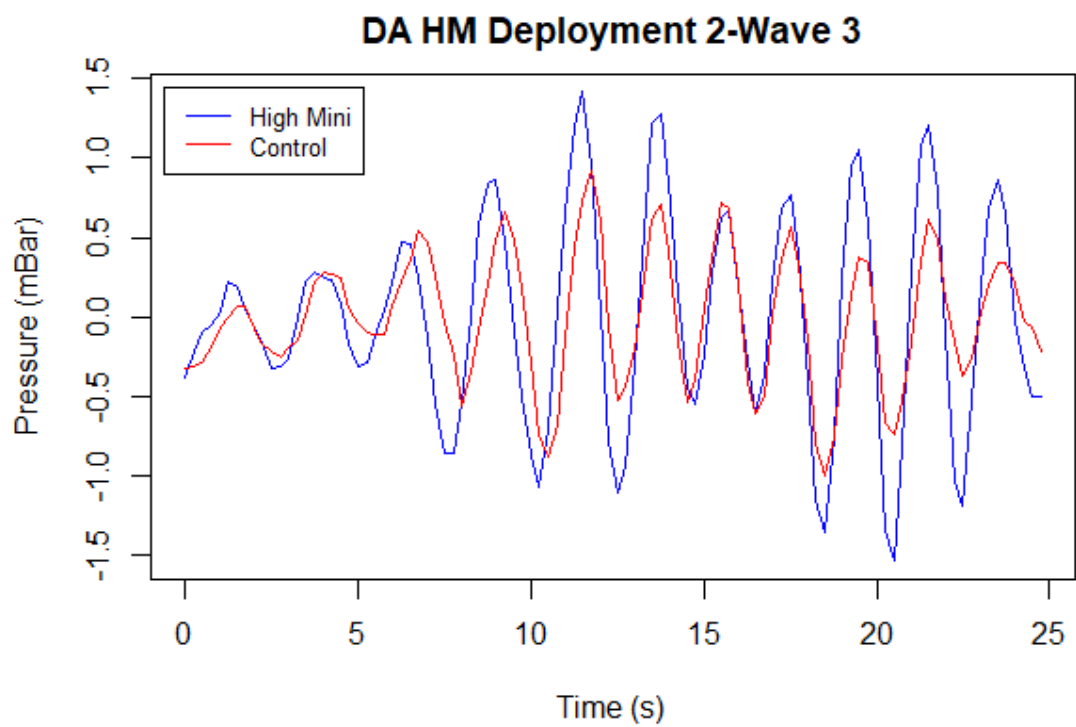


Figure C47. Progression of wave 3 over time at High Mini and High Mini control logger.

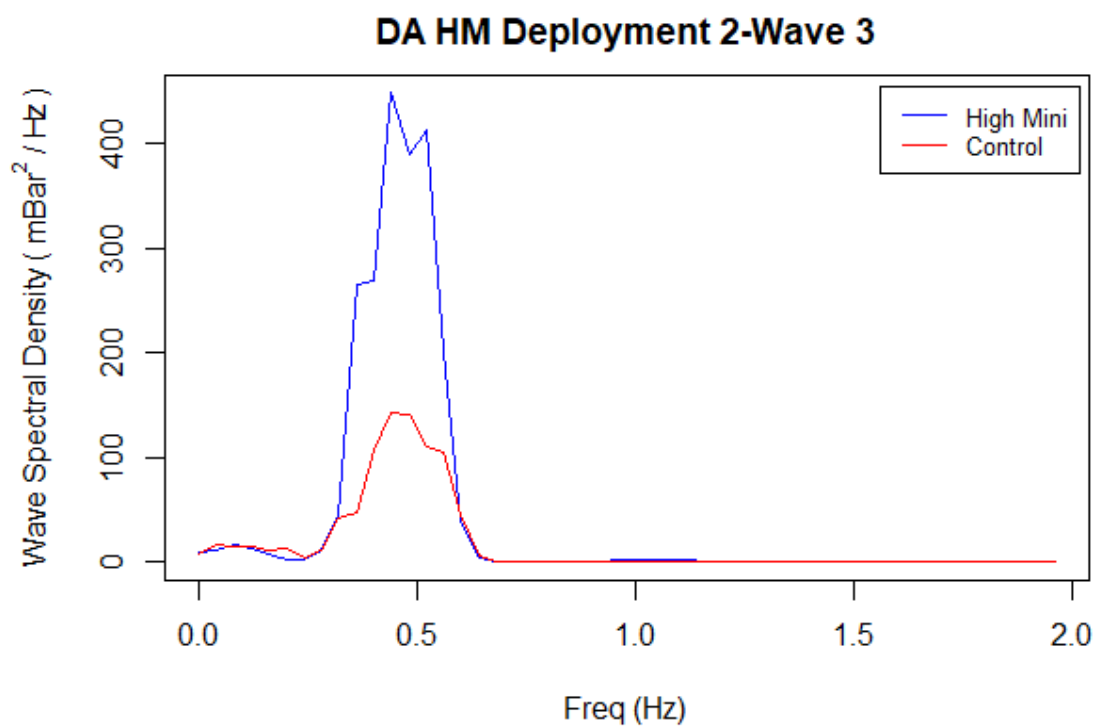


Figure C48. FFT of wave 3 at High Mini and High Mini control logger.

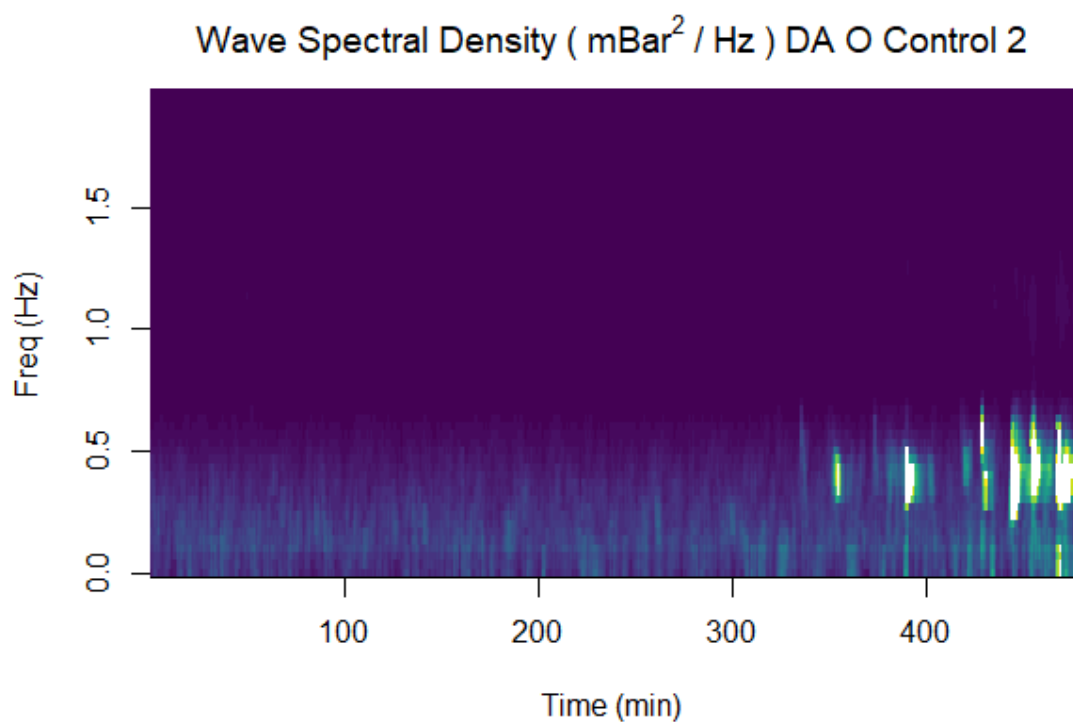


Figure C49. Wave spectral density over duration of full deployment at Deanza Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

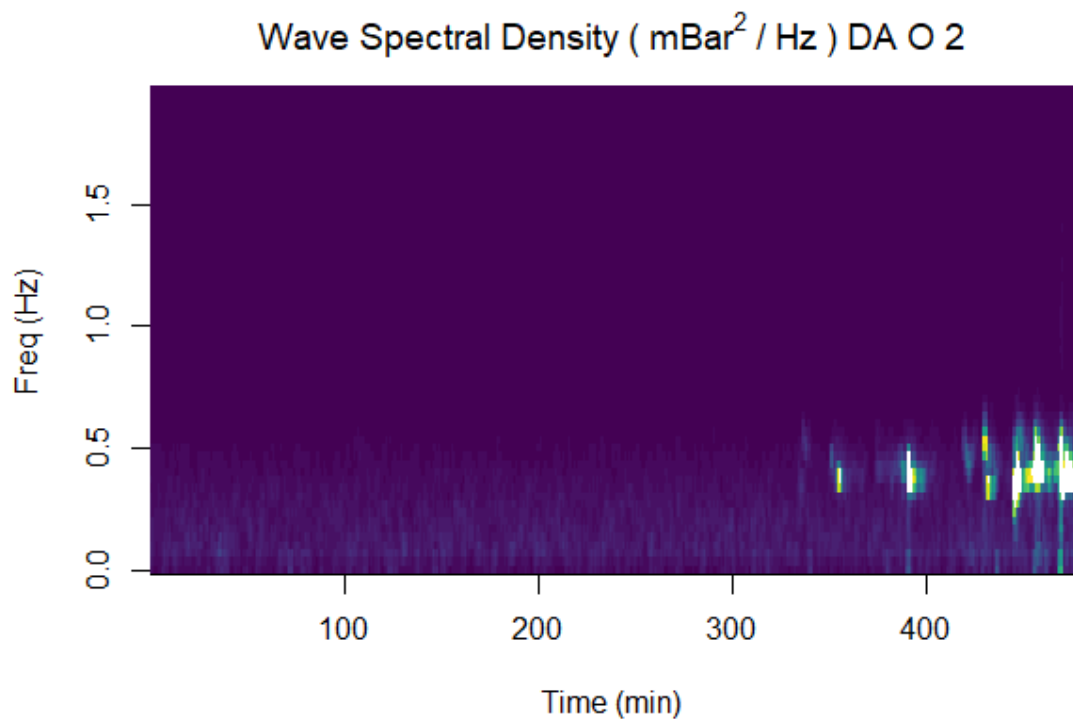


Figure C50. Wave spectral density over duration of full deployment at Deanza Oyster logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

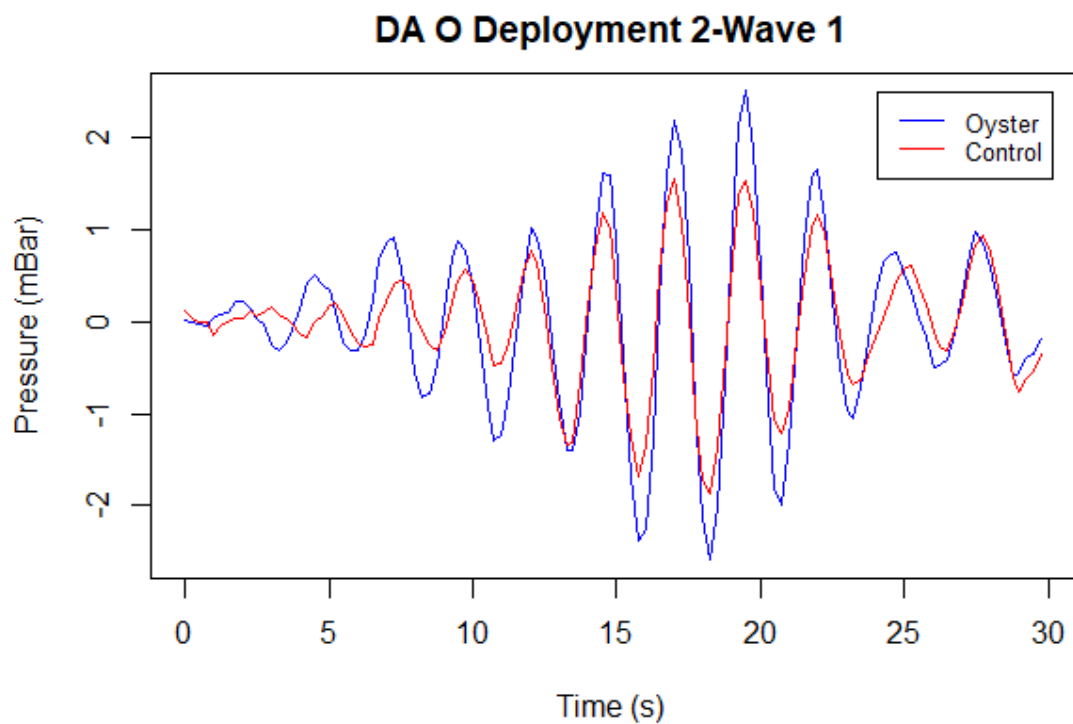


Figure C51. Progression of wave 1 over time at Oyster and Oyster control logger.

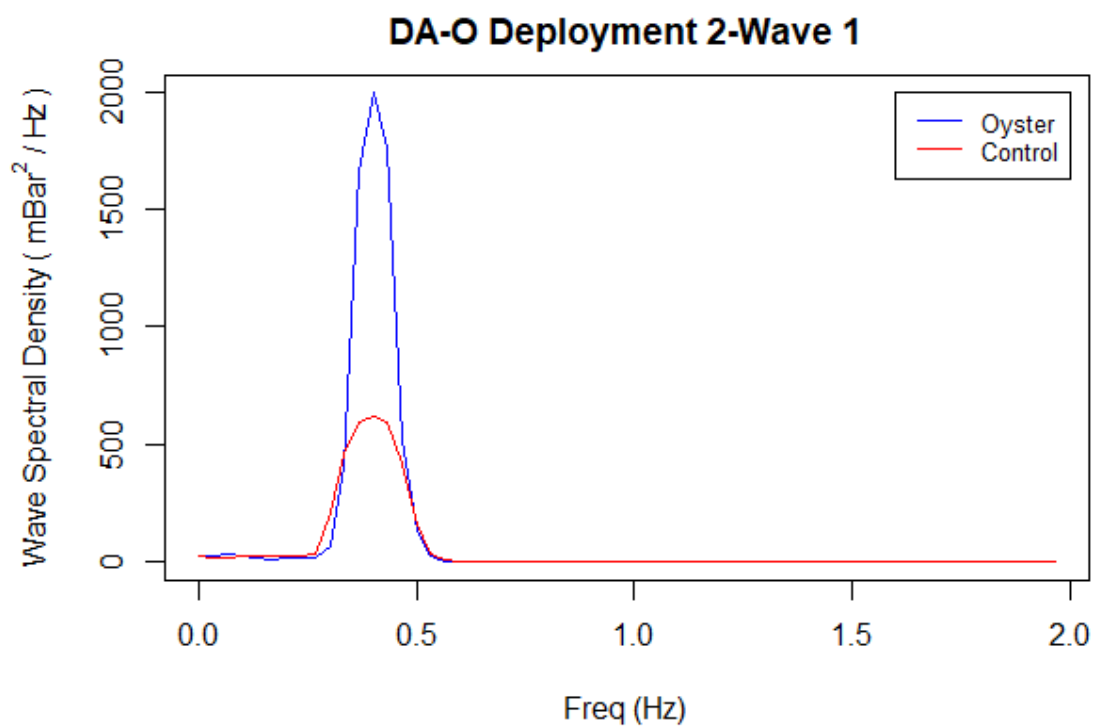


Figure C52. FFT of wave 1 at Oyster and Oyster control logger.

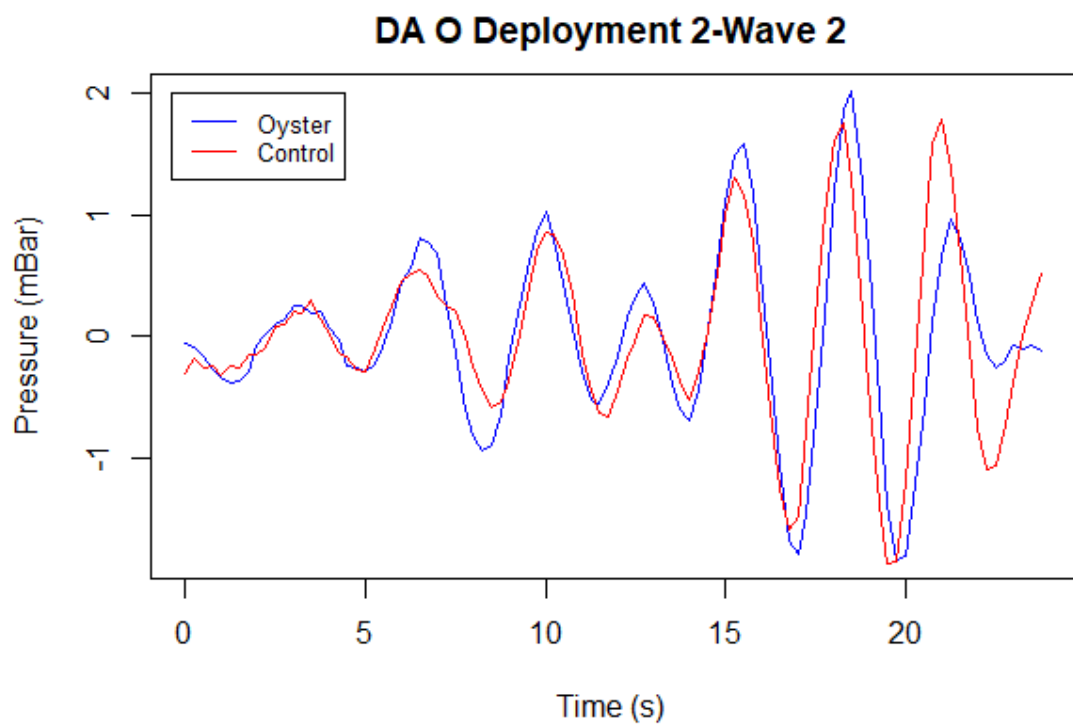


Figure C53. Progression of wave 2 over time at Oyster and Oyster control logger.

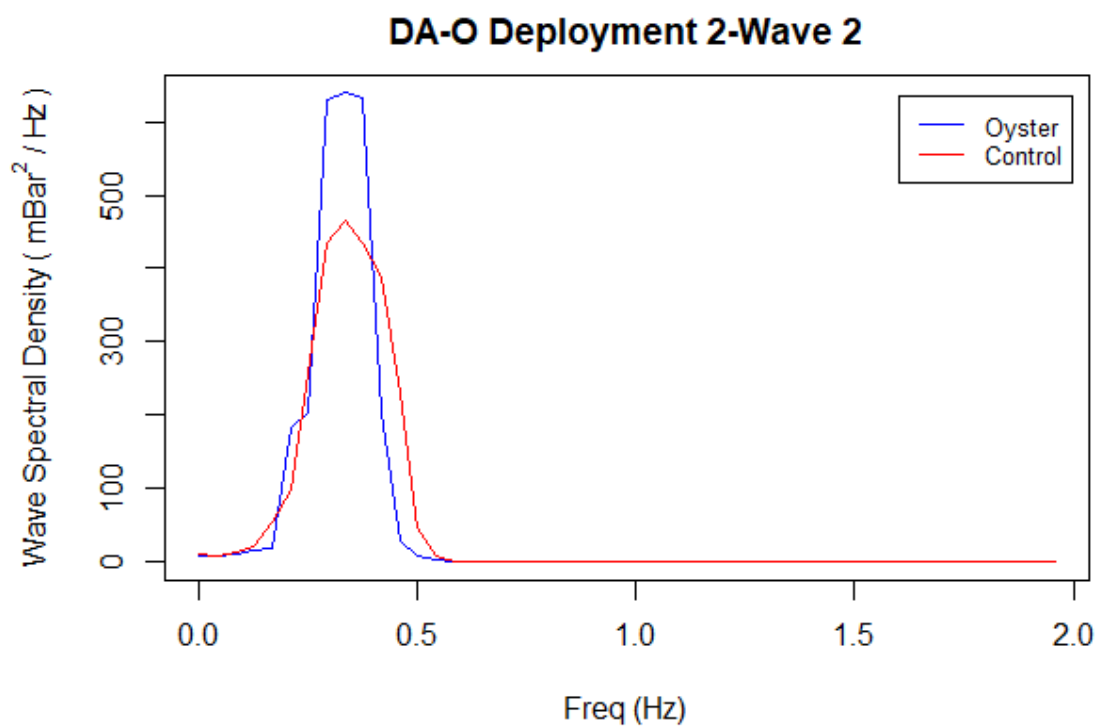


Figure C54. FFT of wave 2 at Oyster and Oyster control logger.

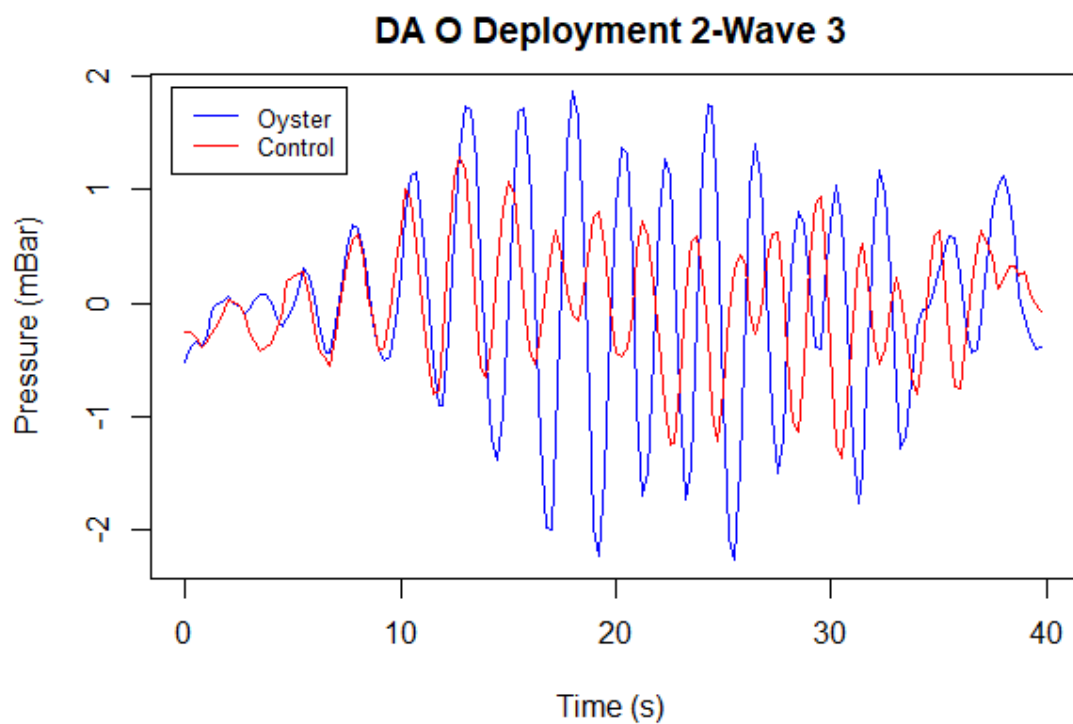


Figure C55. Progression of wave 3 over time at Oyster and Oyster control logger.

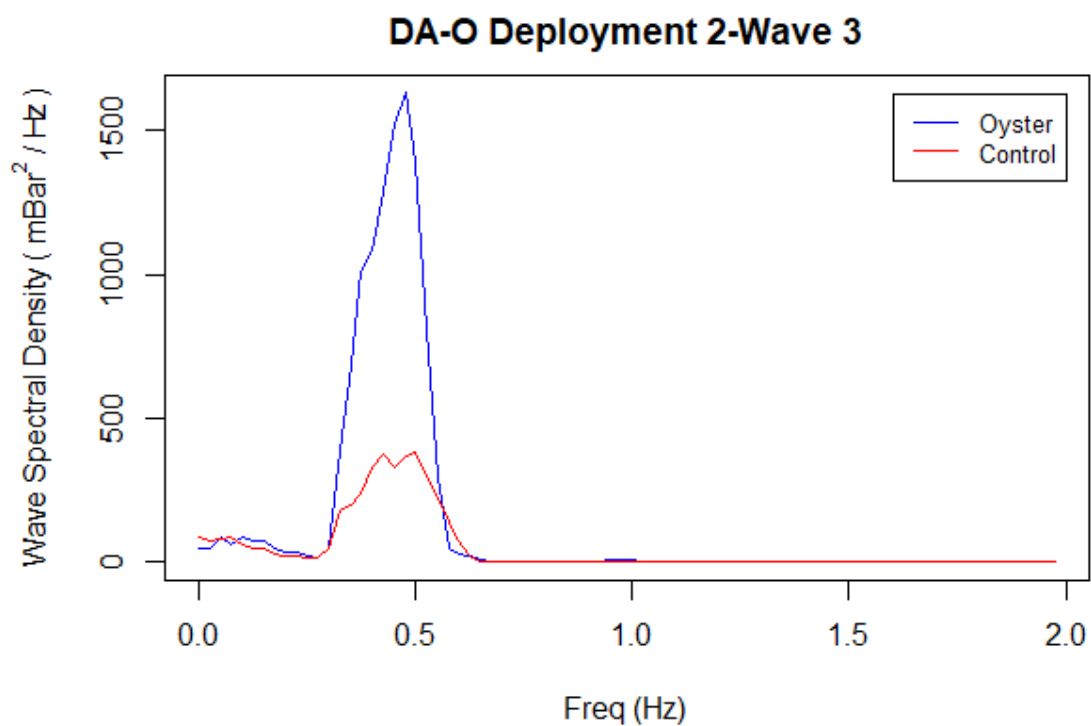


Figure C56. FFT of wave 3 at Oyster and Oyster control logger.

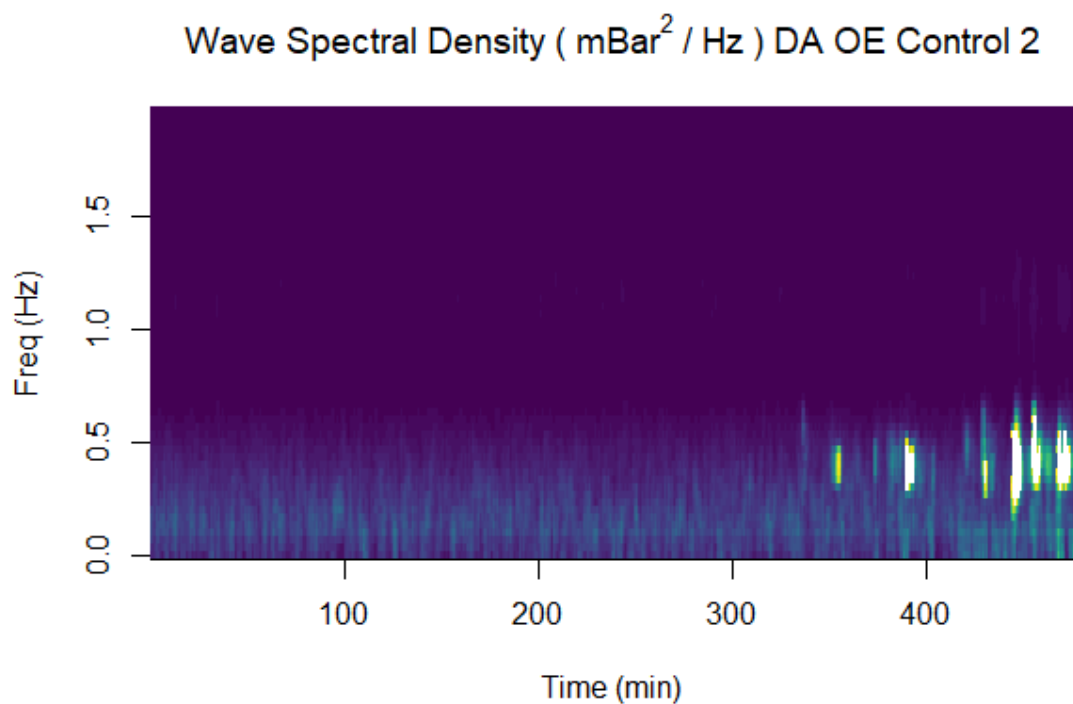


Figure C57. Wave spectral density over duration of full deployment at Deanza Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

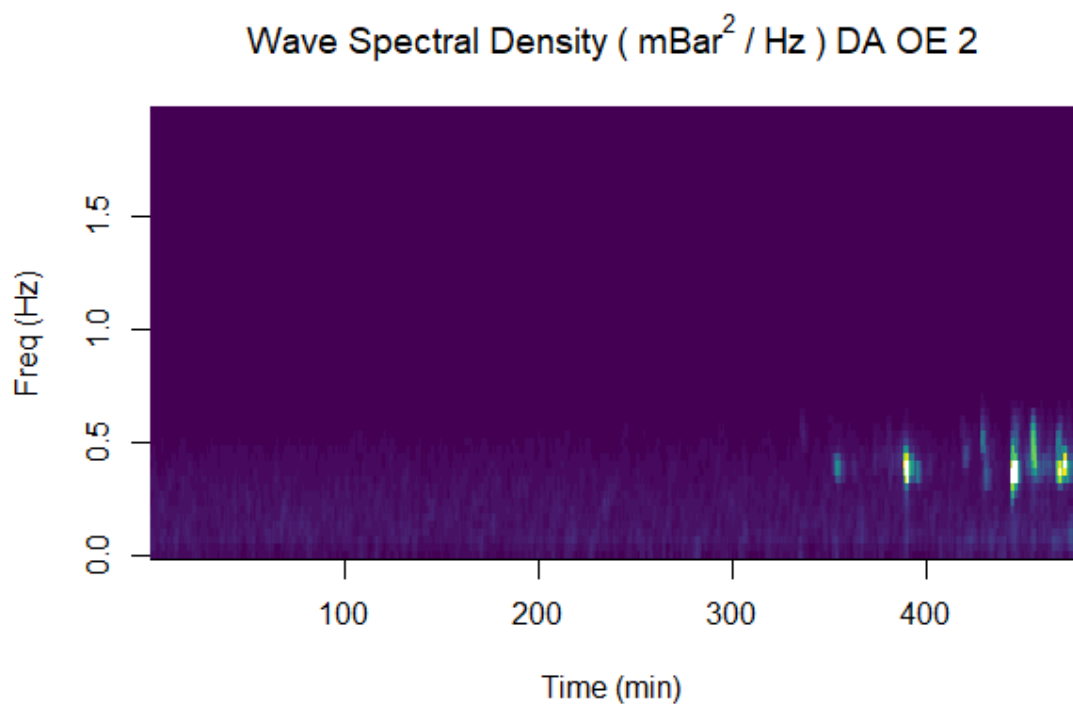


Figure C58. Wave spectral density over duration of full deployment at Deanza Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

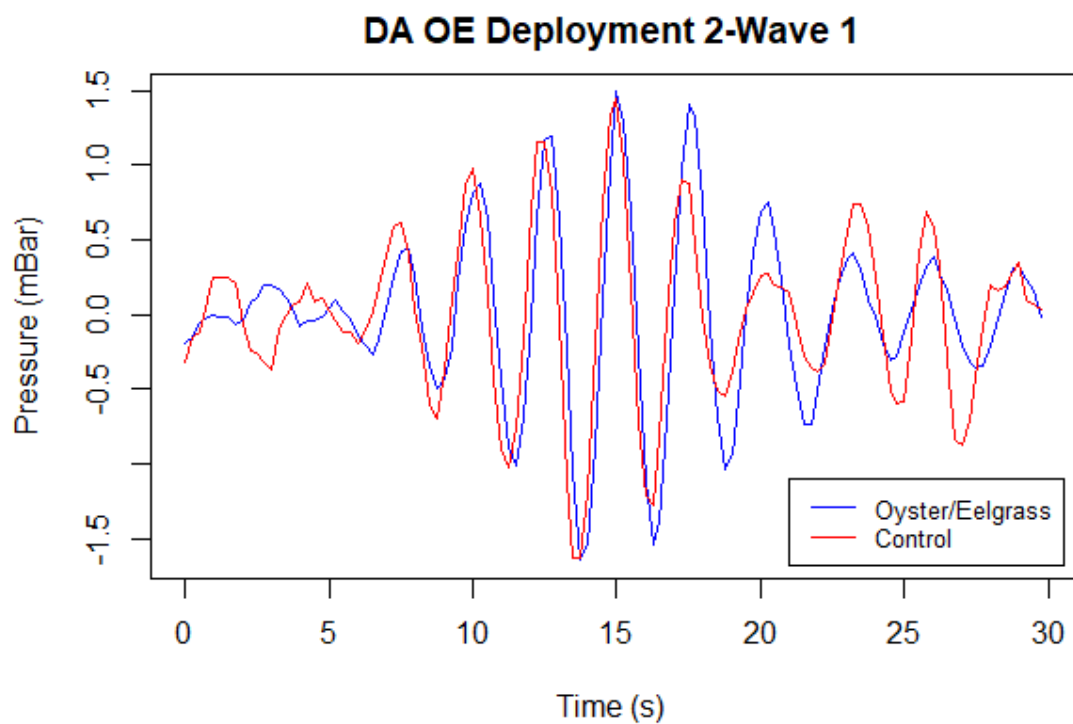


Figure C59. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

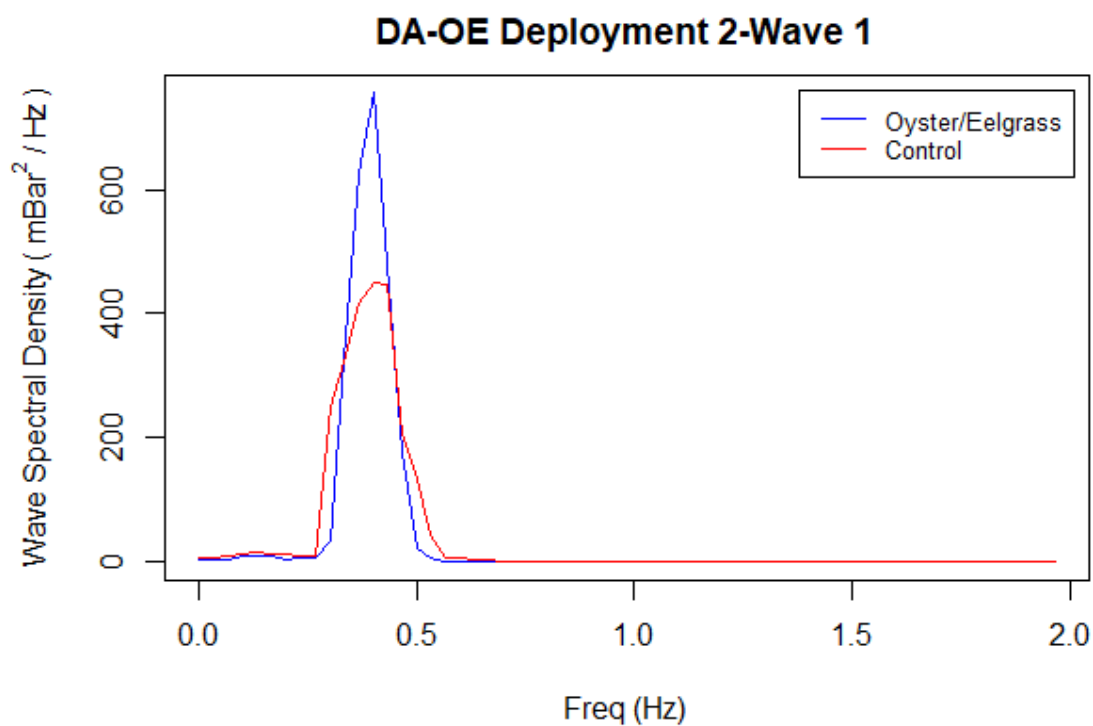


Figure C60. FFT of wave 1 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

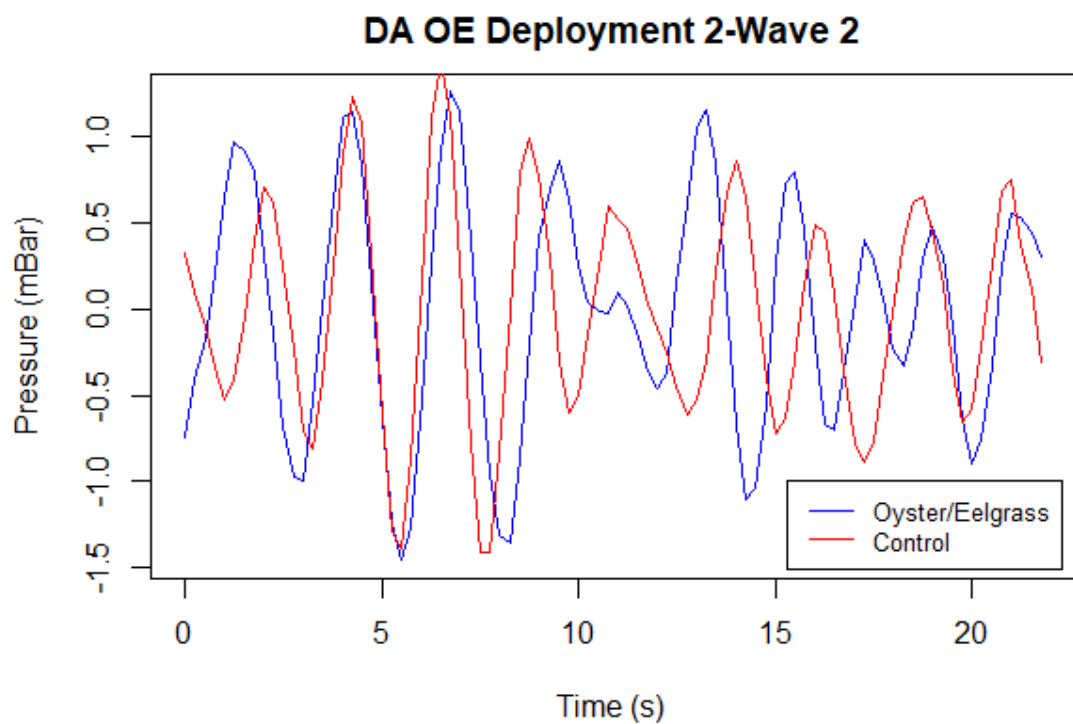


Figure C61. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

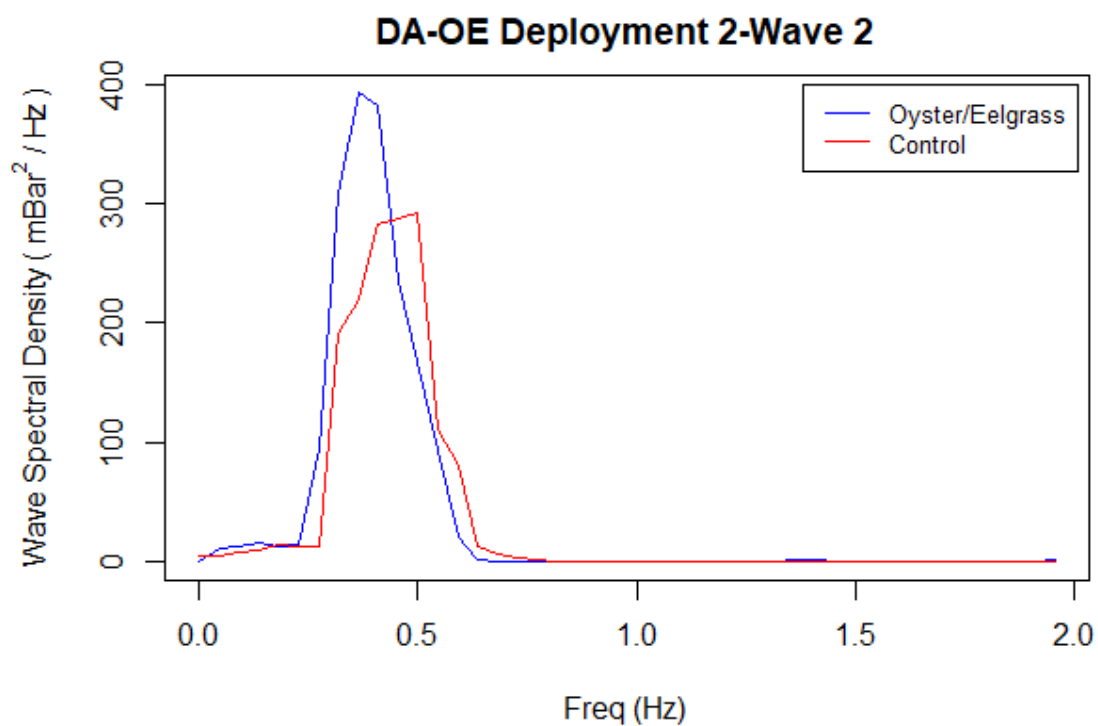


Figure C62. FFT of wave 2 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

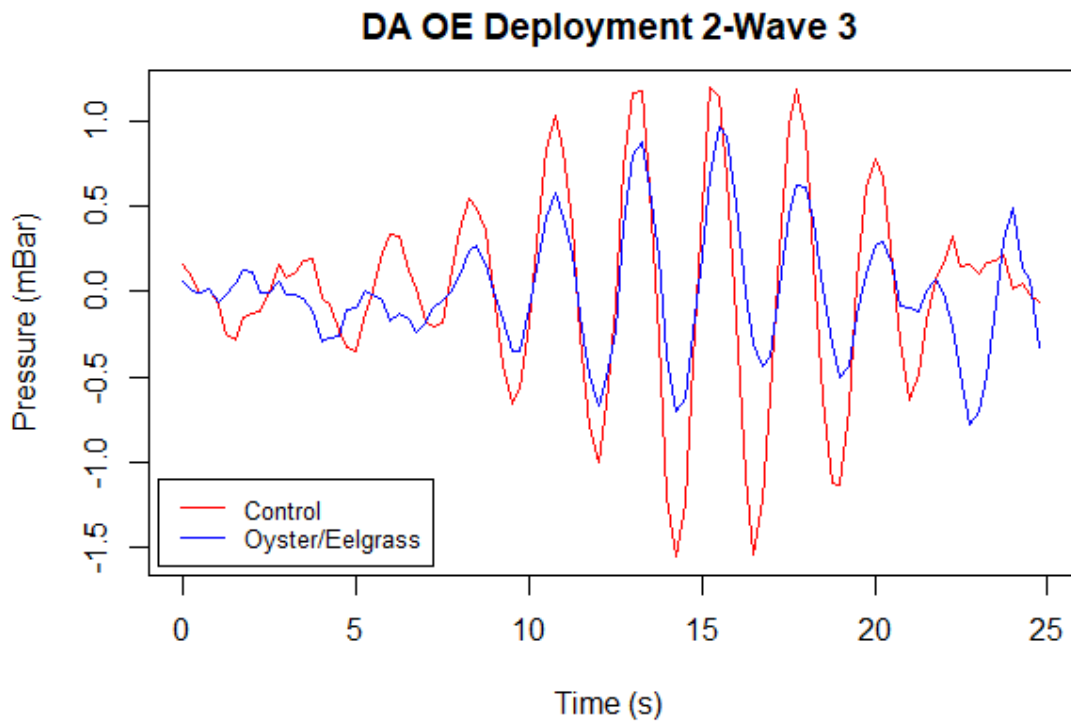


Figure C63. Progression of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

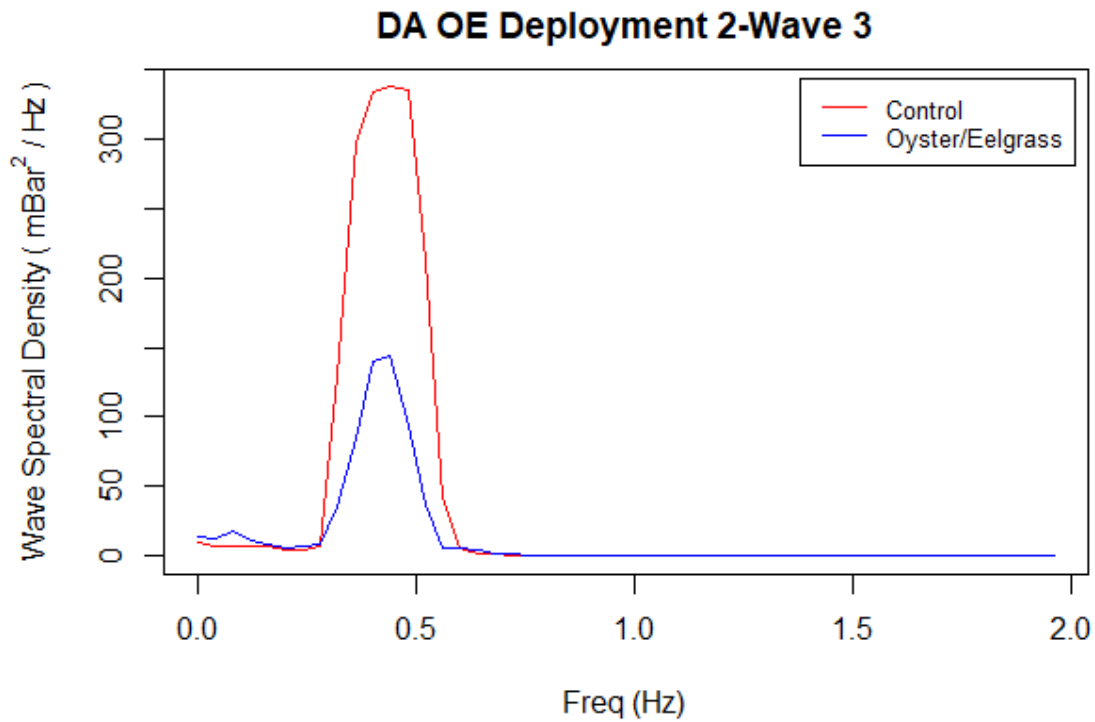


Figure C64. FFT of wave 3 at Oyster/Eelgrass and Oyster/Eelgrass control logger.

PCH: January 30, 2022

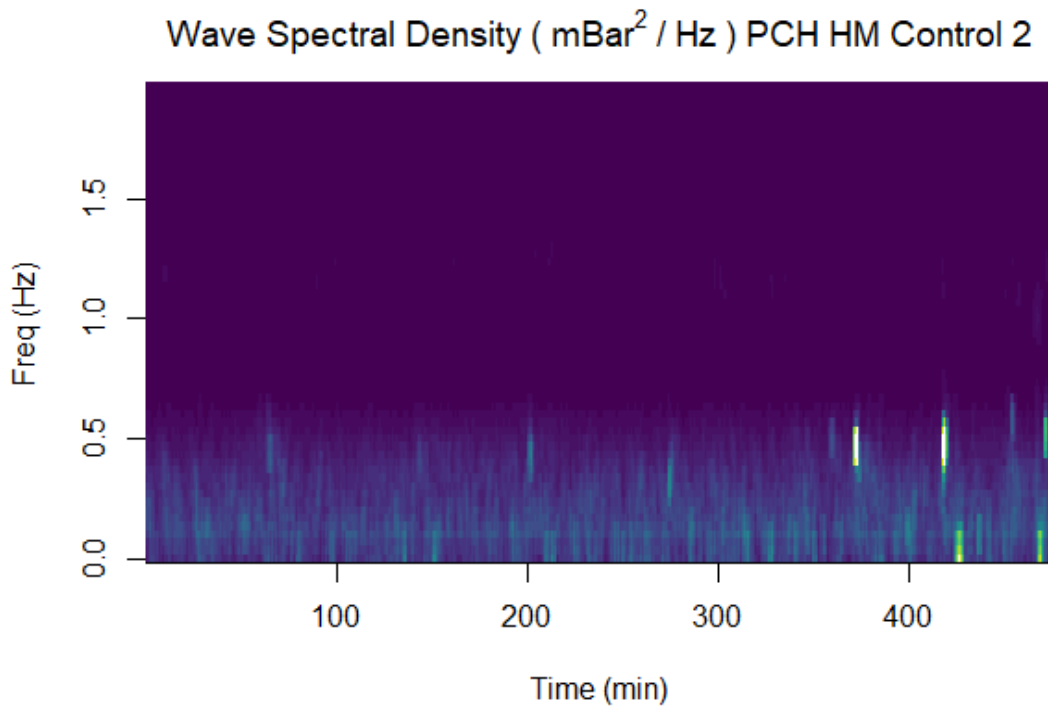


Figure C65. Wave spectral density over duration of full deployment at PCH High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

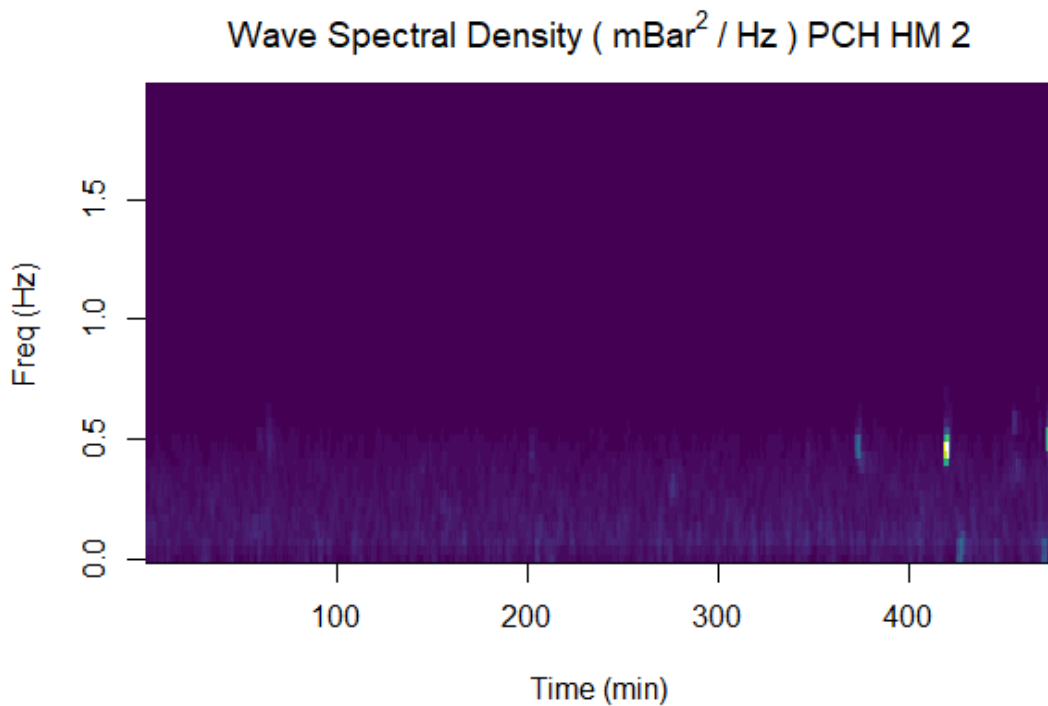


Figure C66. Wave spectral density over duration of full deployment at PCH High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

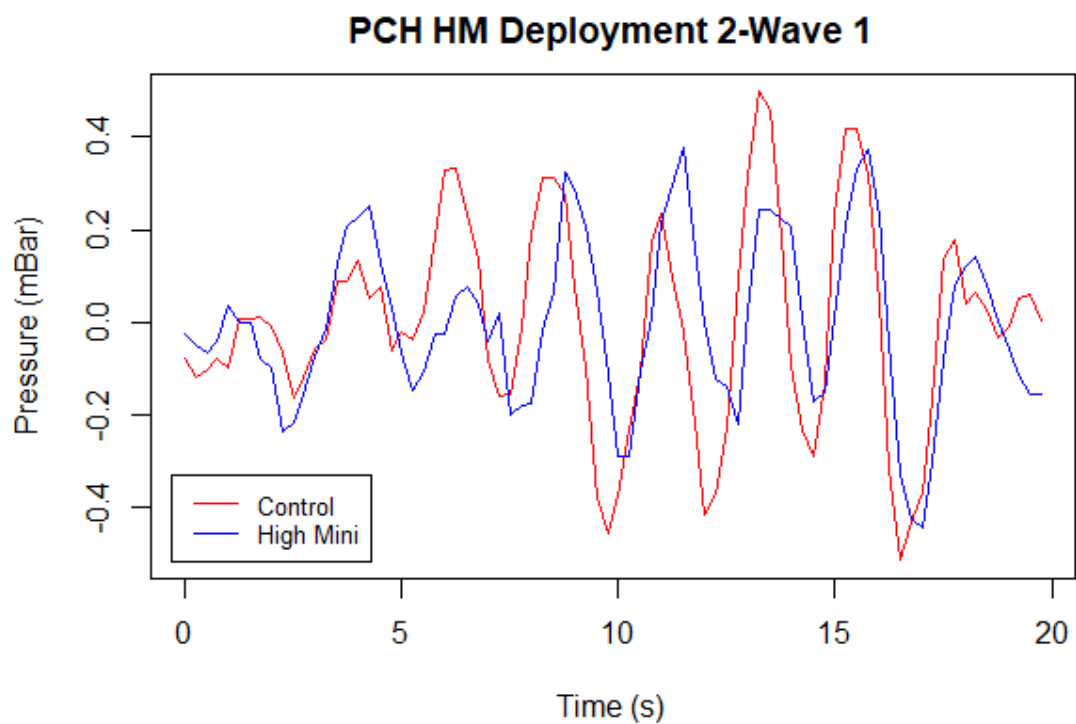


Figure C67. Progression of wave 1 over time at High Mini and High Mini control logger.

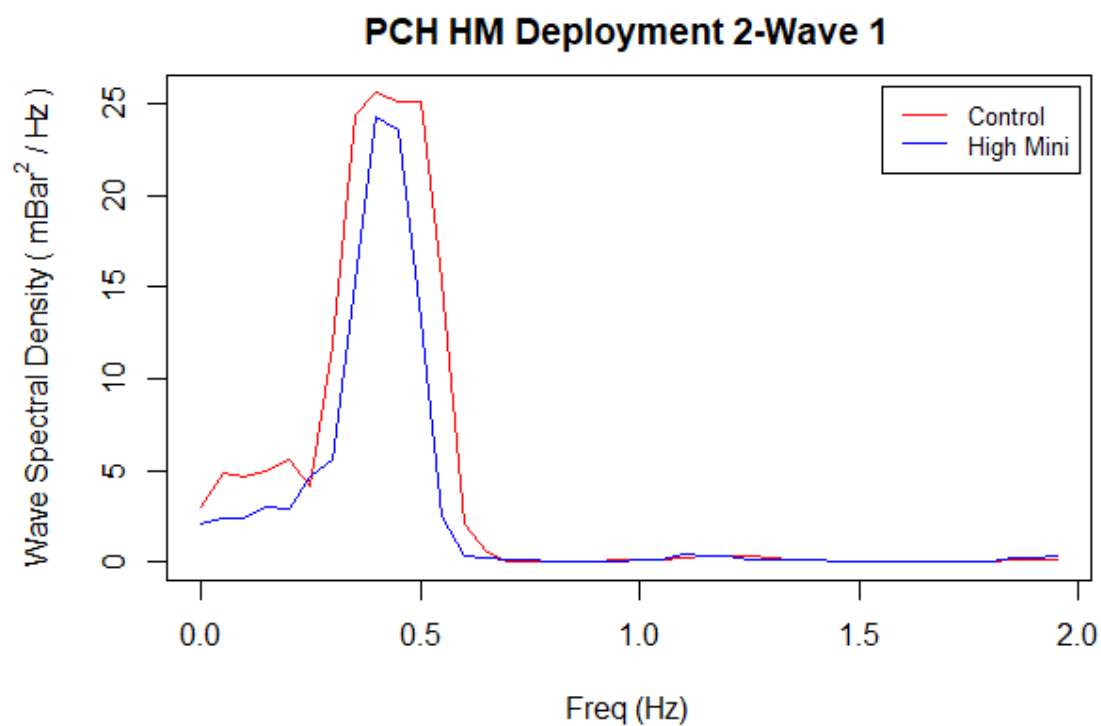


Figure C68. FFT of wave 1 over time at High Mini and High Mini control logger.

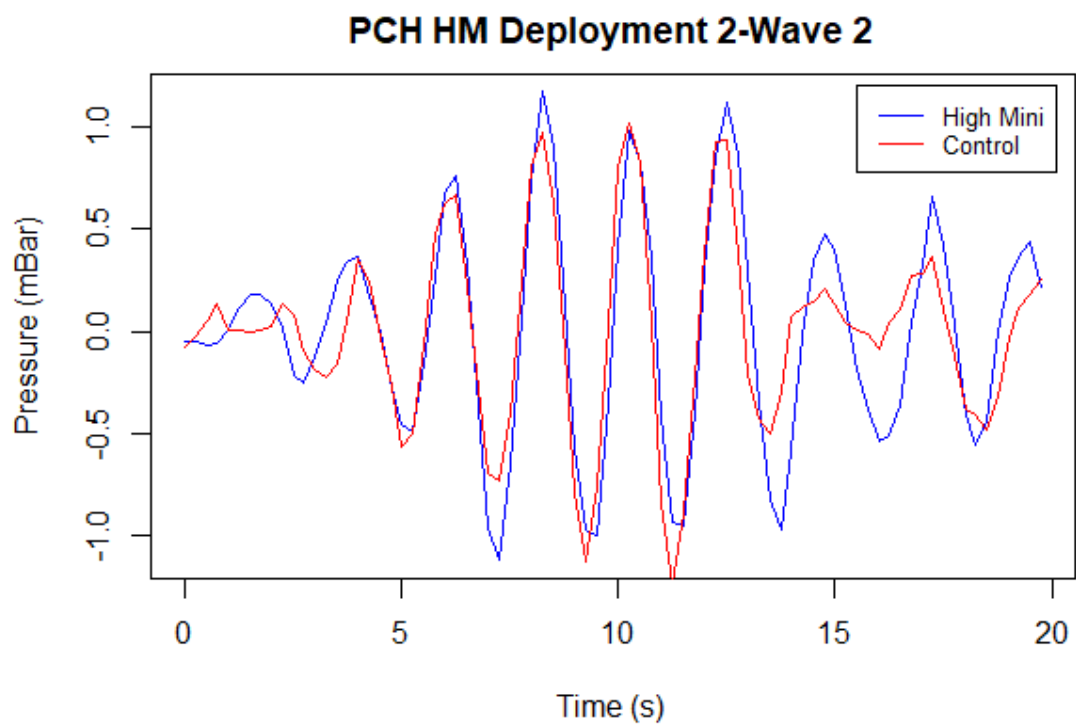


Figure C69. Progression of wave 2 over time at High Mini and High Mini control logger.

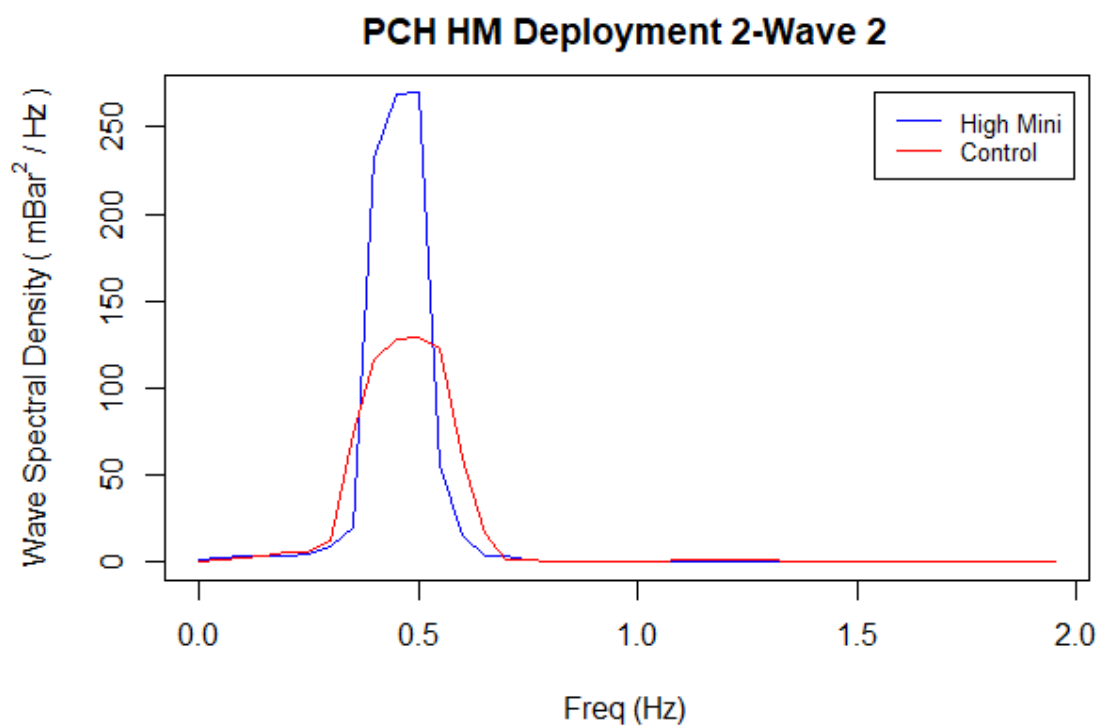


Figure C70. FFT of wave 2 over time at High Mini and High Mini control logger.

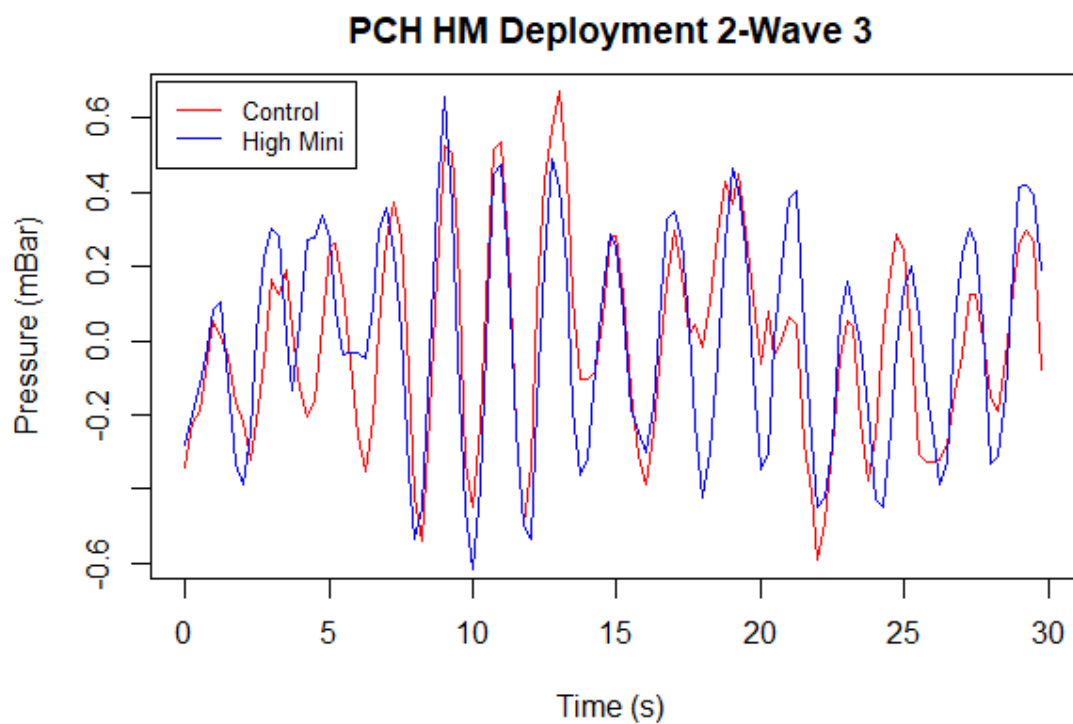


Figure C71. Progression of wave 3 over time at High Mini and High Mini control logger.

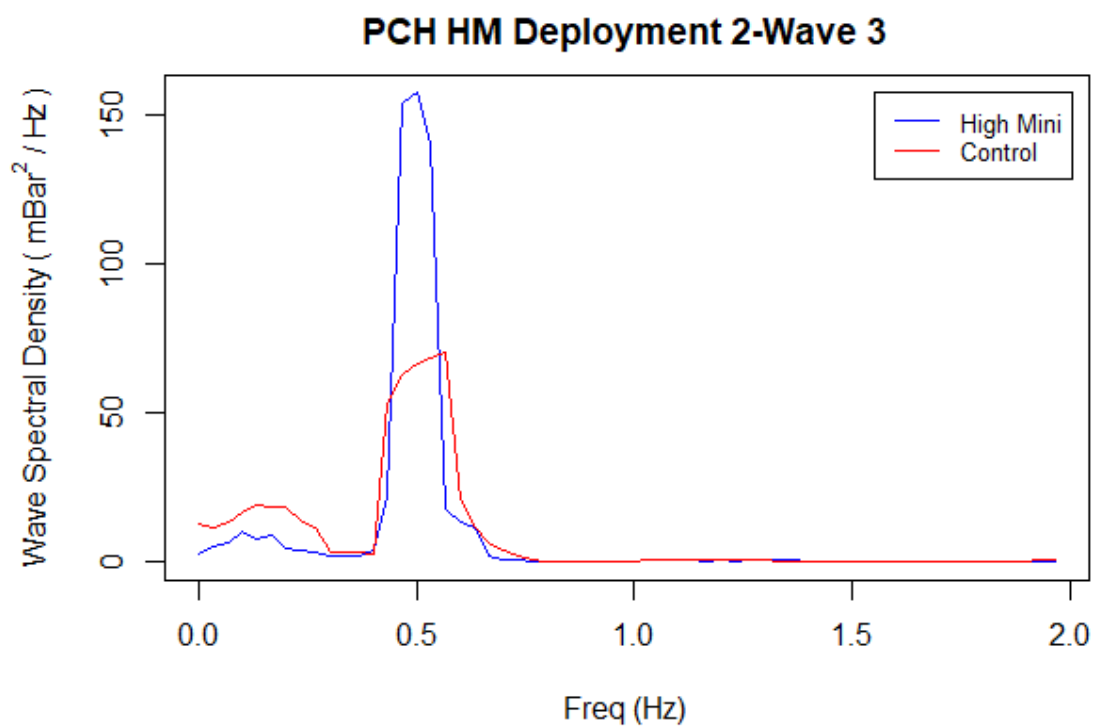


Figure C72. FFT of wave 3 over time at High Mini and High Mini control logger.

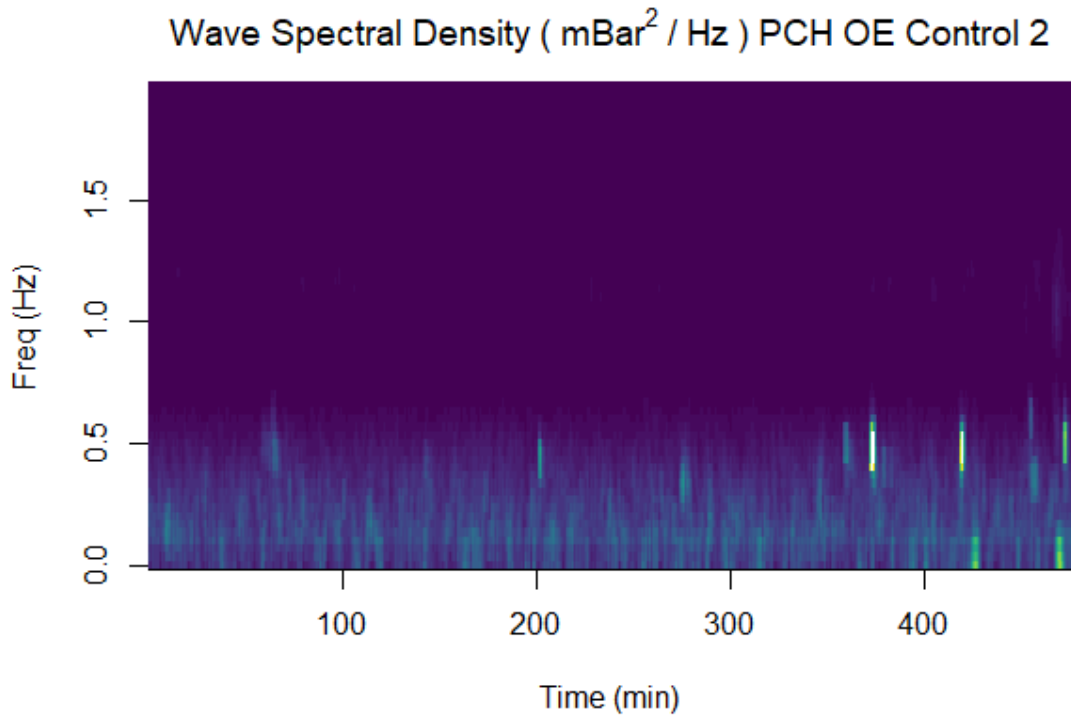


Figure C73. Wave spectral density over duration of full deployment at PCH Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

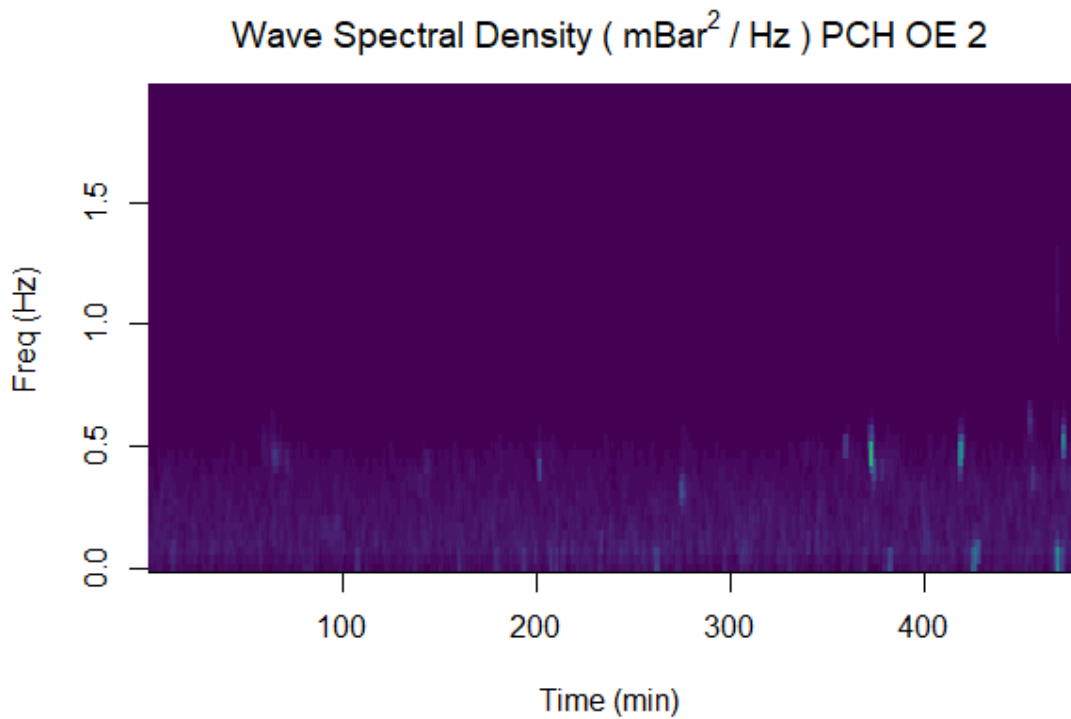


Figure C74. Wave spectral density over duration of full deployment at PCH Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

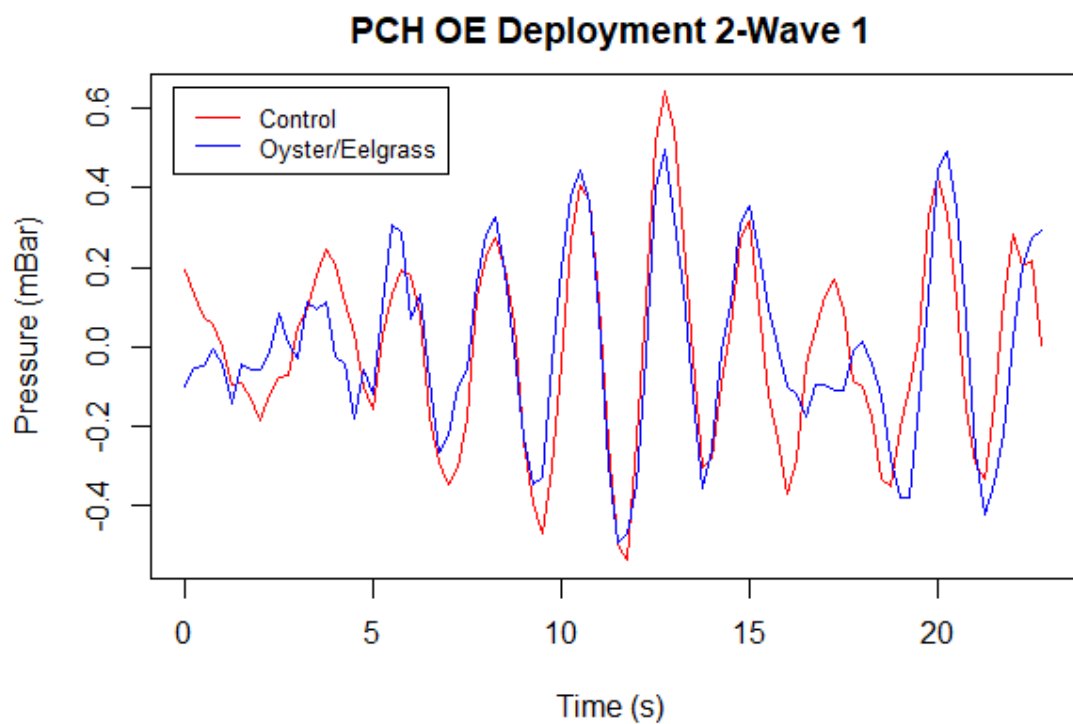


Figure C75. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

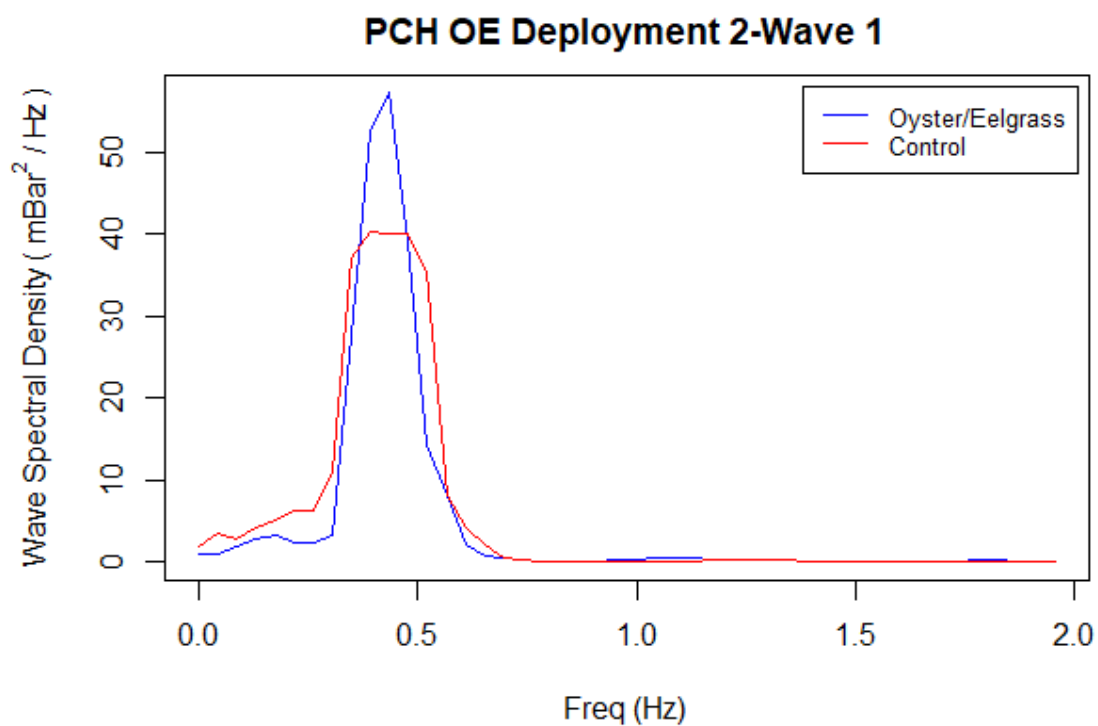


Figure C76. FFT of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

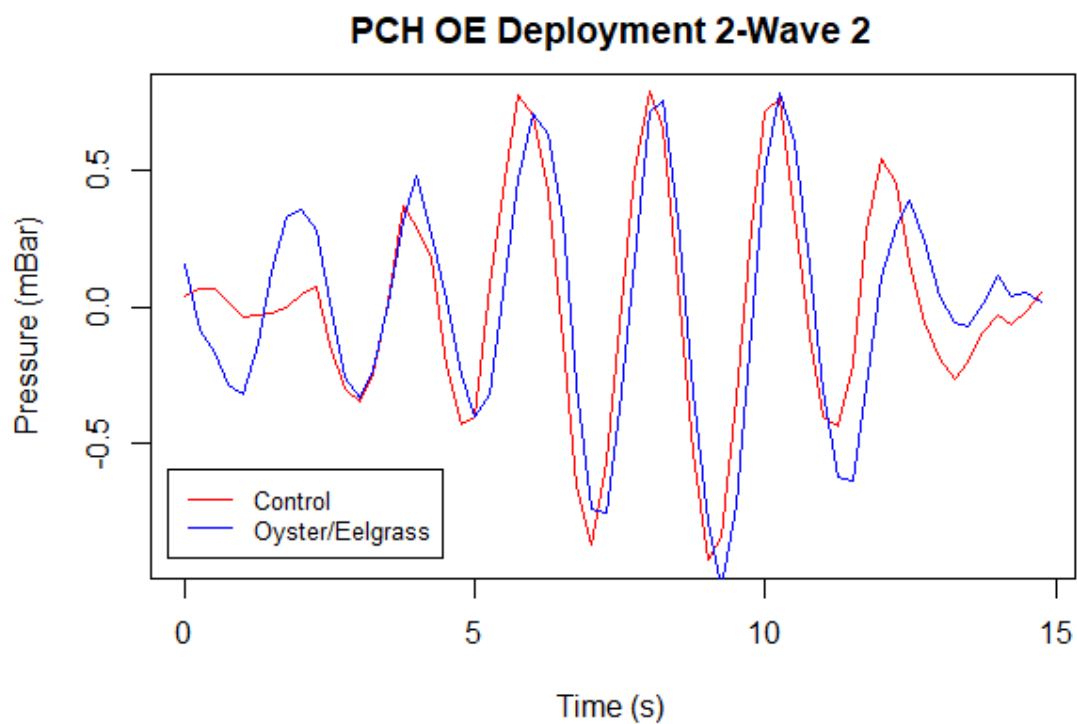


Figure C77. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

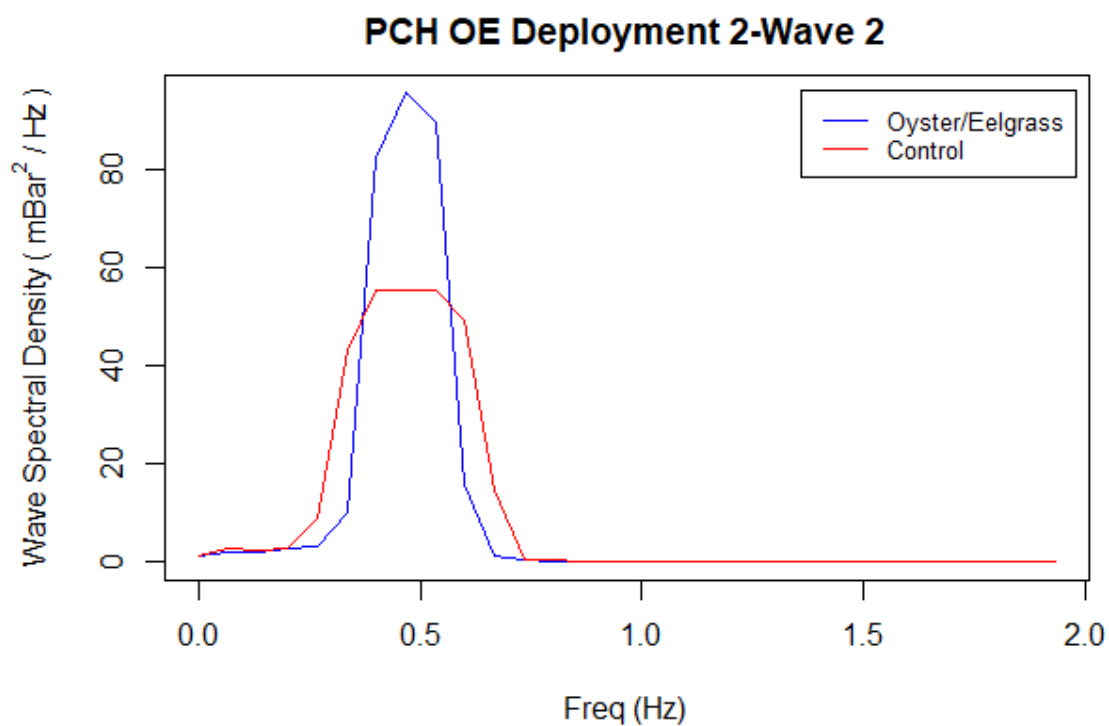


Figure C78. FFT of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

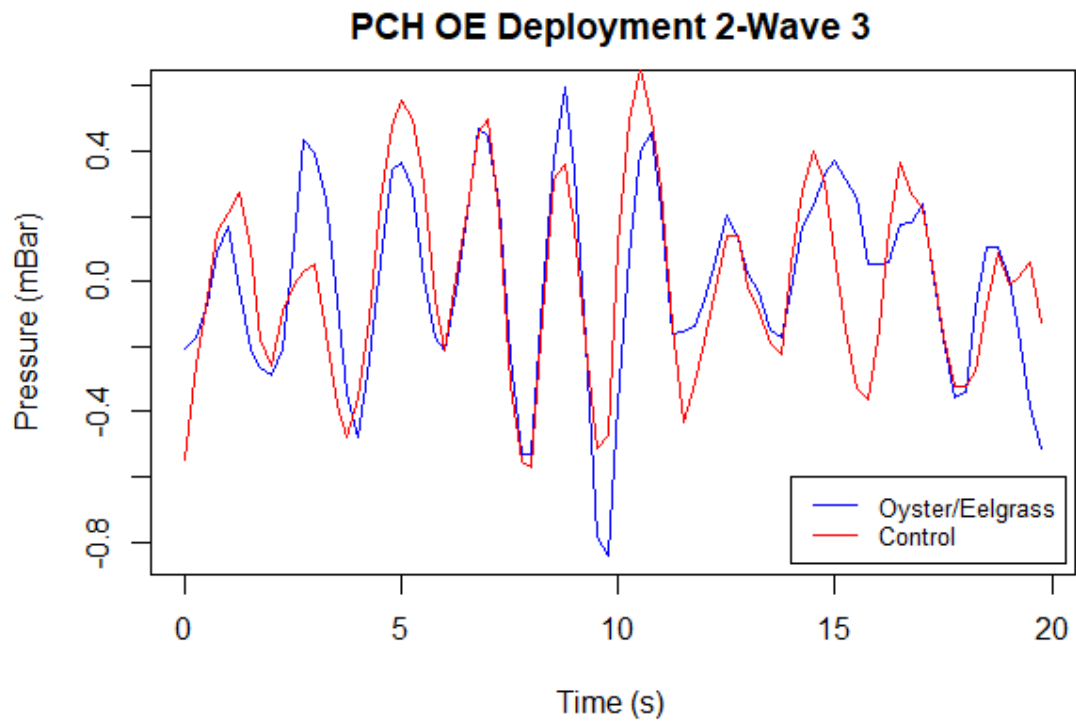


Figure C79. Progression of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

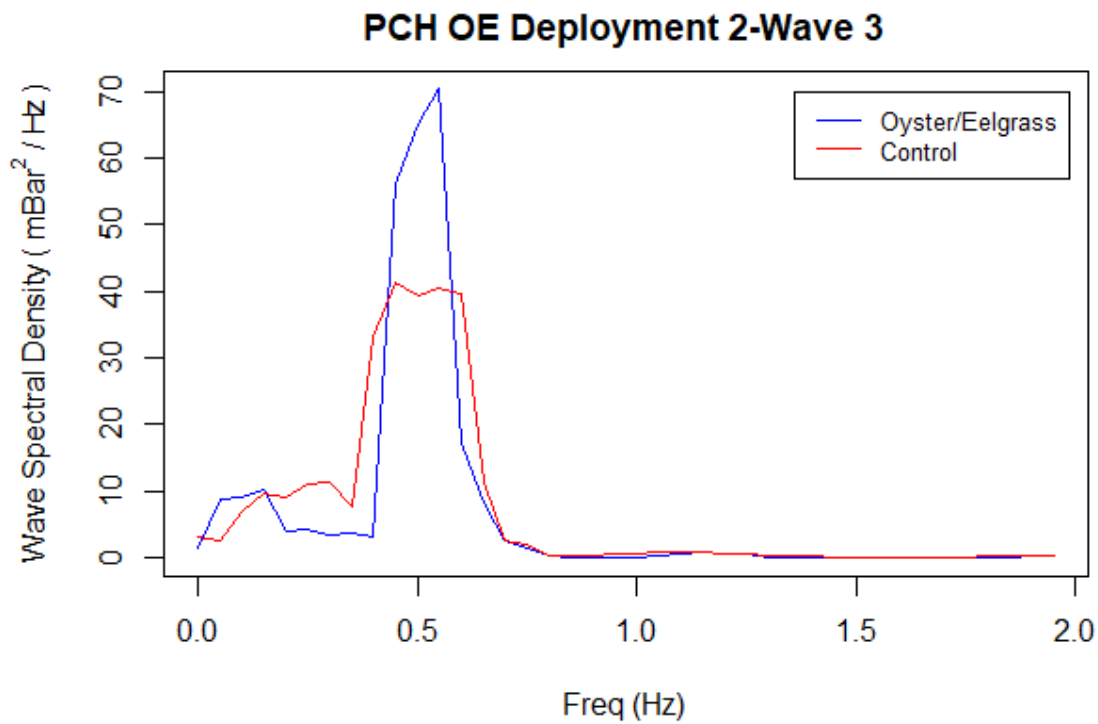


Figure C80. FFT of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

Westcliff: January 17, 2022

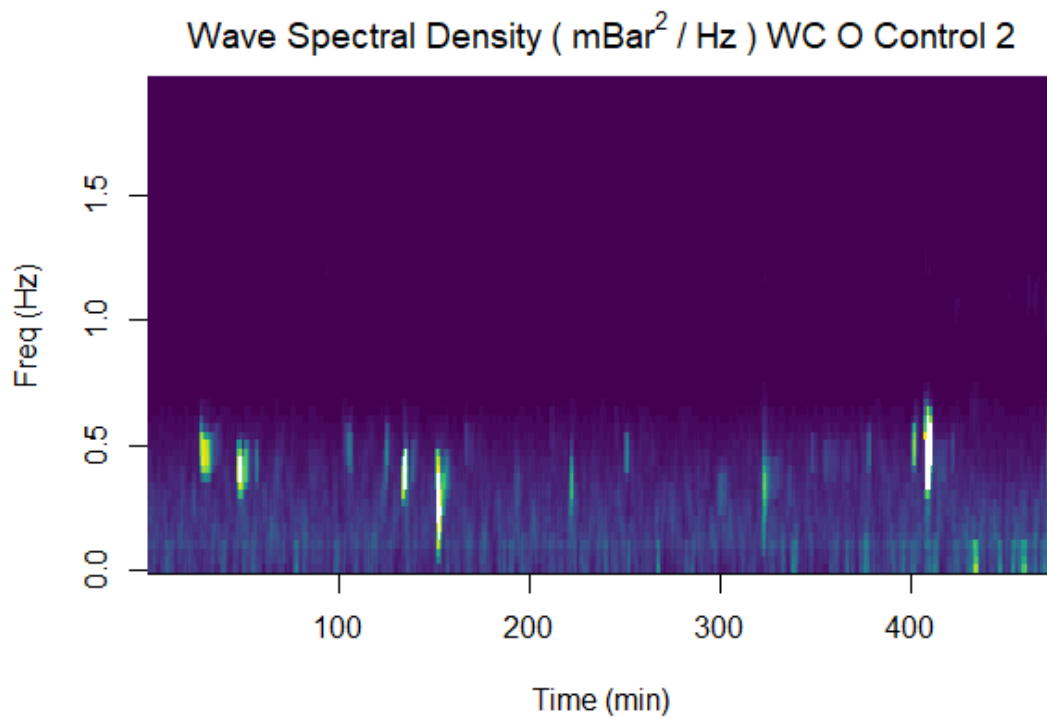


Figure C81. Wave spectral density over duration of full deployment at Westcliff Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

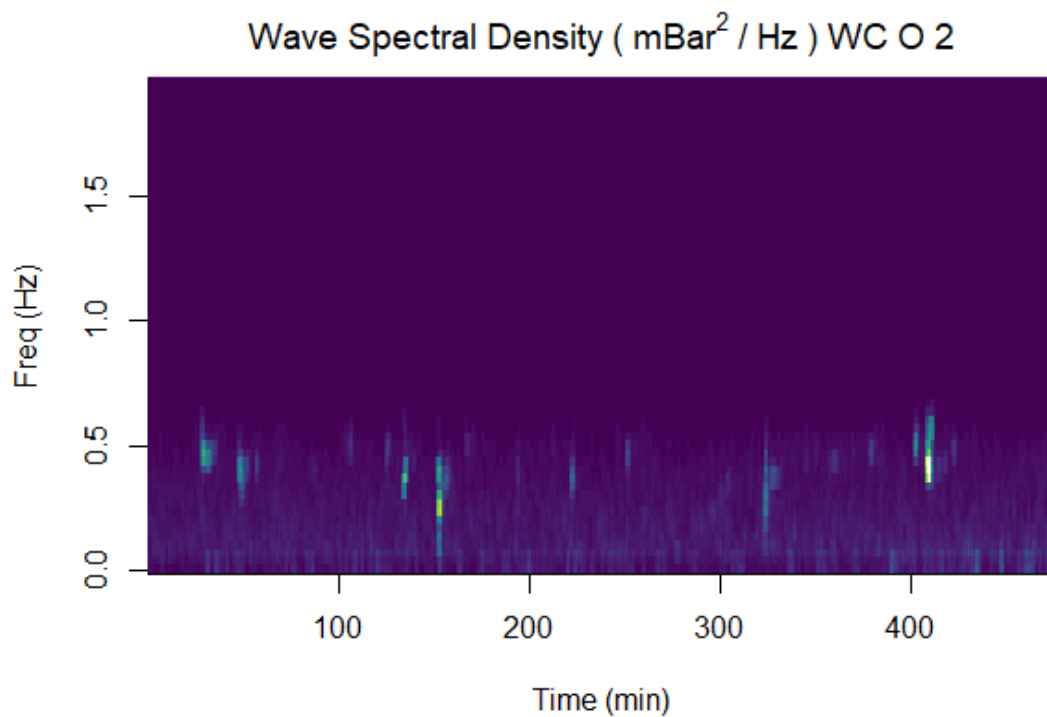


Figure C82. Wave spectral density over duration of full deployment at PCH Oyster logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

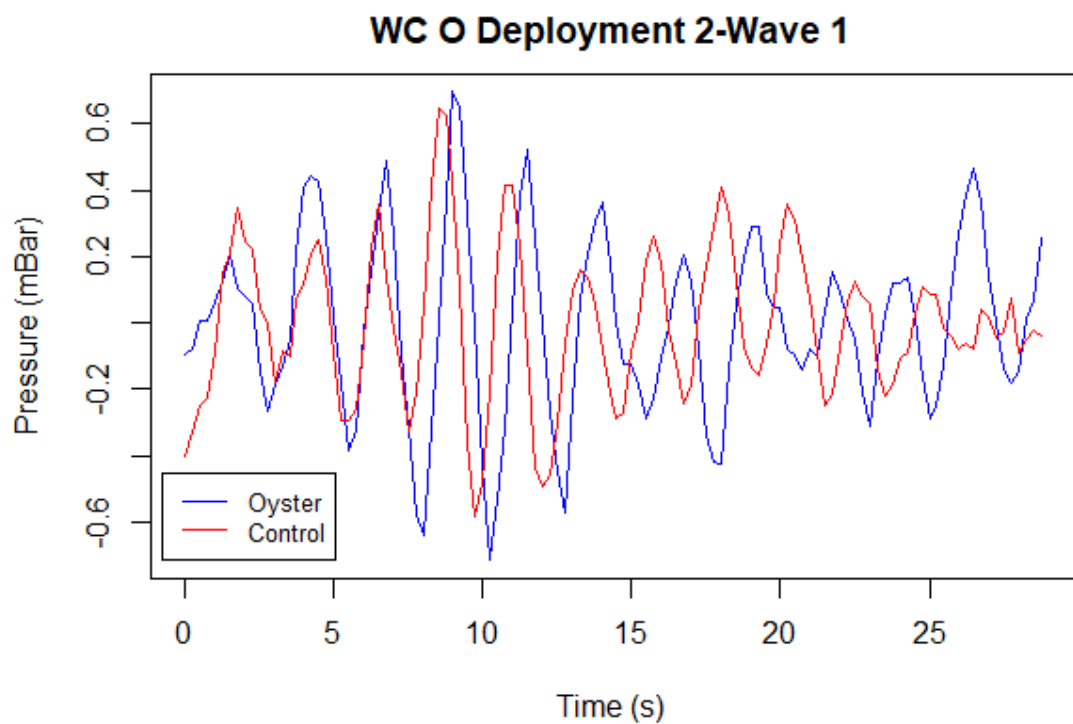


Figure C83. Progression of wave 1 over time at Oyster and Oyster control logger.

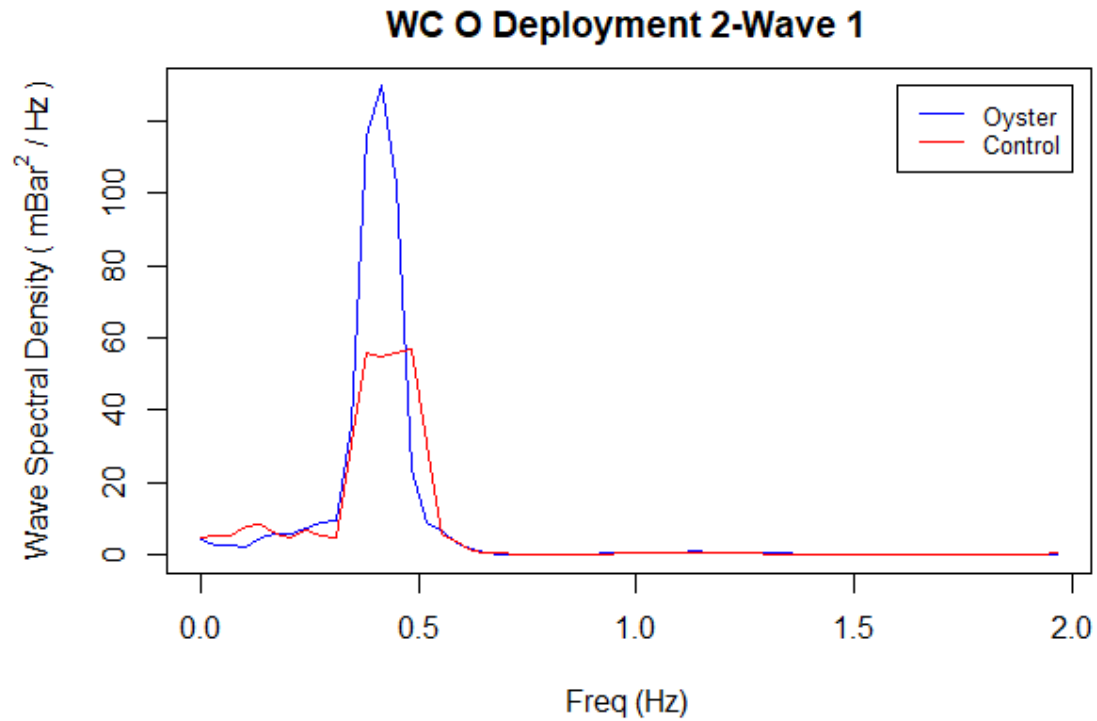


Figure C84. FFT of wave 1 over time at Oyster and Oyster control logger.

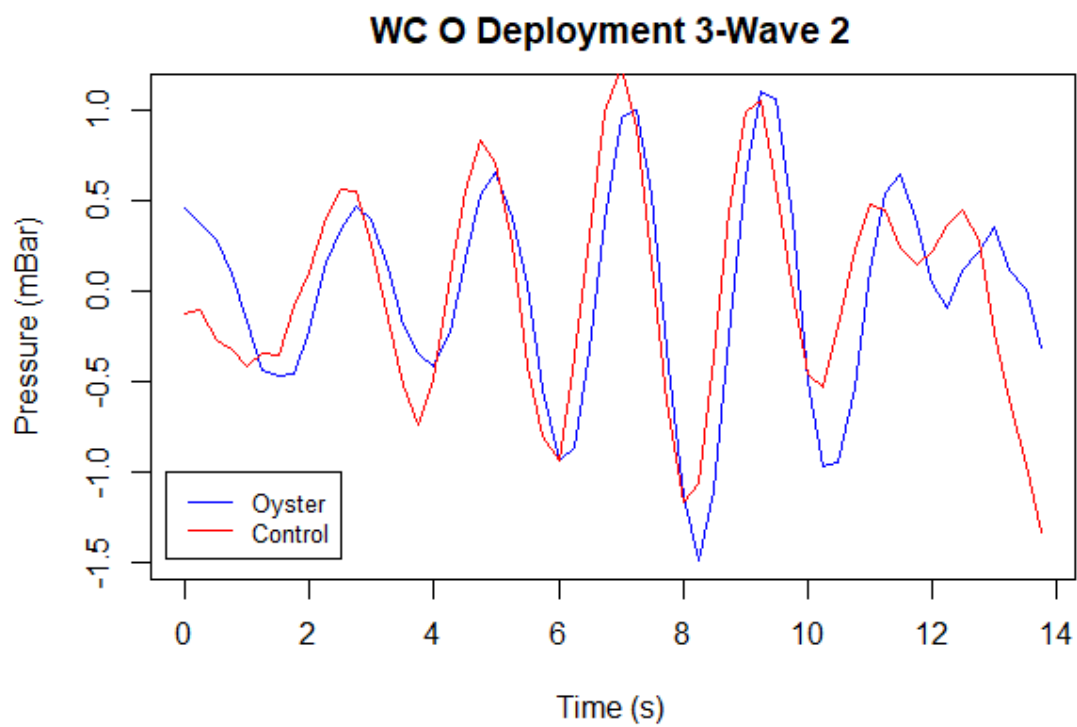


Figure C85. Progression of wave 2 over time at Oyster and Oyster control logger.

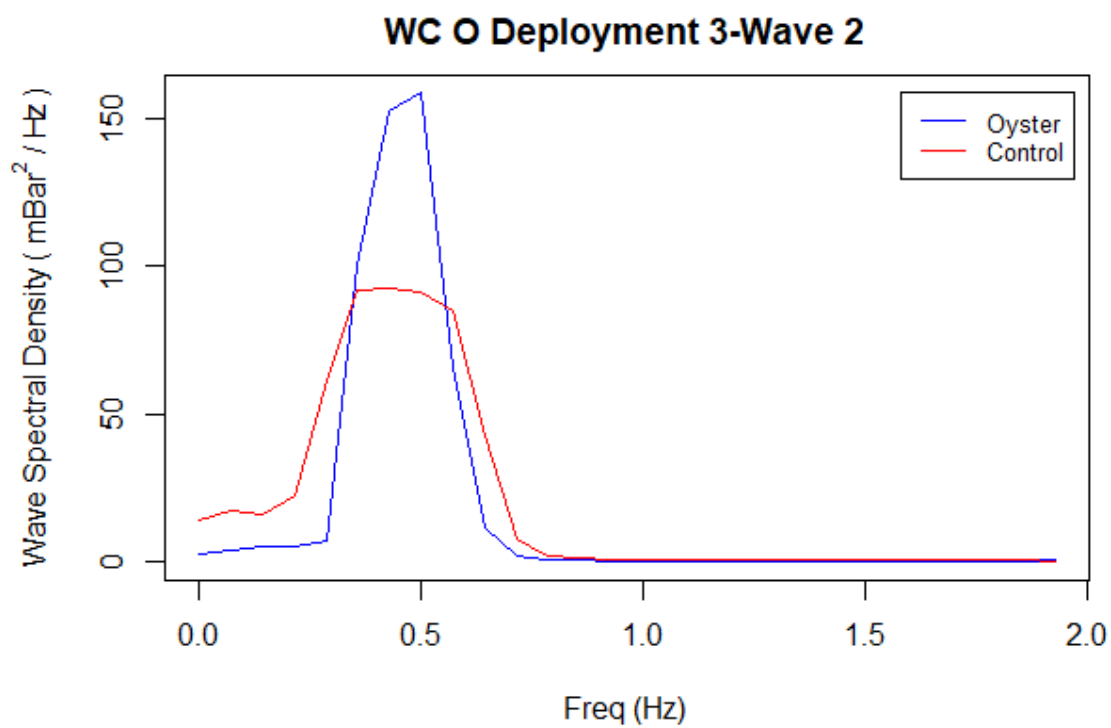


Figure C86. FFT of wave 2 over time at Oyster and Oyster control logger.

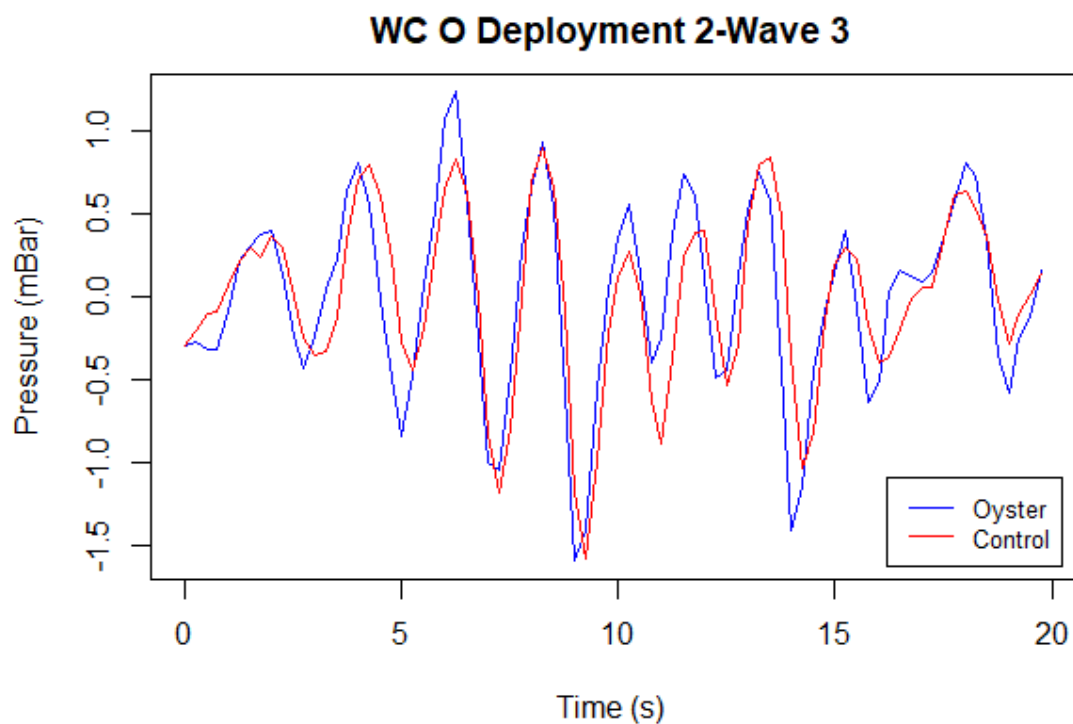


Figure C87. Progression of wave 3 over time at Oyster and Oyster control logger.

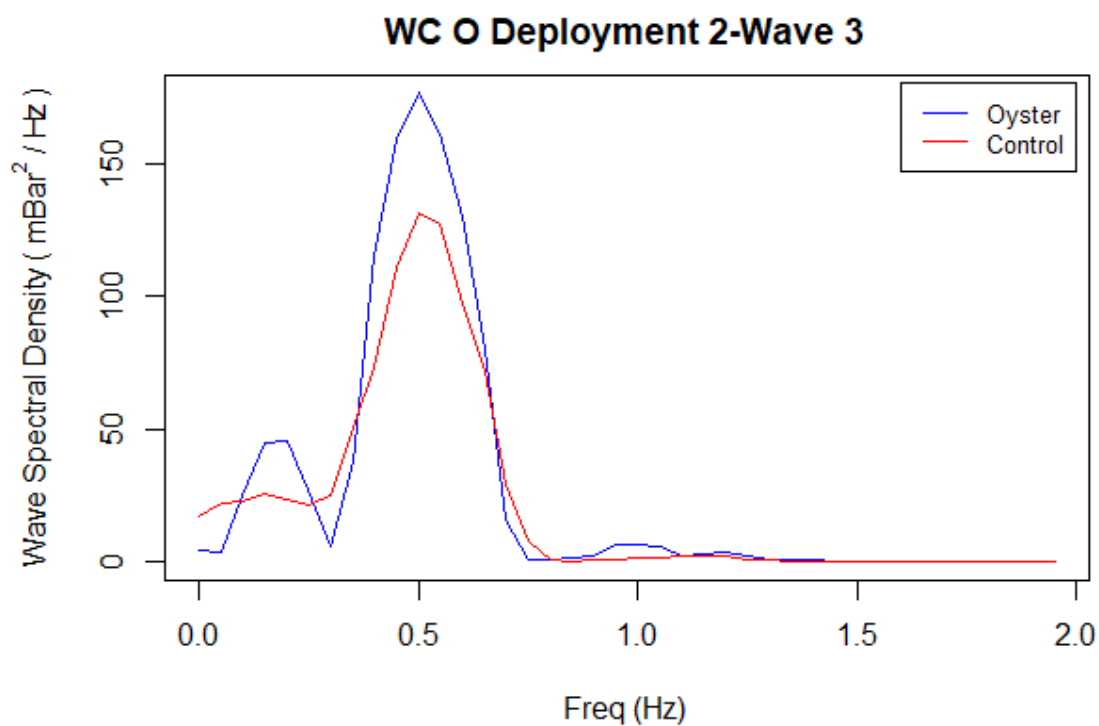


Figure C88. FFT of wave 3 over time at Oyster and Oyster control logger.

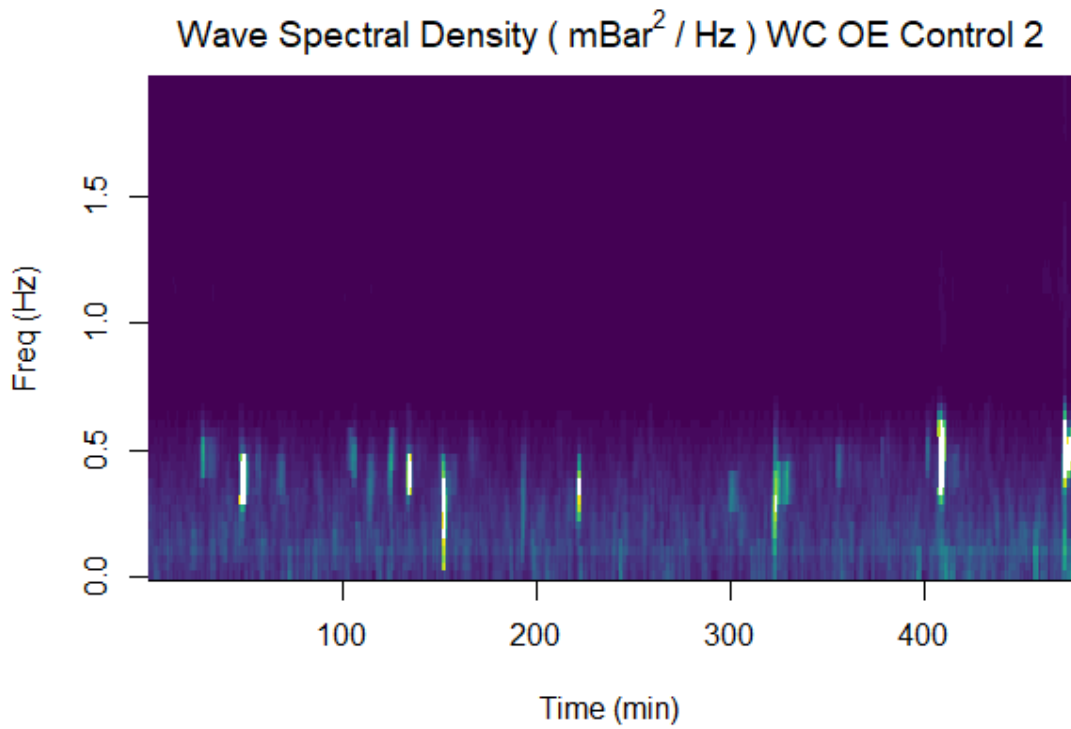


Figure C89. Wave spectral density over duration of full deployment at Westcliff Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

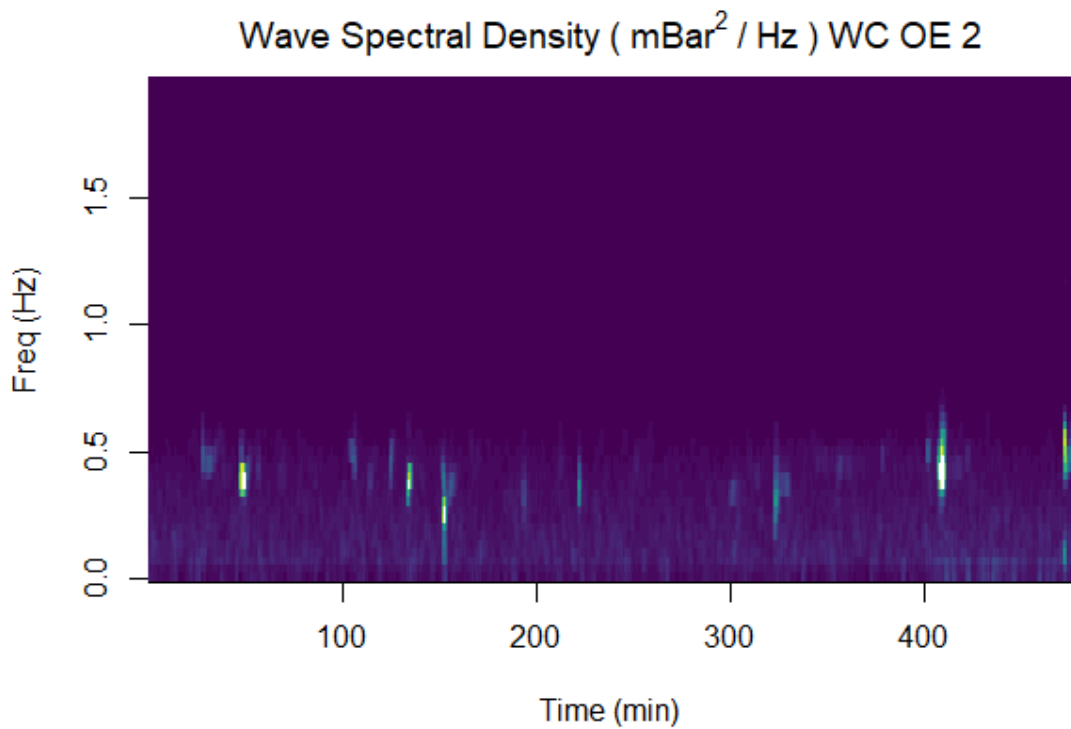


Figure C90. Wave spectral density over duration of full deployment at Westcliff Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

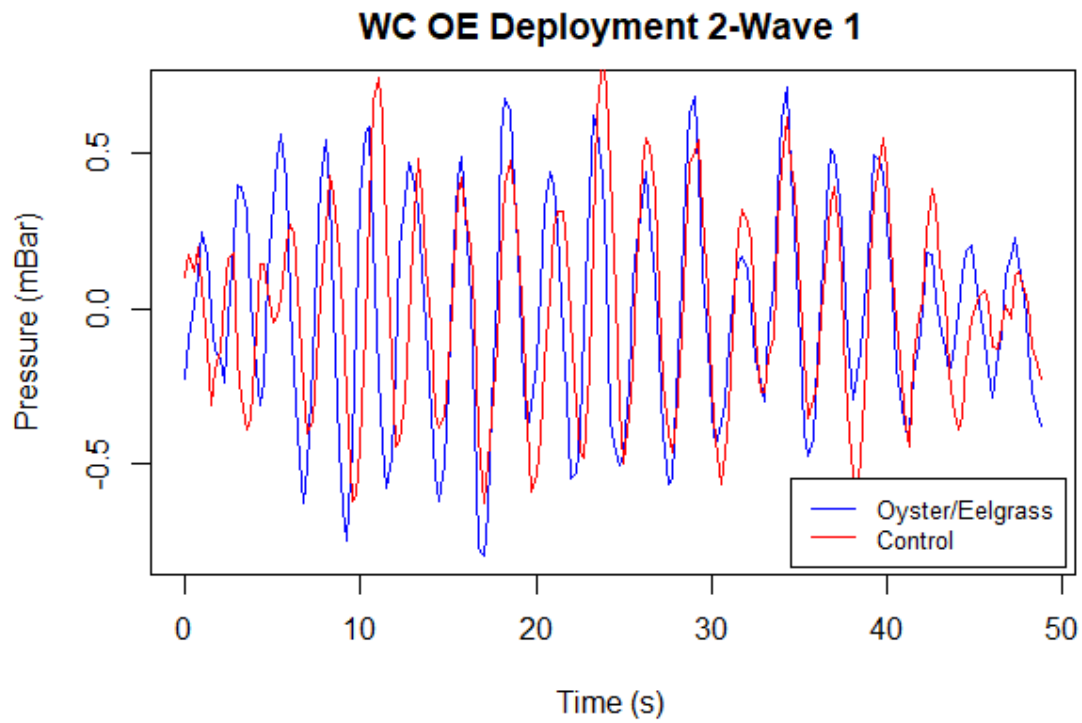


Figure C91. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

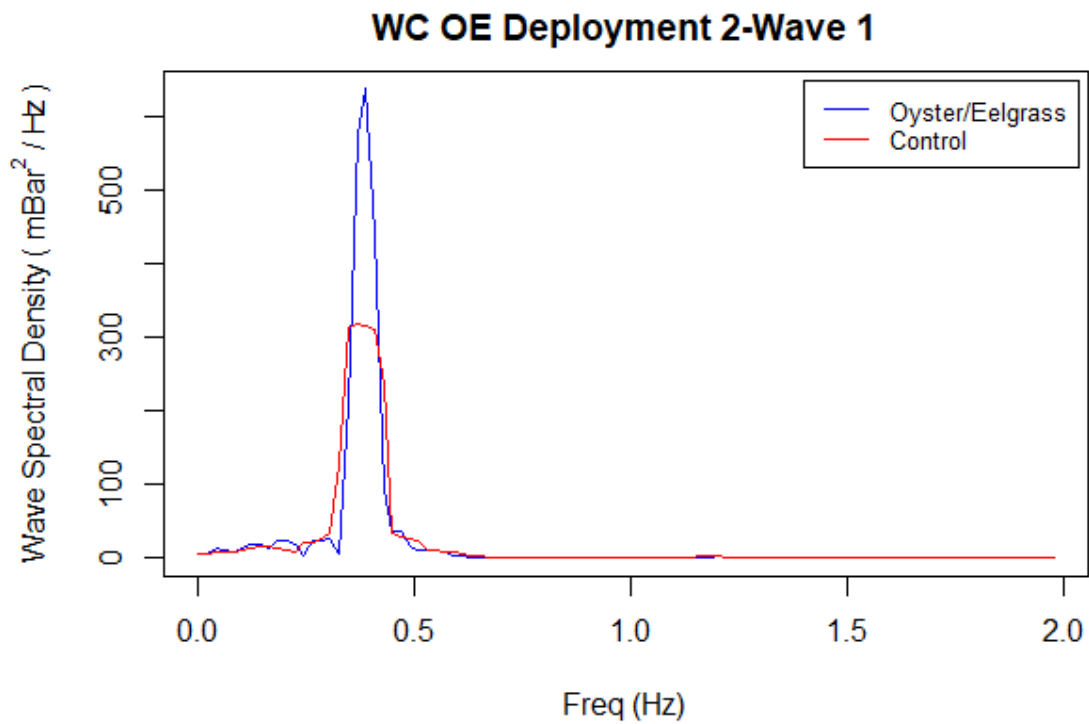


Figure C92. FFT of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

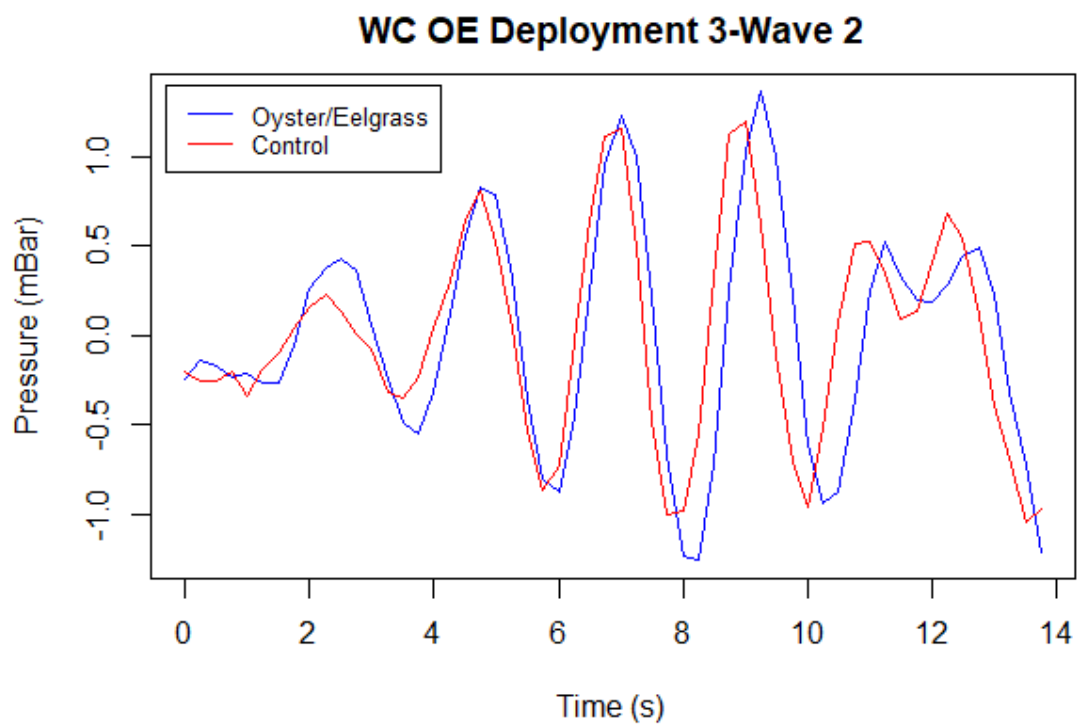


Figure C93. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

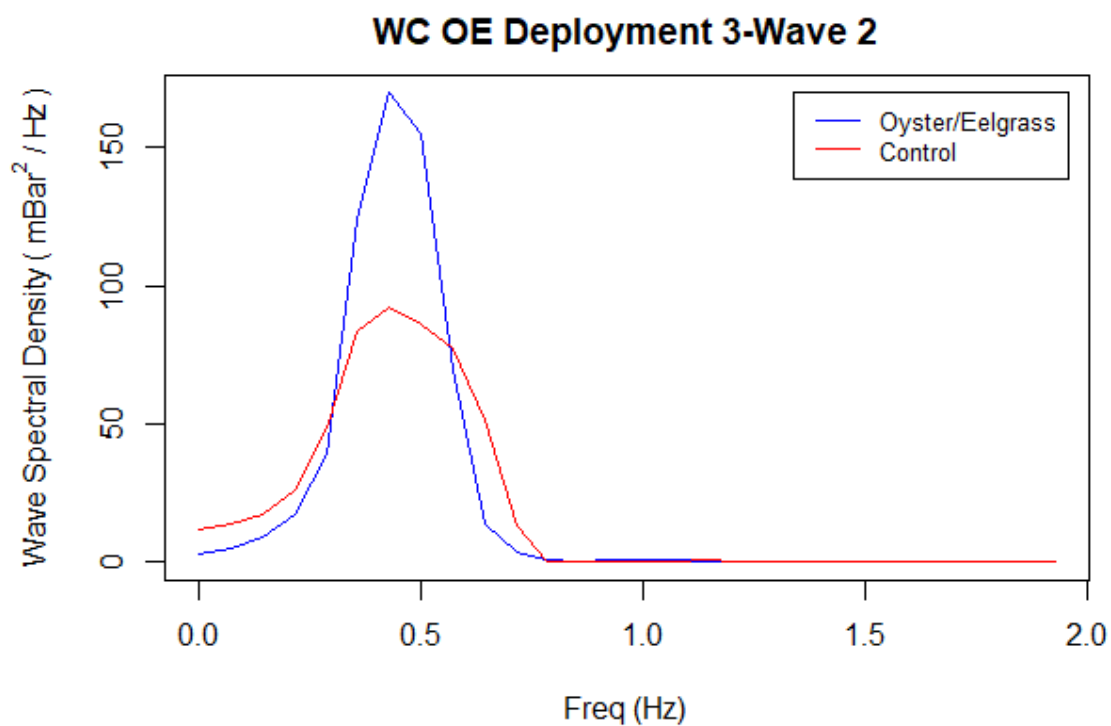


Figure C94. FFT of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

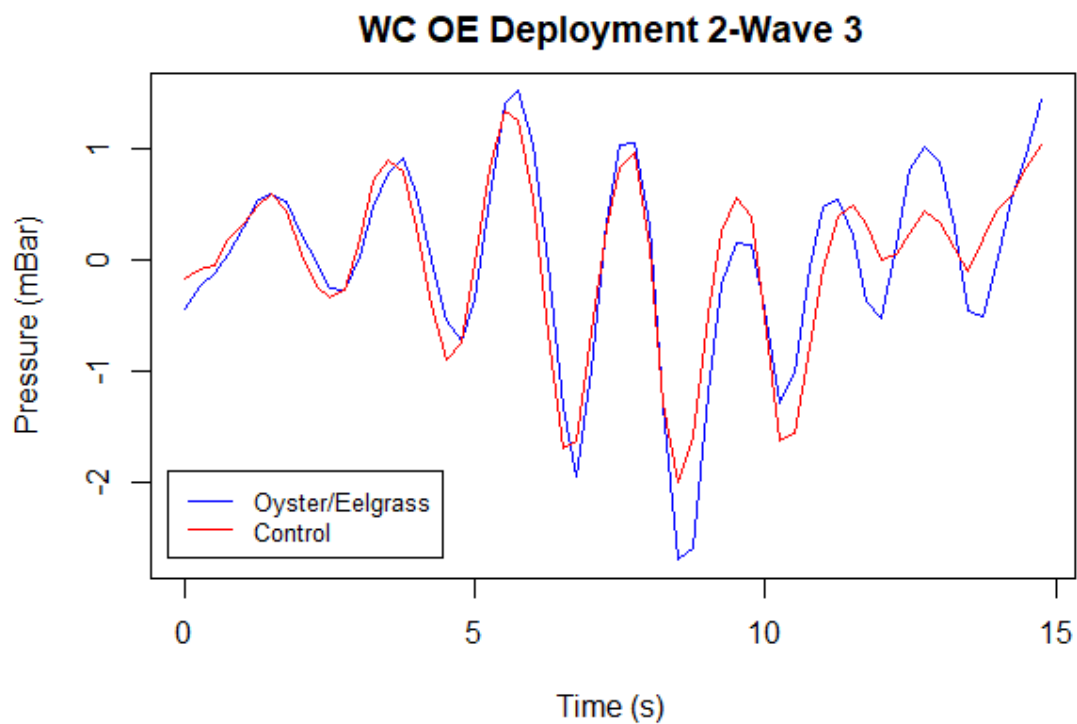


Figure C95. Progression of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

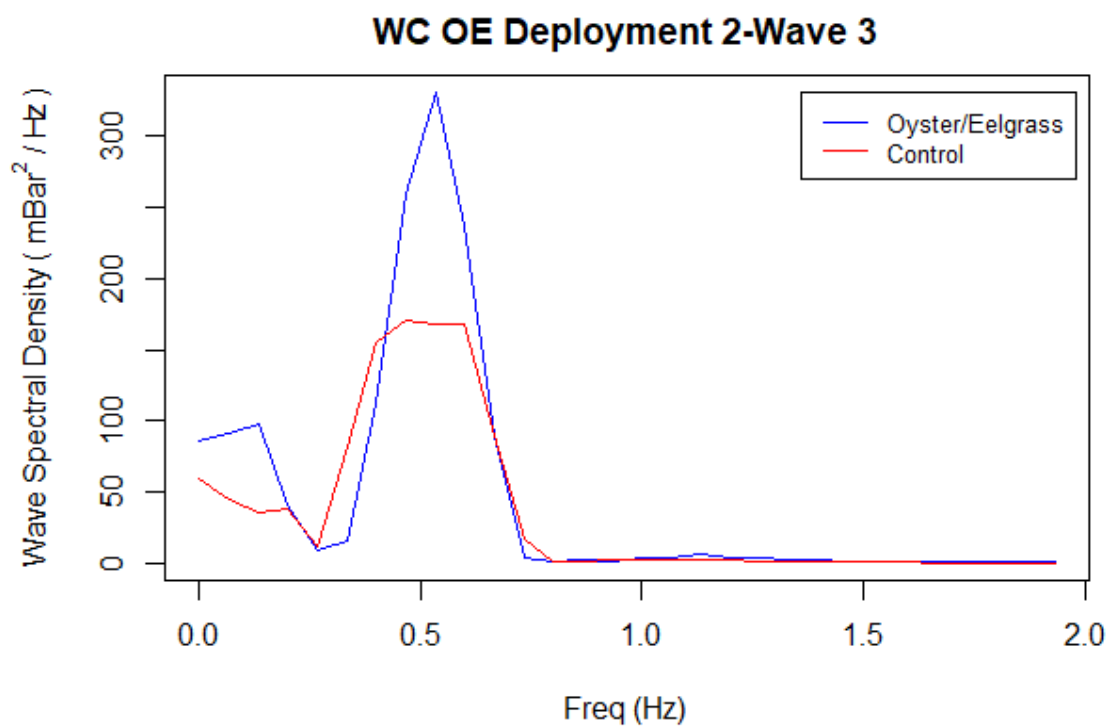


Figure C96. FFT of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

DEPLOYMENT 3

Deanza: January 29, 2022

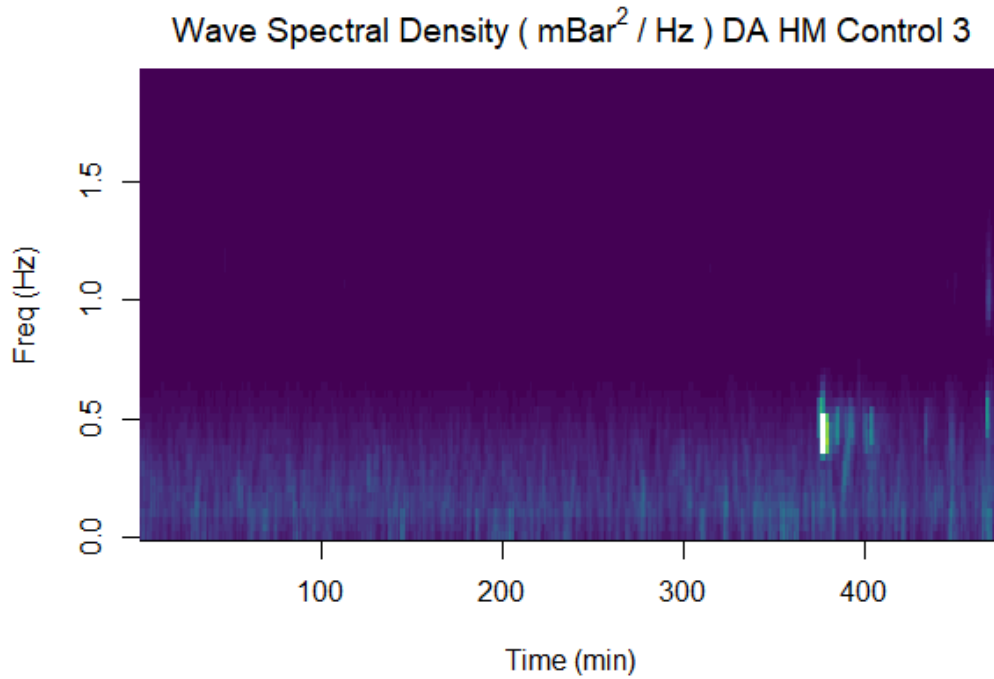


Figure C97. Wave spectral density over duration of full deployment at Deanza High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

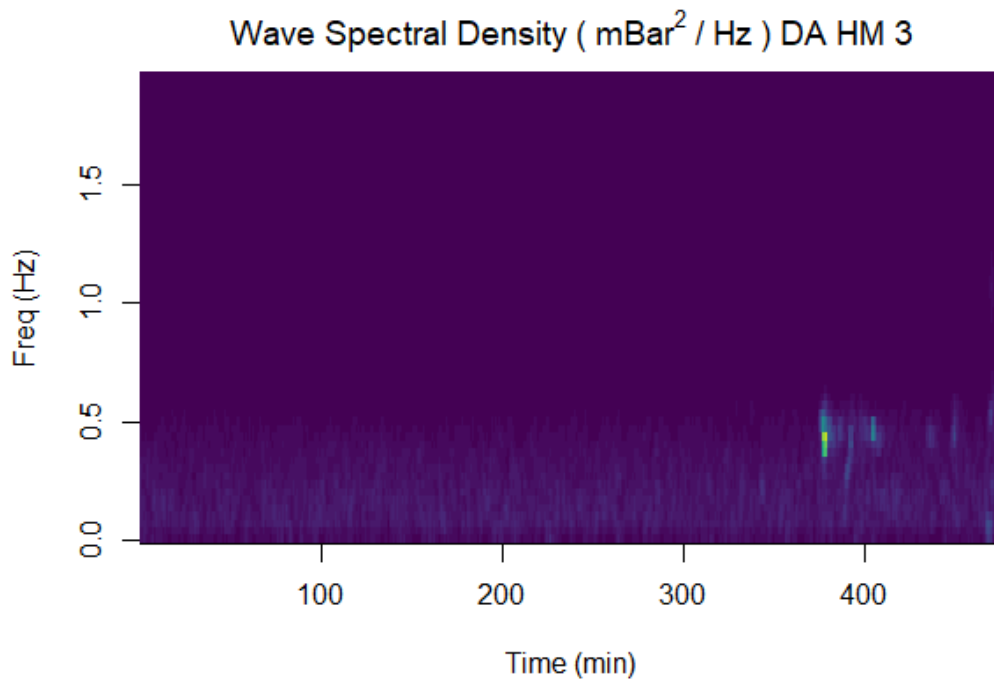


Figure C98. Wave spectral density over duration of full deployment at Deanza High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

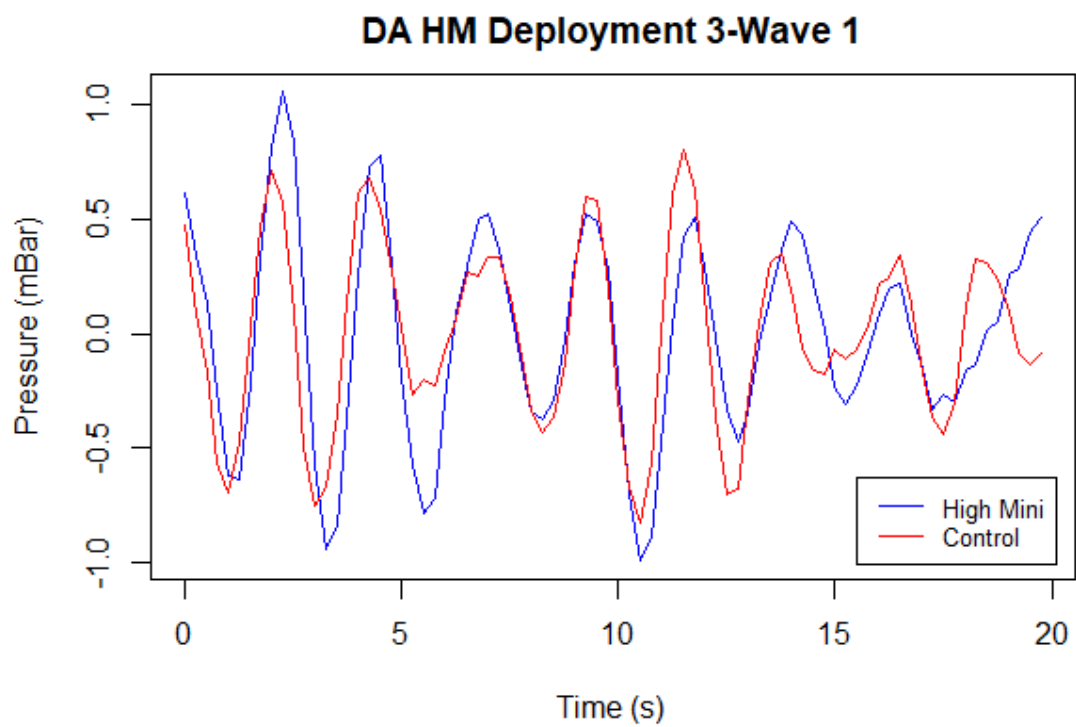


Figure C99. Progression of wave 1 over time at High Mini and High Mini control logger.

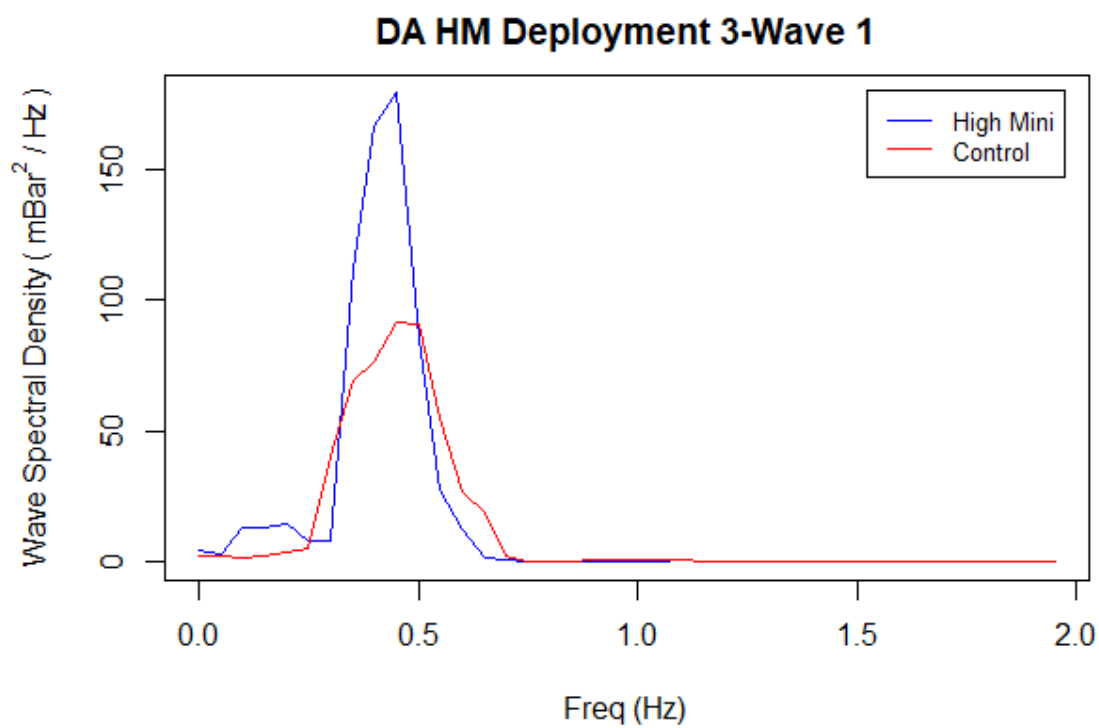


Figure C100. FFT of wave 1 over time at High Mini and High Mini control logger.

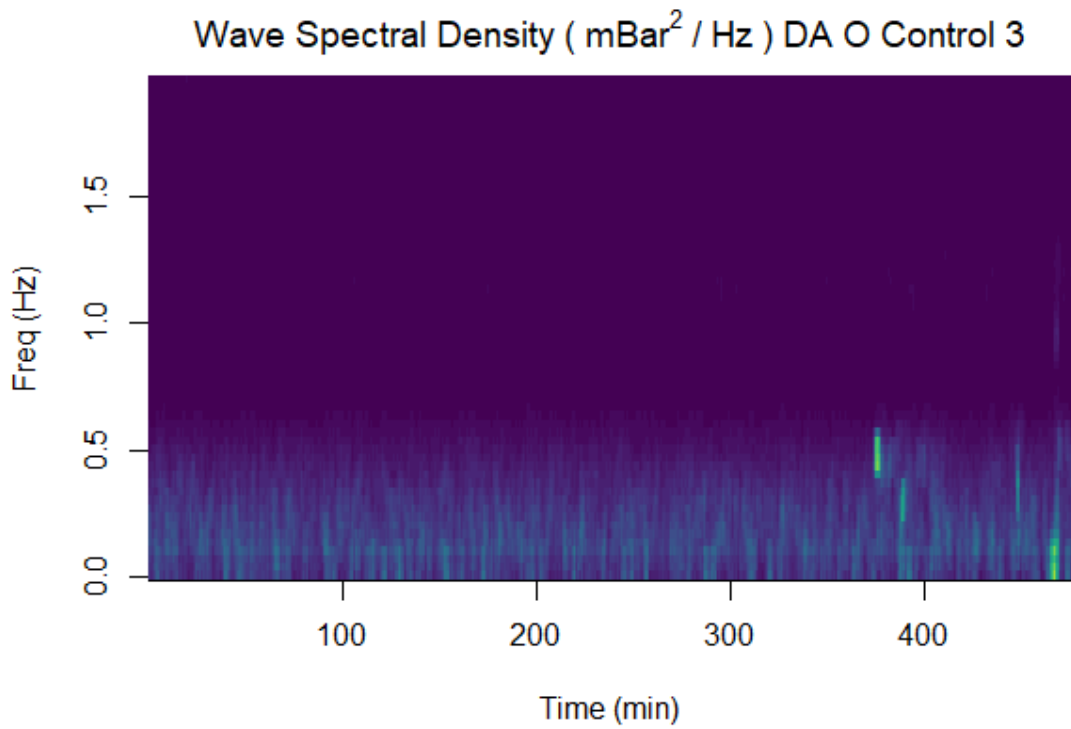


Figure C101. Wave spectral density over duration of full deployment at Deanza Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

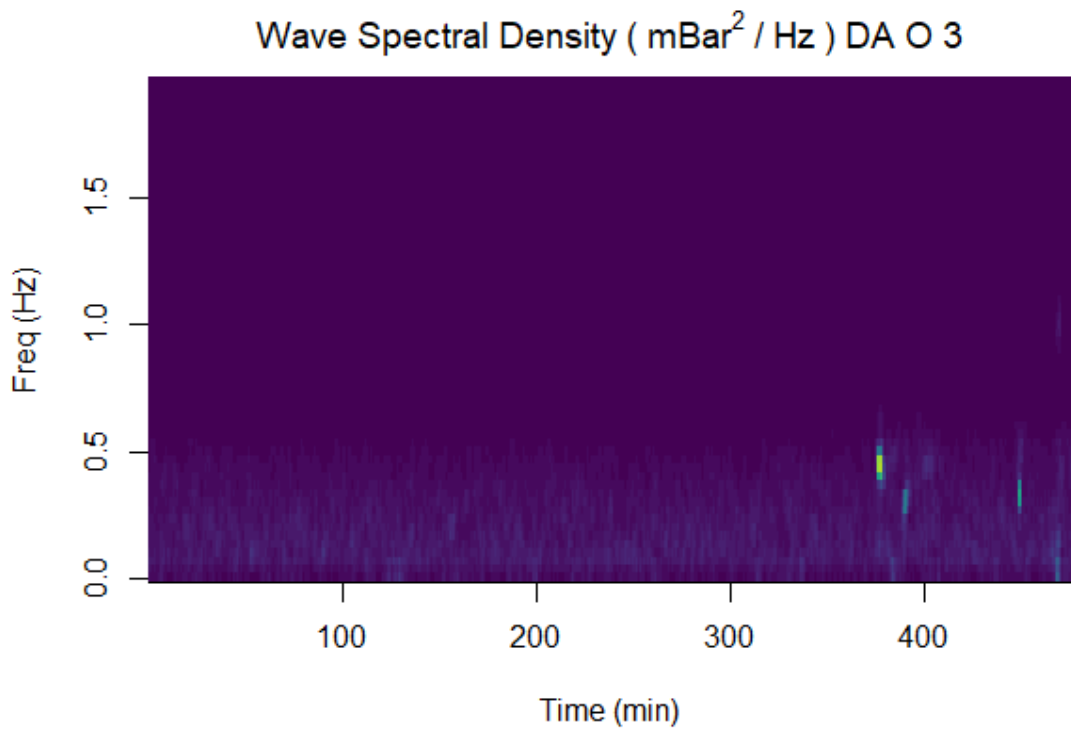


Figure C102. Wave spectral density over duration of full deployment at Deanza Oyster logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

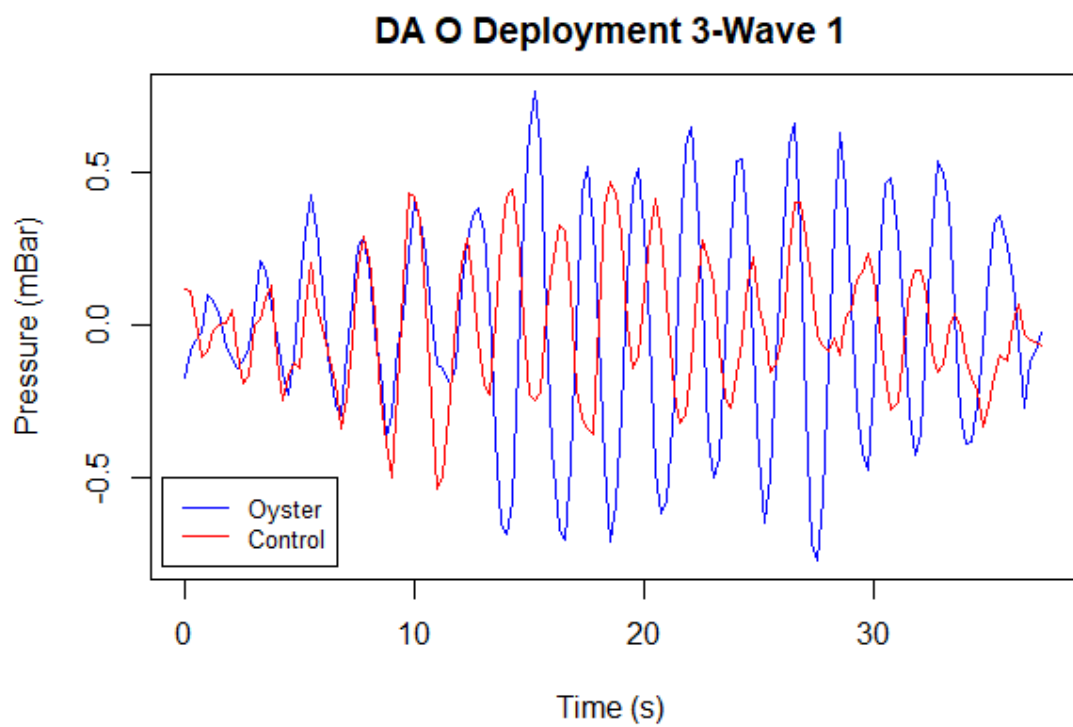


Figure C103. Progression of wave 1 over time at Oyster and Oyster Control logger.

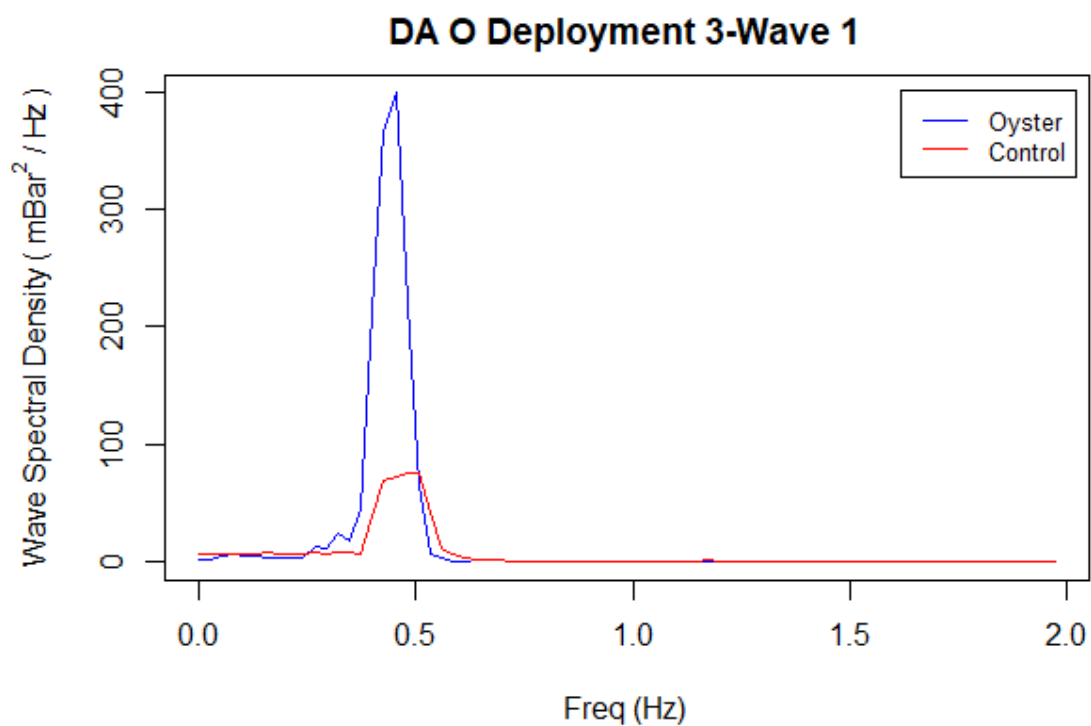


Figure C104. FFT of wave 1 over time at Oyster and Oyster control logger.

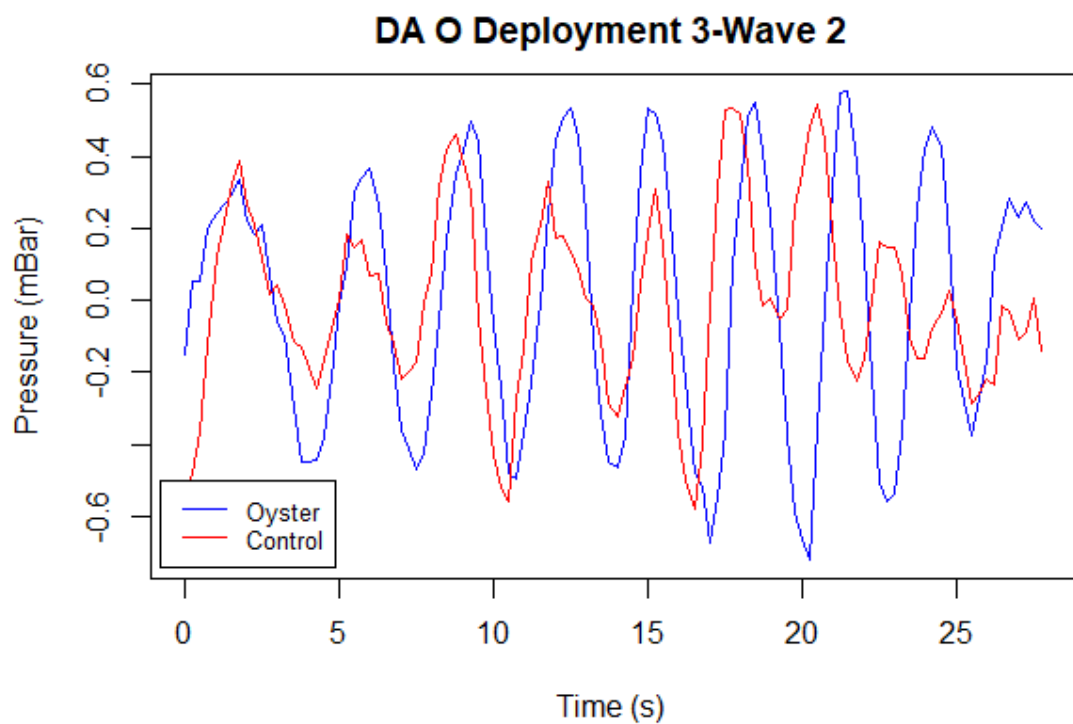


Figure C105. Progression of wave 2 over time at Oyster and Oyster Control logger.

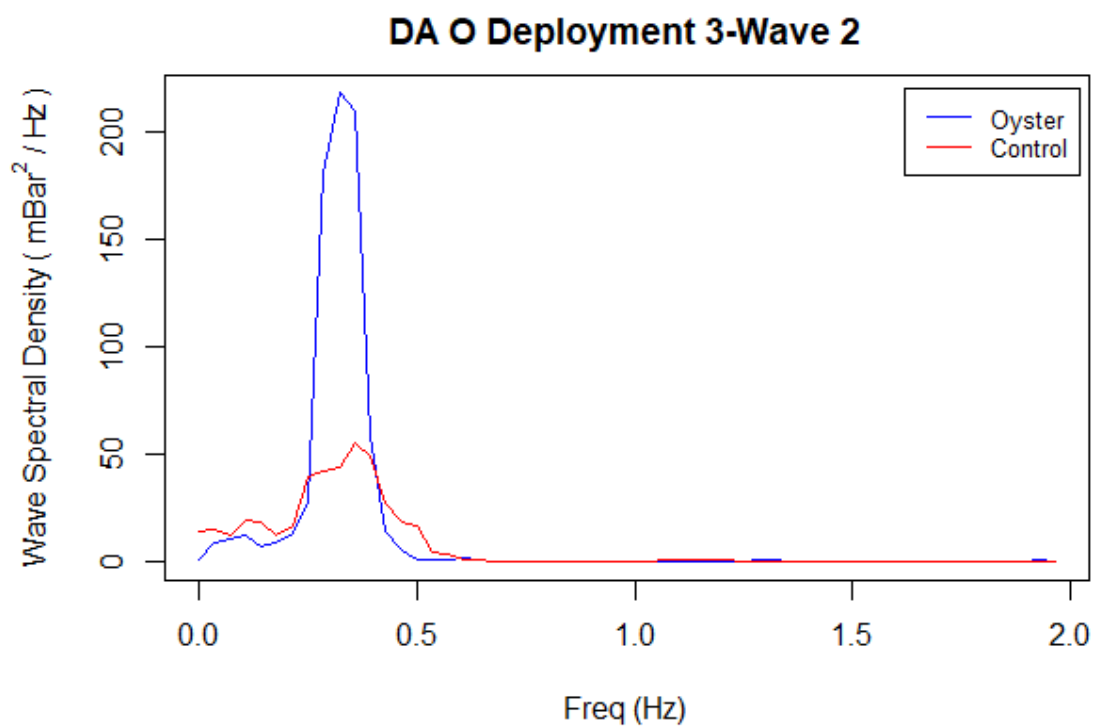


Figure C106. FFT of wave 2 over time at Oyster and Oyster control logger.

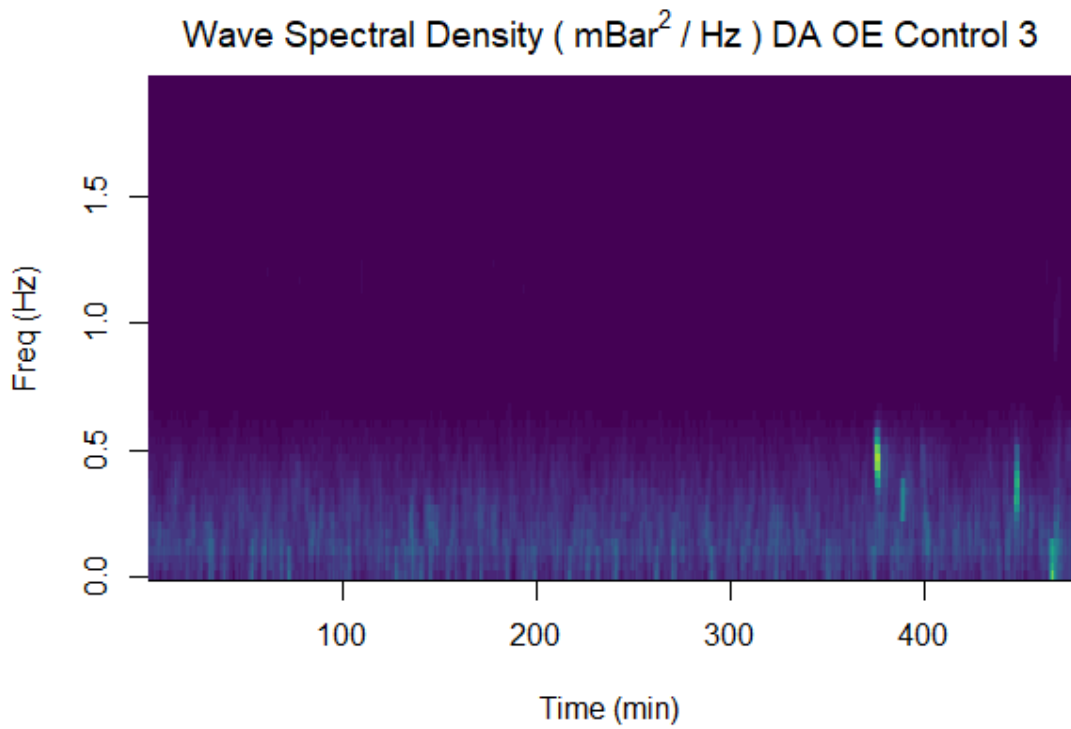


Figure C107. Wave spectral density over duration of full deployment at Deanza Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

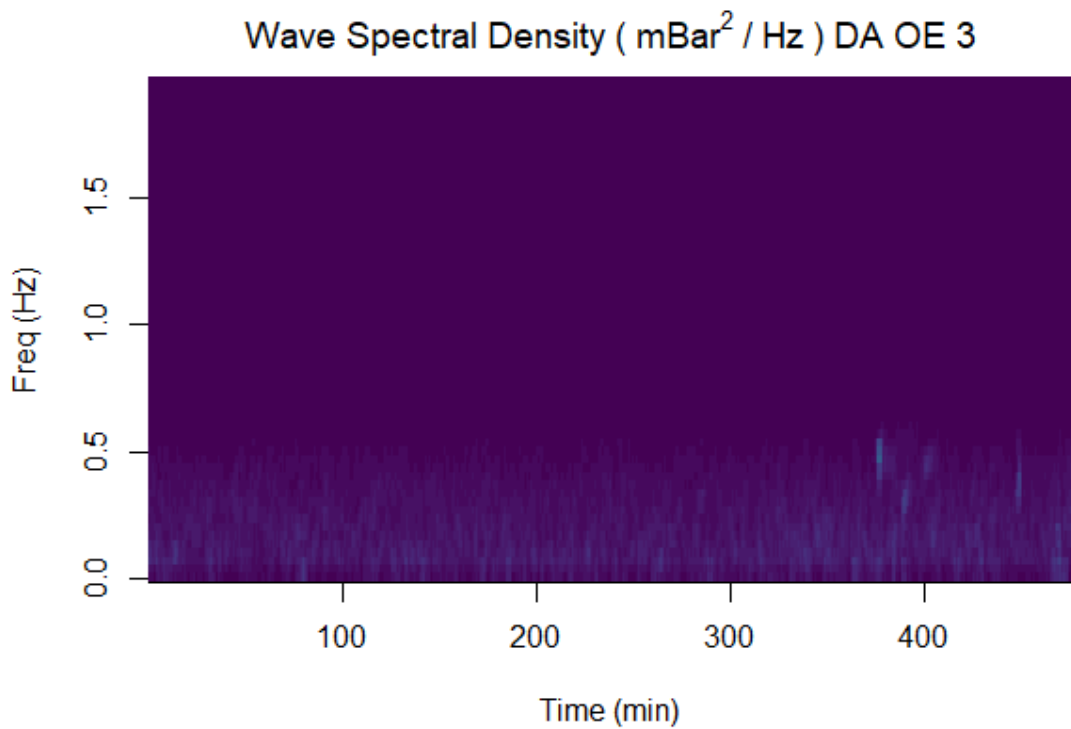


Figure C108. Wave spectral density over duration of full deployment at Deanza Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

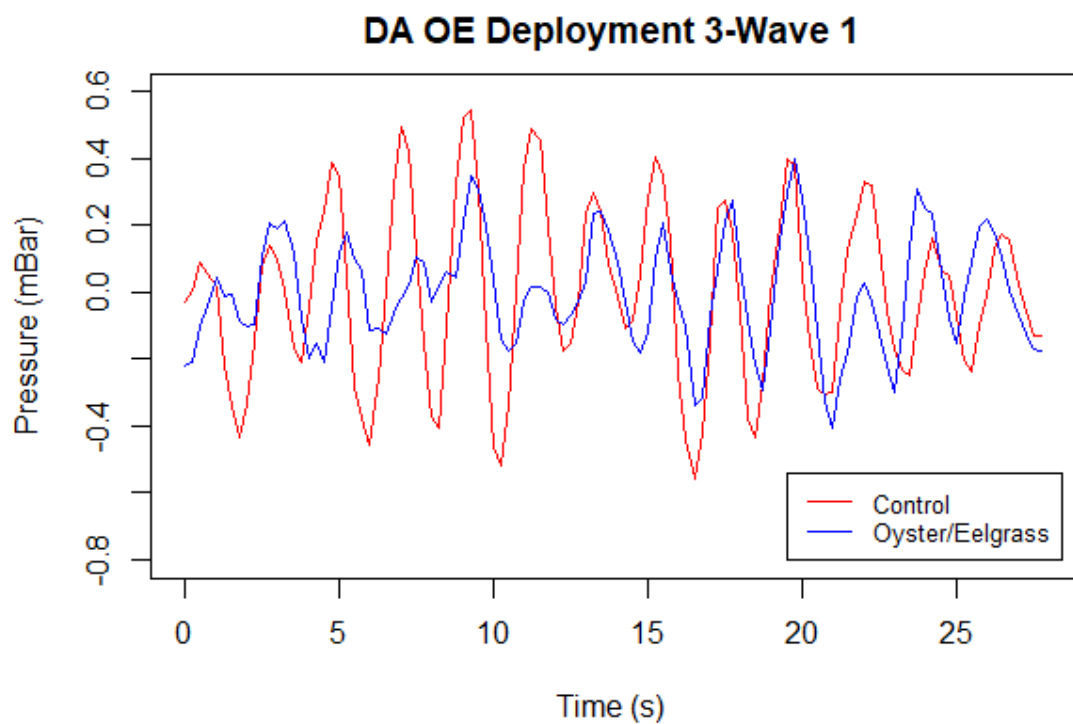


Figure C109. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

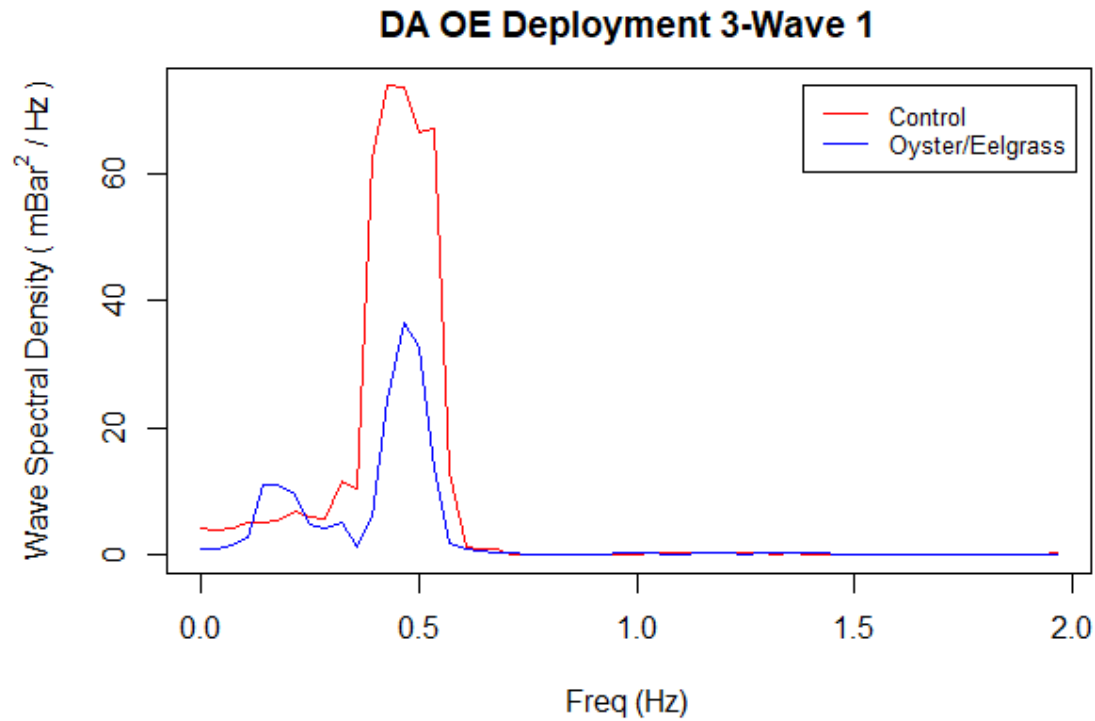


Figure C110. FFT of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

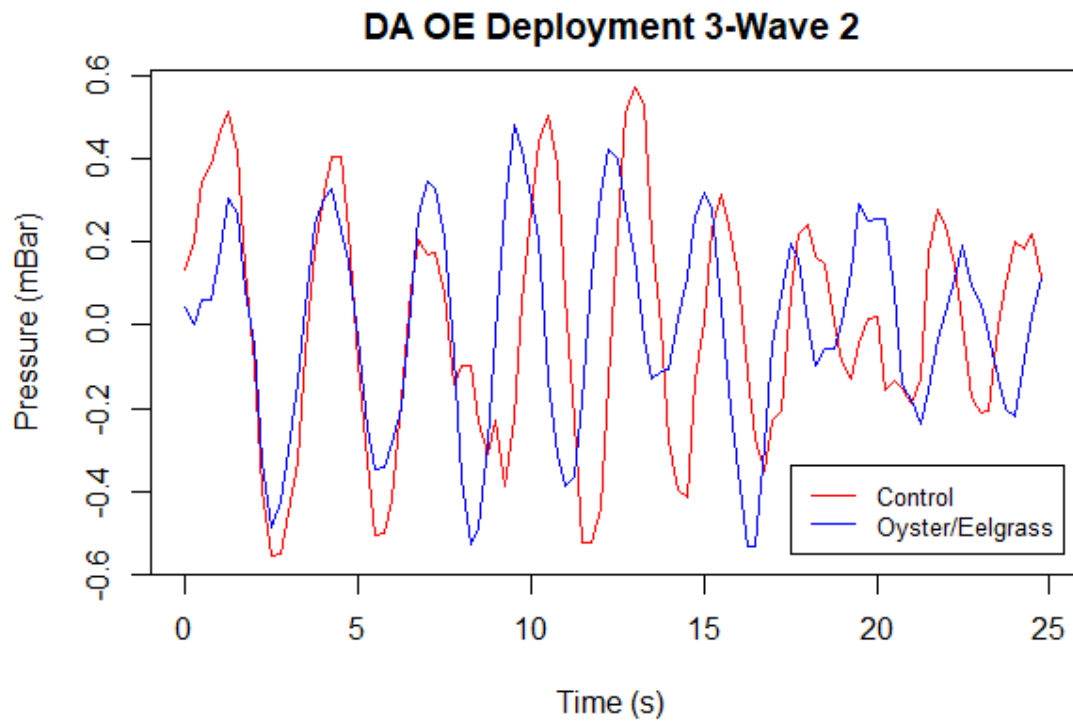


Figure C111. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

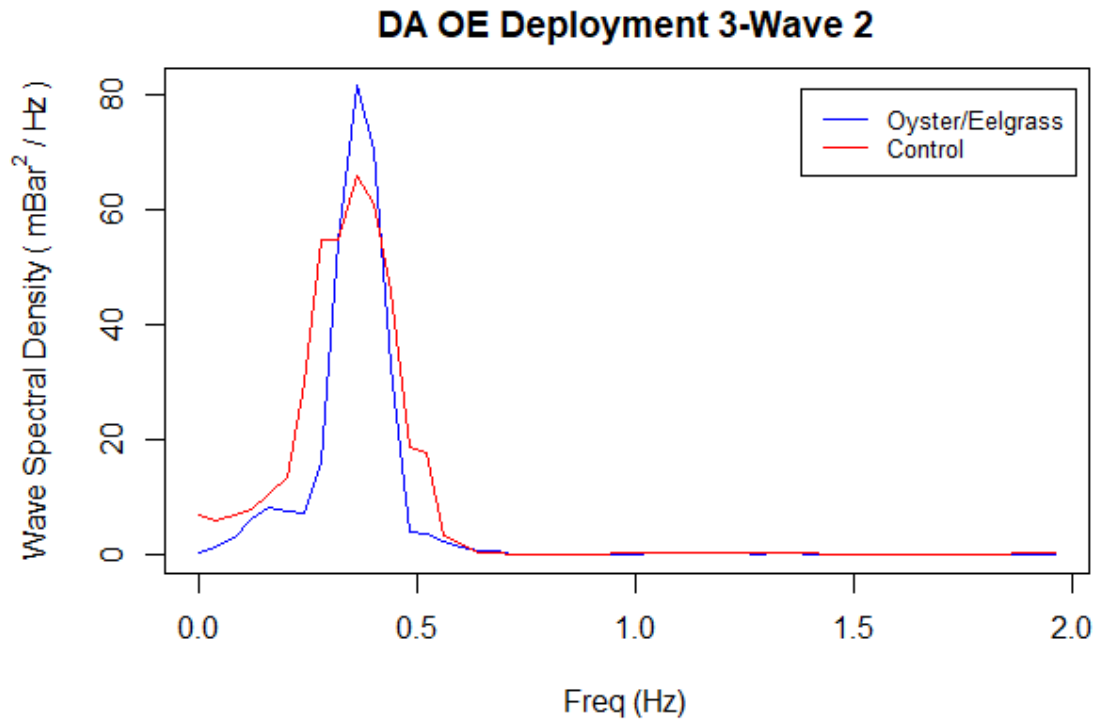


Figure C112. FFT of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

PCH: February 14, 2022

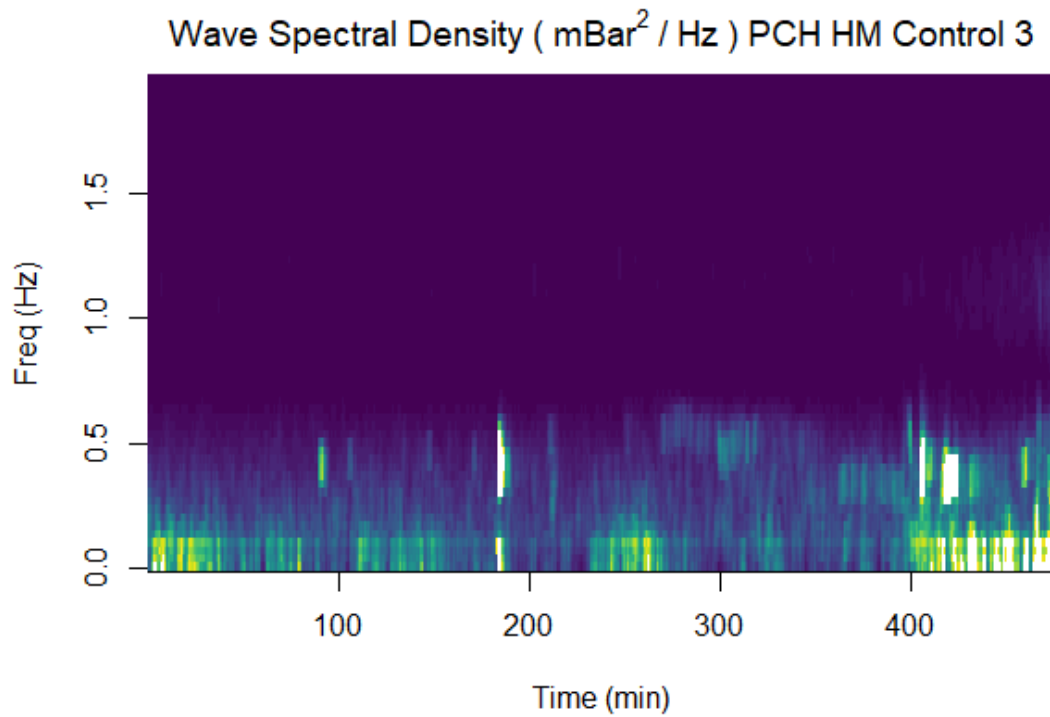


Figure C113. Wave spectral density over duration of full deployment at PCH High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

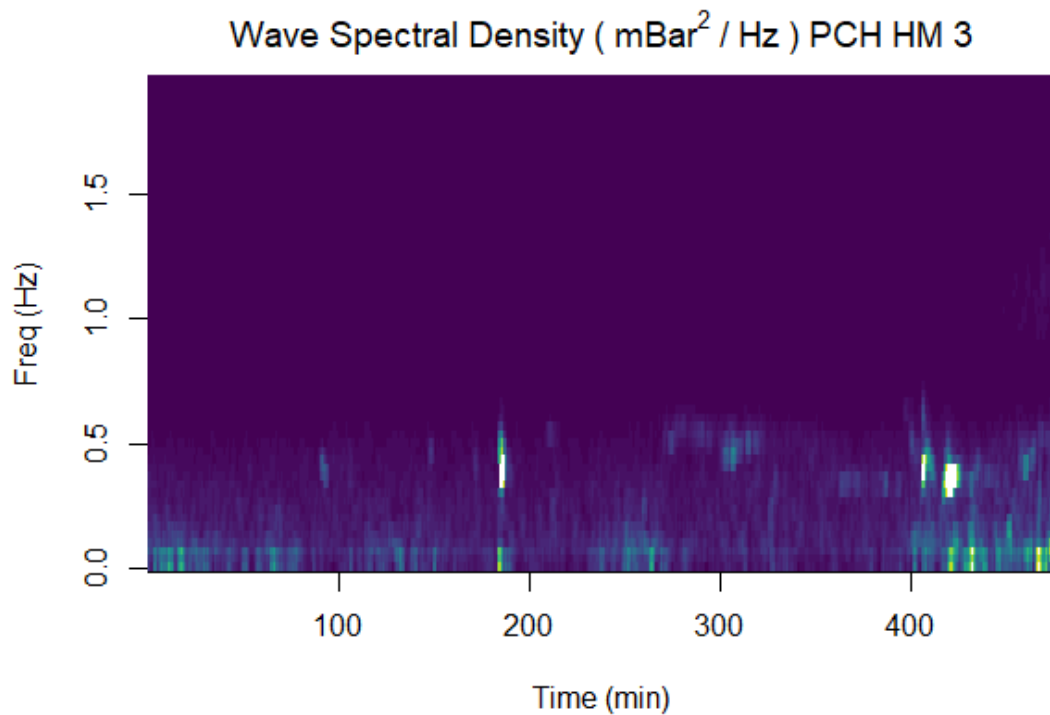


Figure C114. Wave spectral density over duration of full deployment at PCH High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

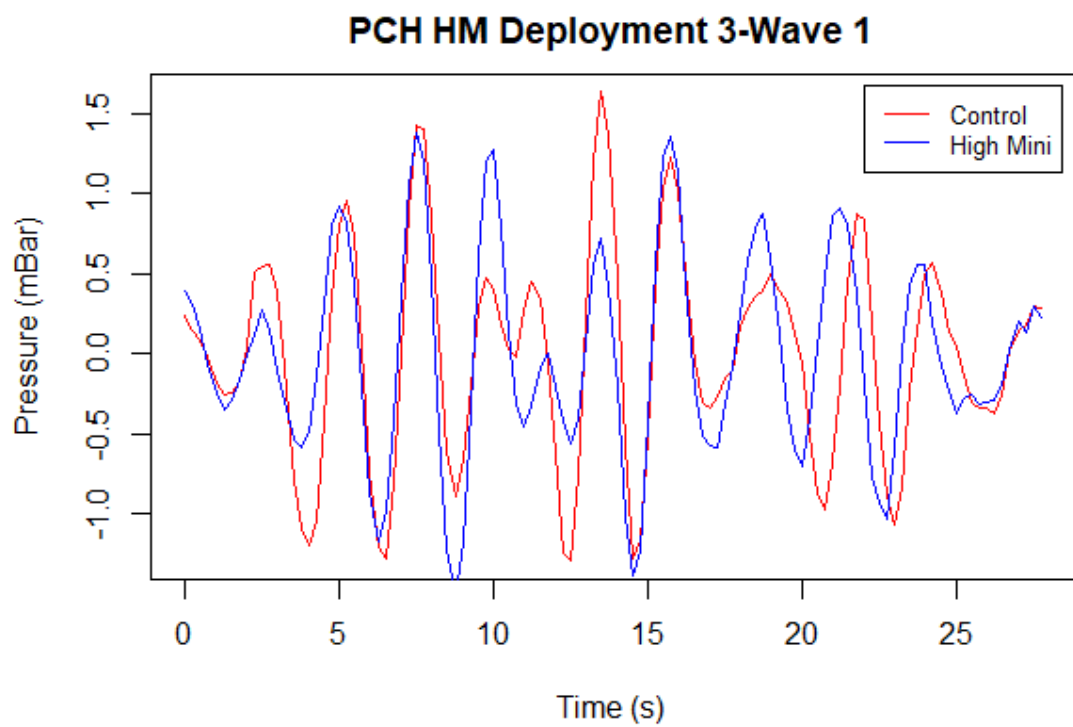


Figure C115. Progression of wave 1 over time at High Mini and High Mini control logger.

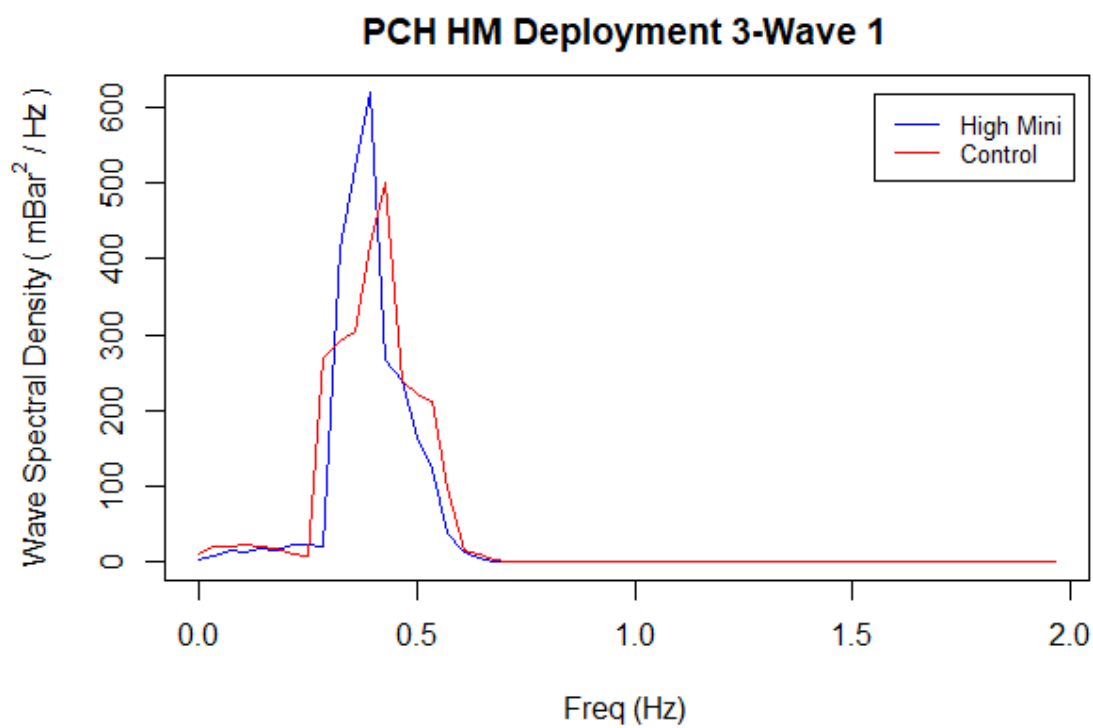


Figure C116. FFT of wave 1 over time at High Mini and High Mini control logger.

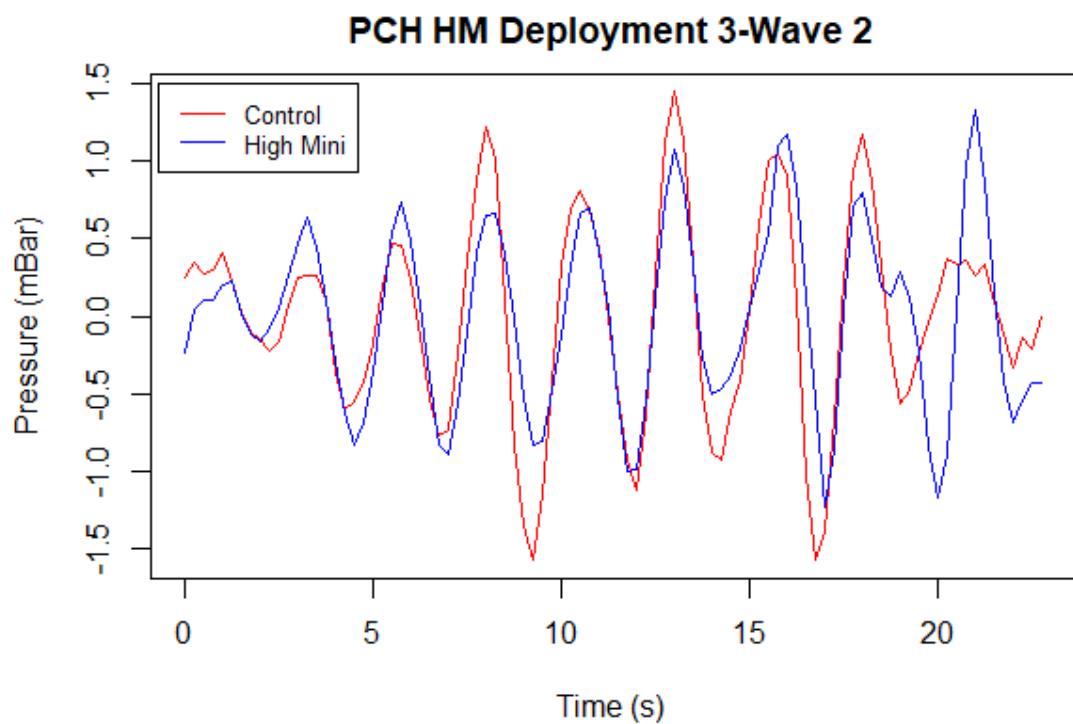


Figure C117. Progression of wave 2 over time at High Mini and High Mini control logger.

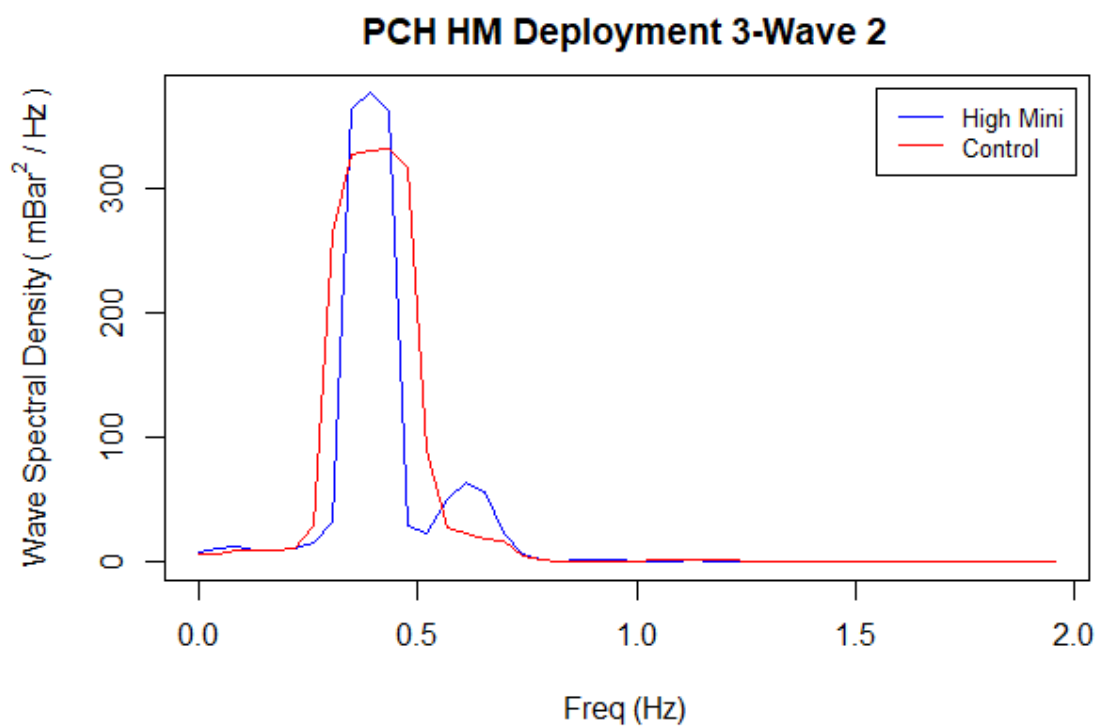


Figure C118. FFT of wave 2 over time at High Mini and High Mini control logger.

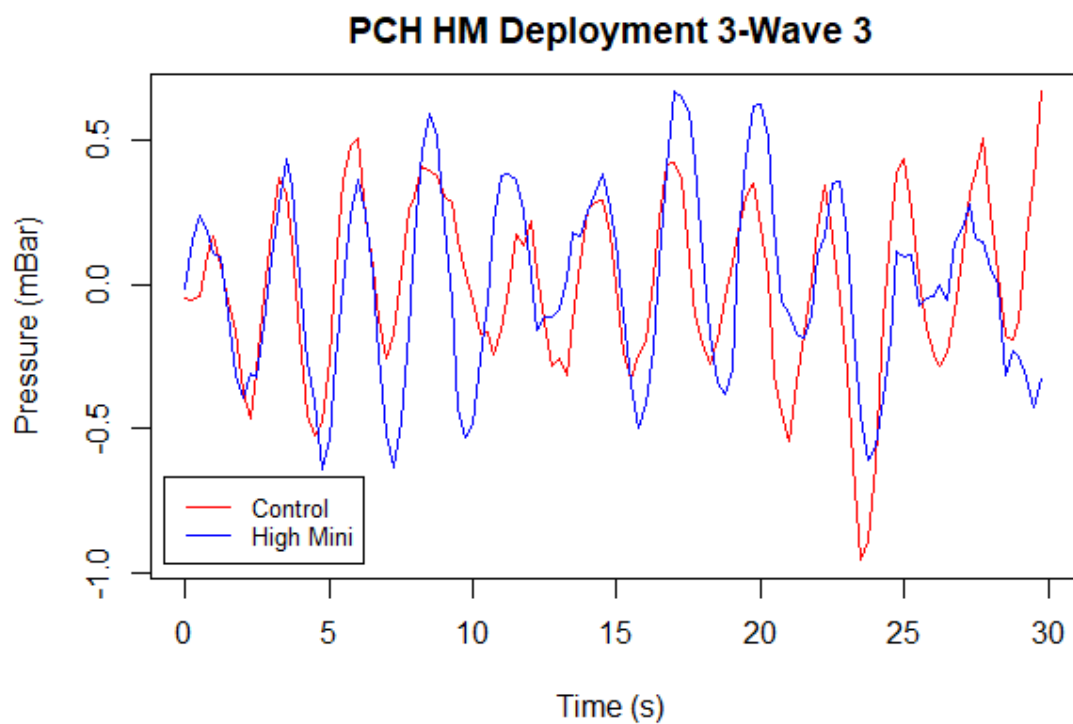


Figure C119. Progression of wave 3 over time at High Mini and High Mini control logger.

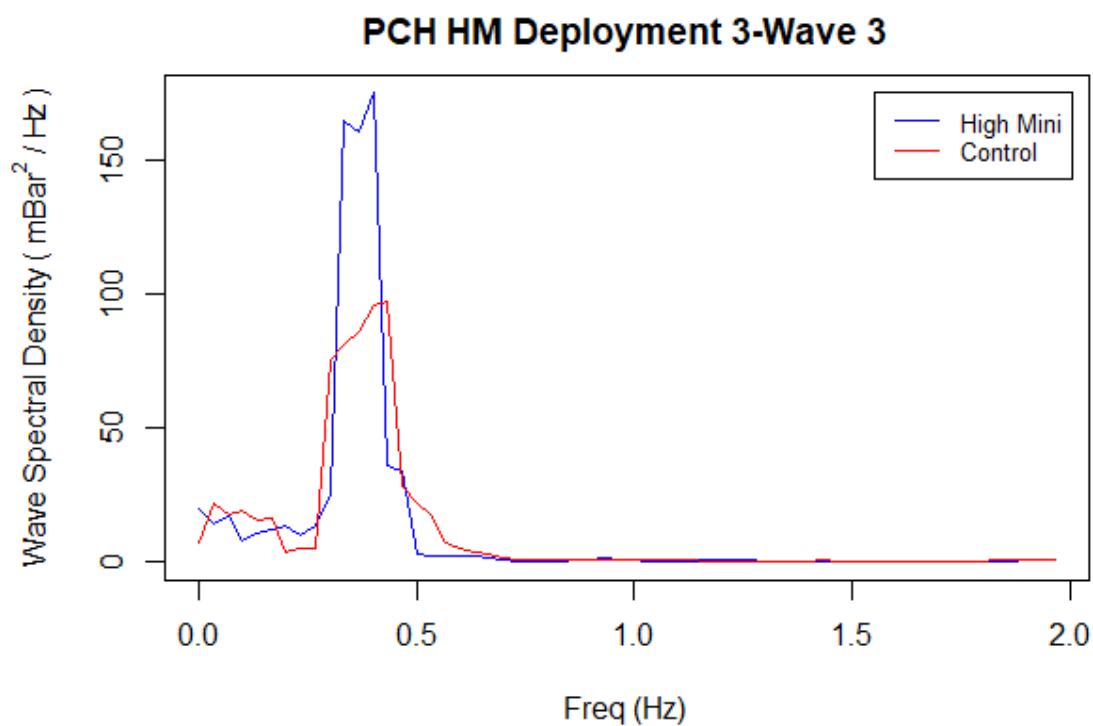


Figure C120. FFT of wave 3 over time at High Mini and High Mini control logger.

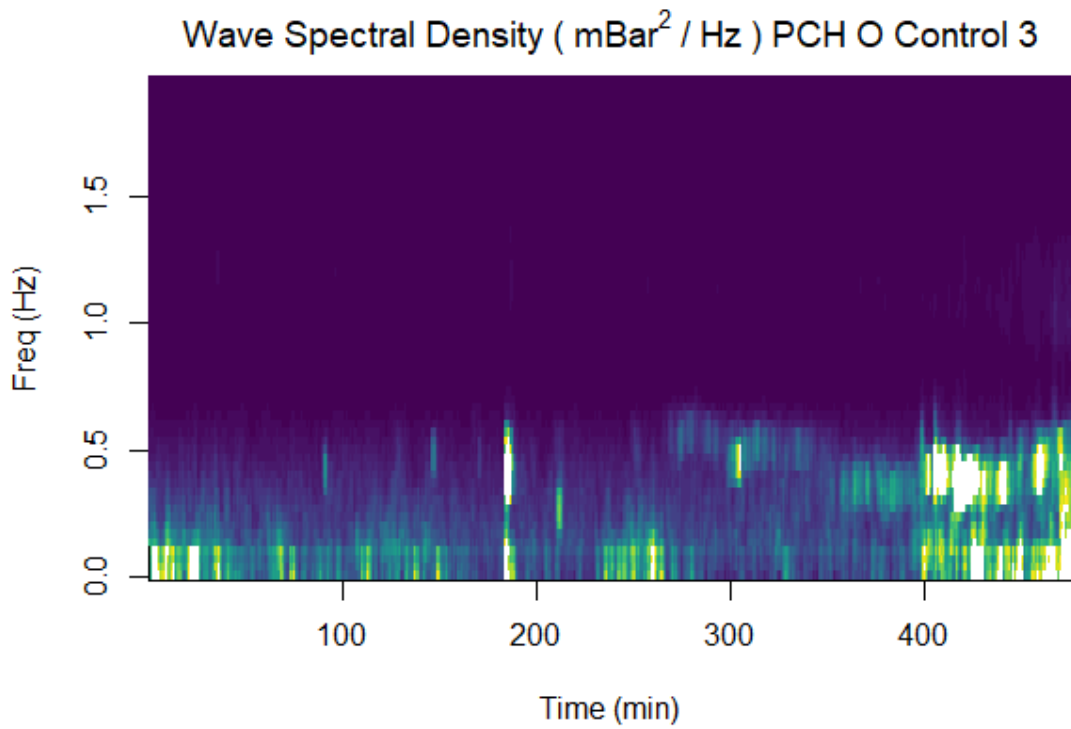


Figure C121. Wave spectral density over duration of full deployment at PCH Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

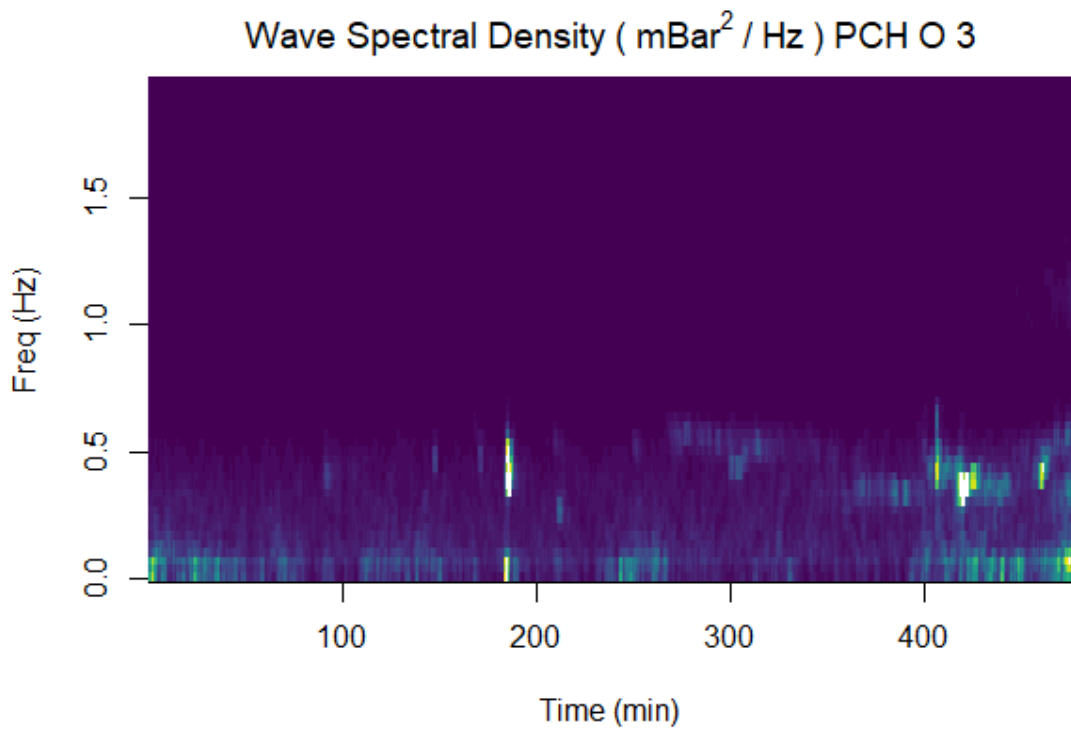


Figure C122. Wave spectral density over duration of full deployment at PCH Oyster logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

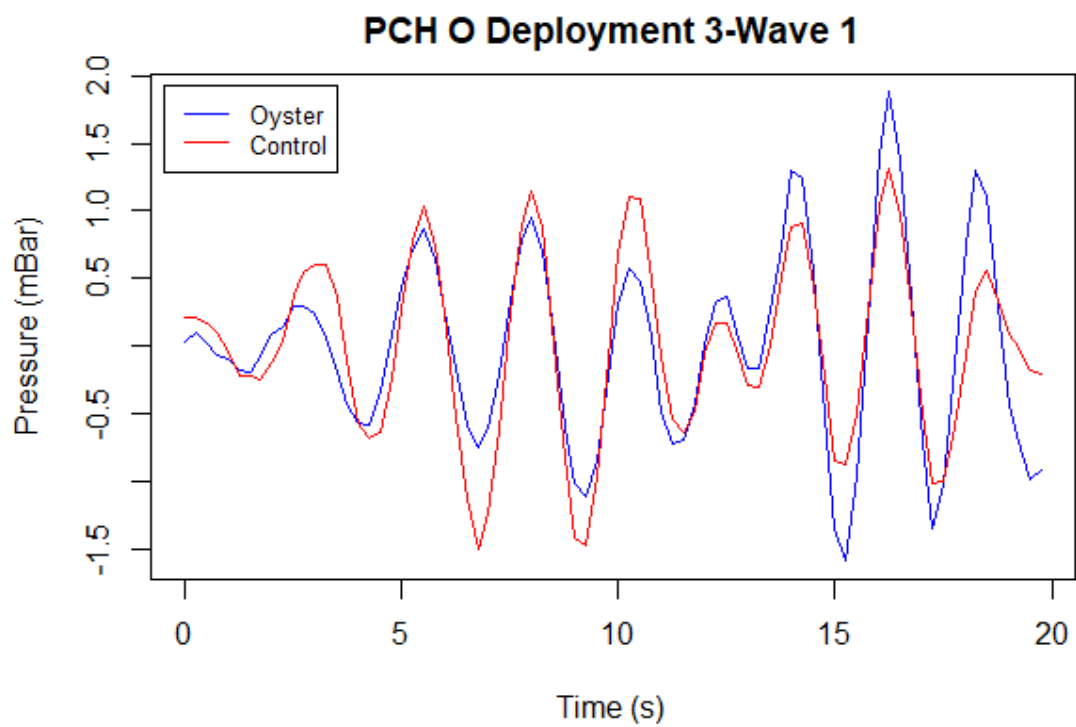


Figure C123. Progression of wave 1 over time at Oyster and Oyster control logger.

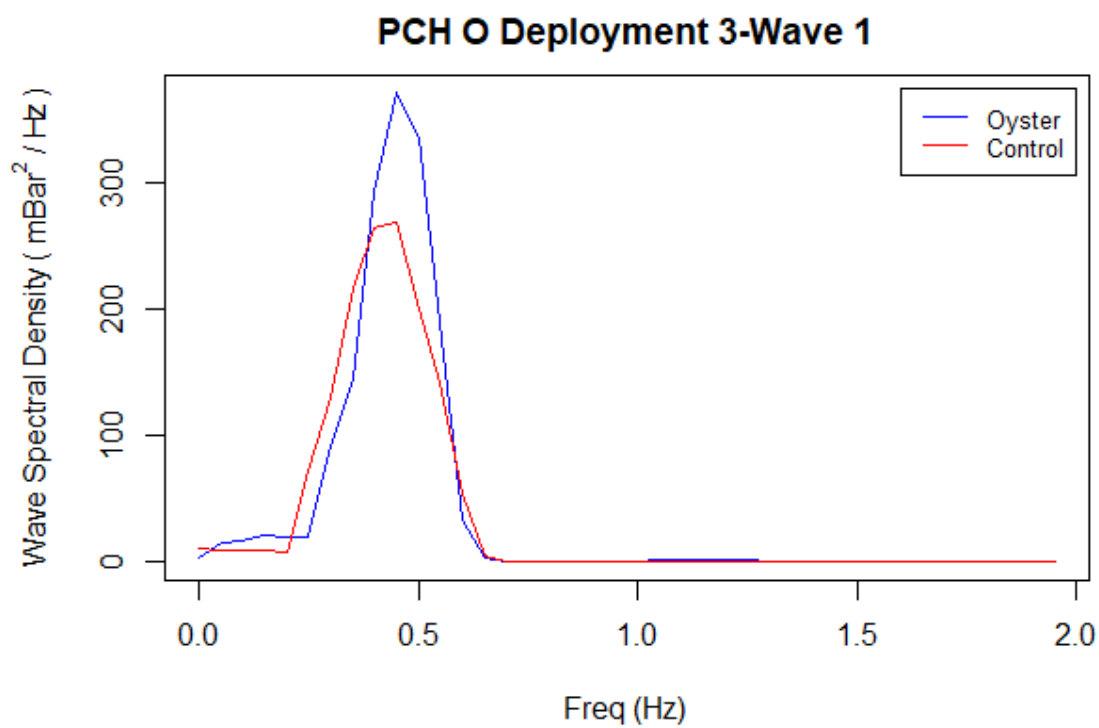


Figure C124. FFT of wave 1 over time at Oyster and Oyster control logger.

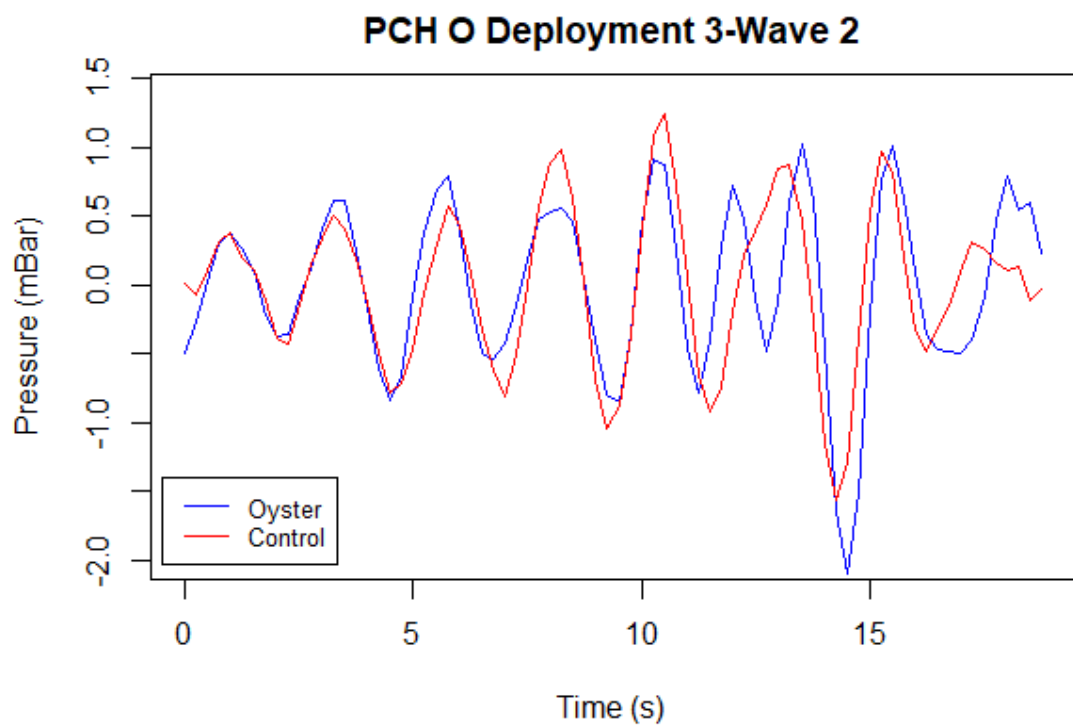


Figure C125. Progression of wave 2 over time at Oyster and Oyster control logger.

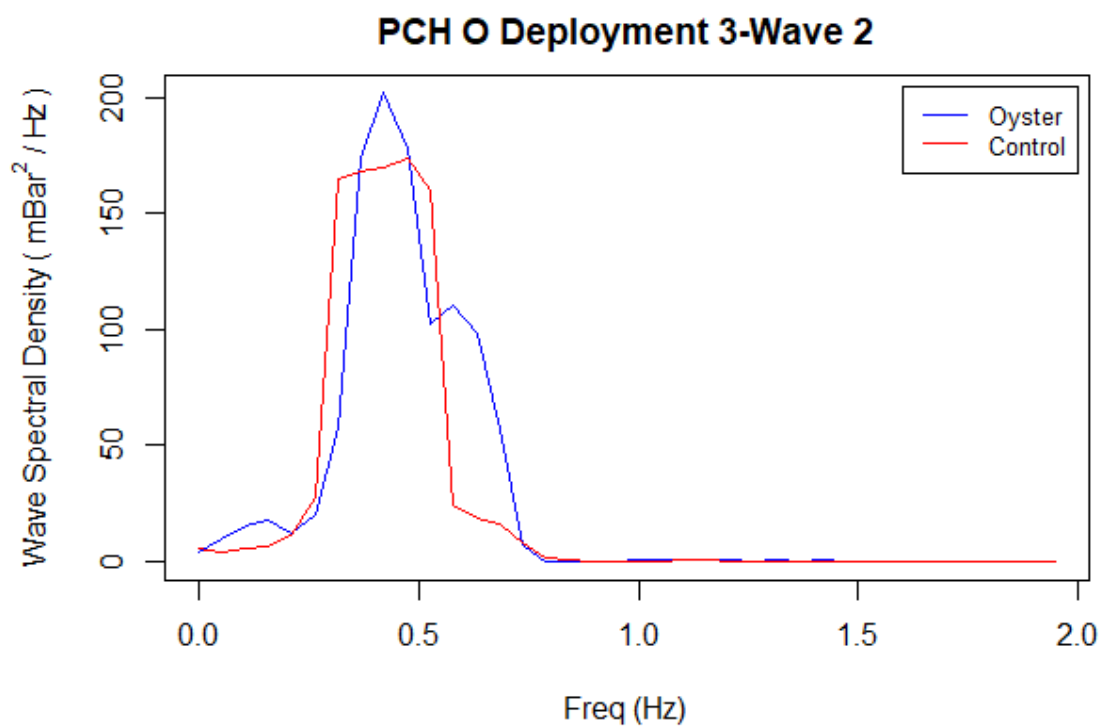


Figure C126. FFT of wave 2 over time at Oyster and Oyster control logger.

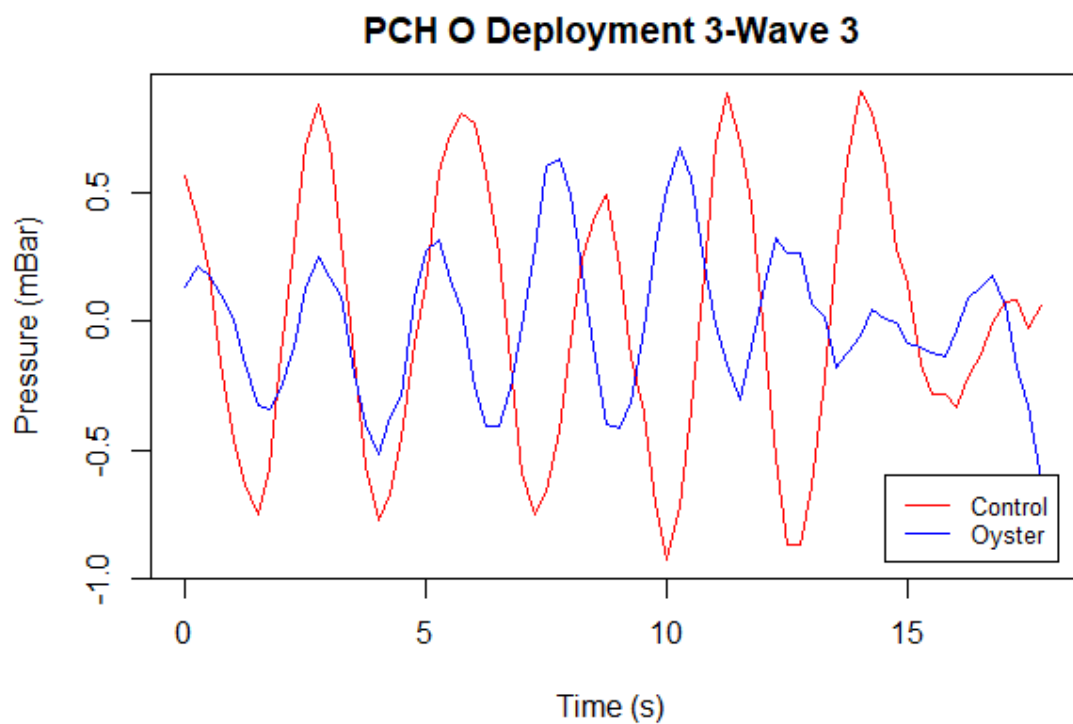


Figure C127. Progression of wave 3 over time at Oyster and Oyster control logger.

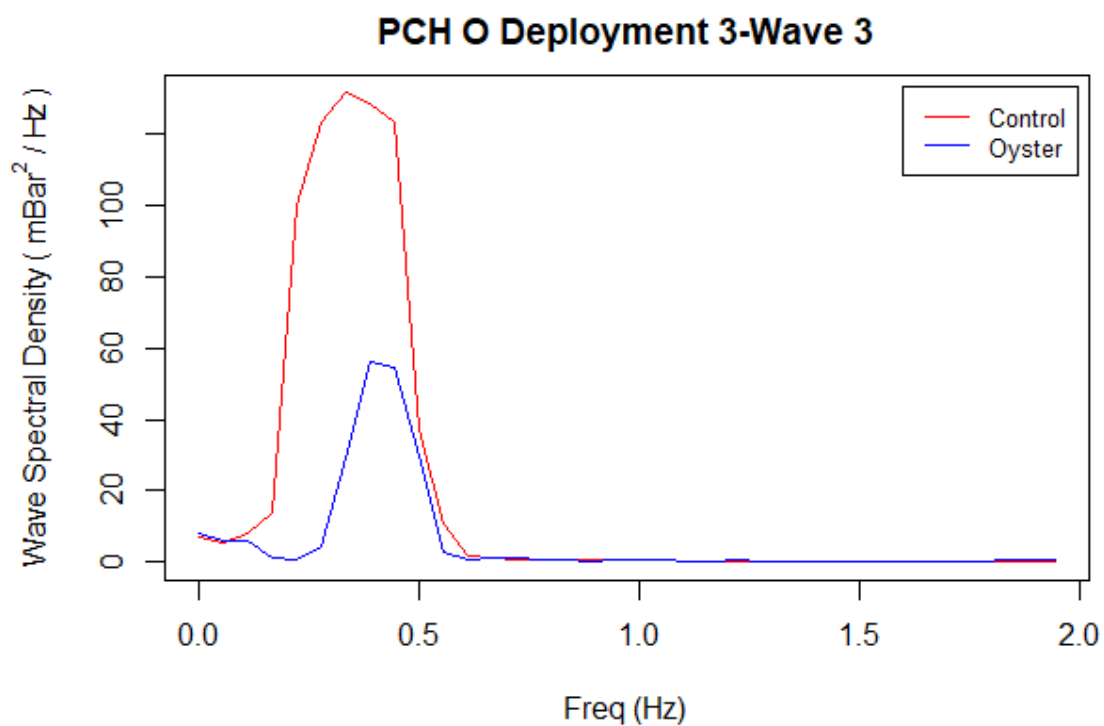


Figure C128. FFT of wave 3 over time at Oyster and Oyster control logger.

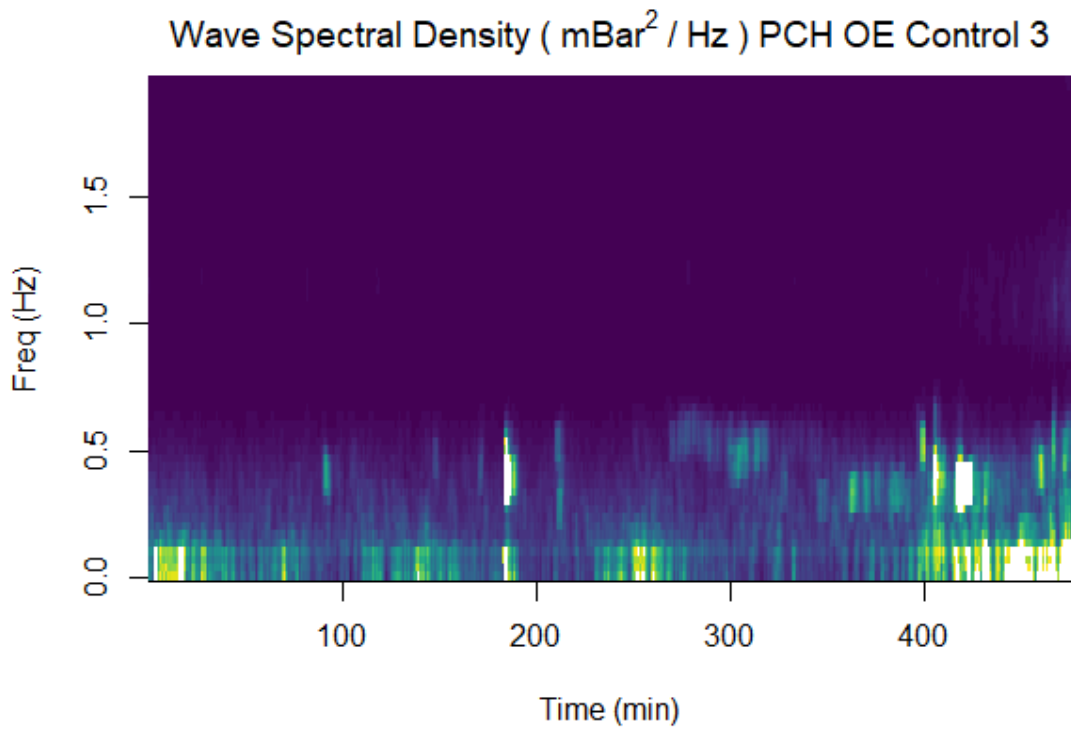


Figure C129. Wave spectral density over duration of full deployment at PCH Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

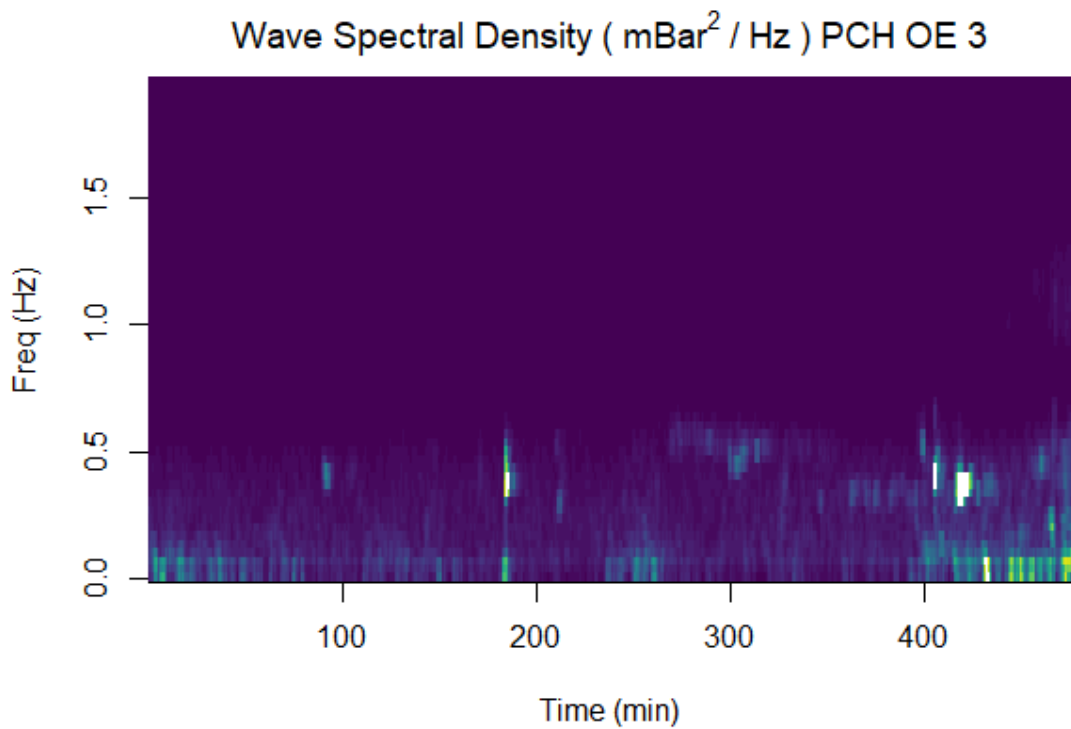


Figure C130. Wave spectral density over duration of full deployment at PCH Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

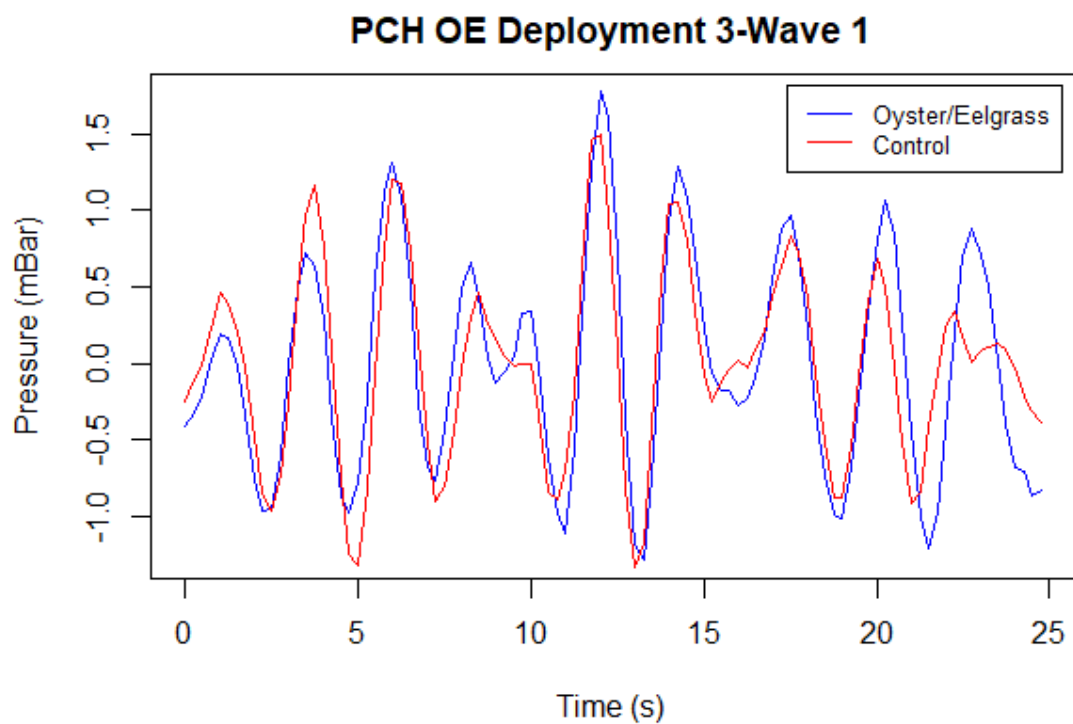


Figure C131. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

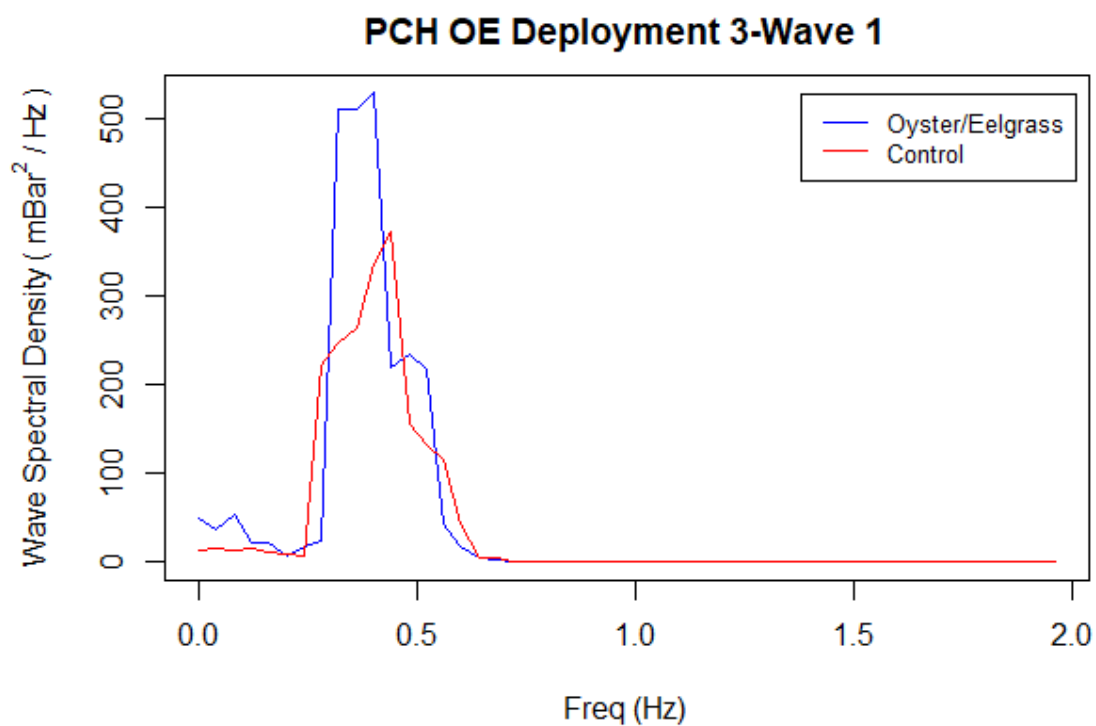


Figure C132. FFT of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

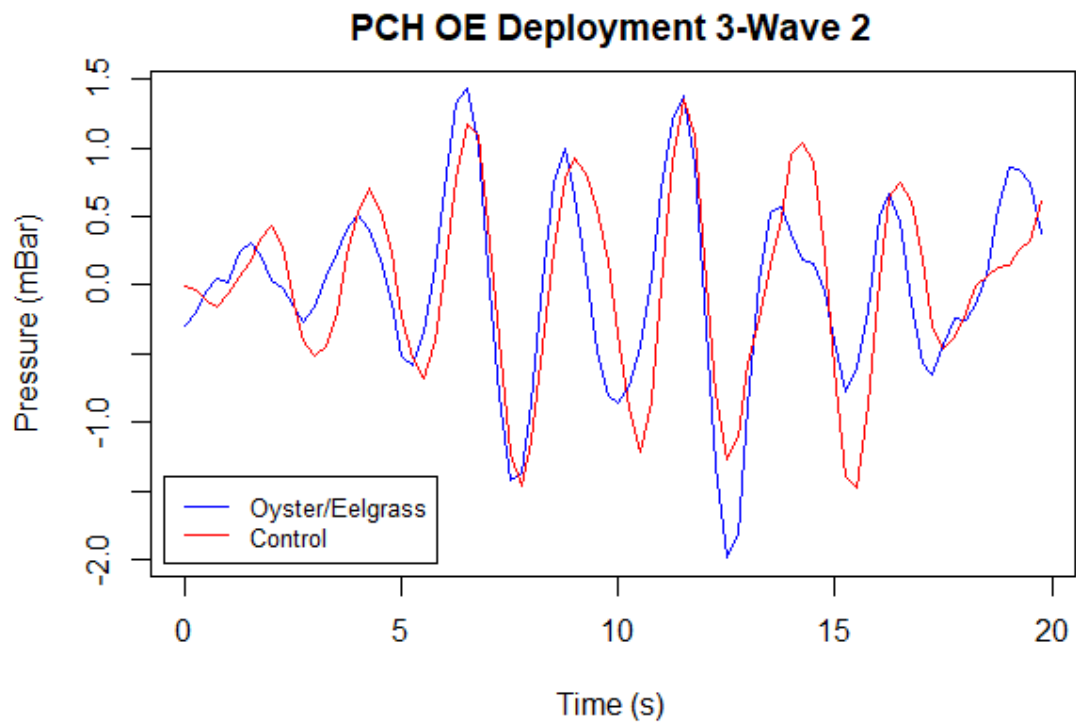


Figure C133. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

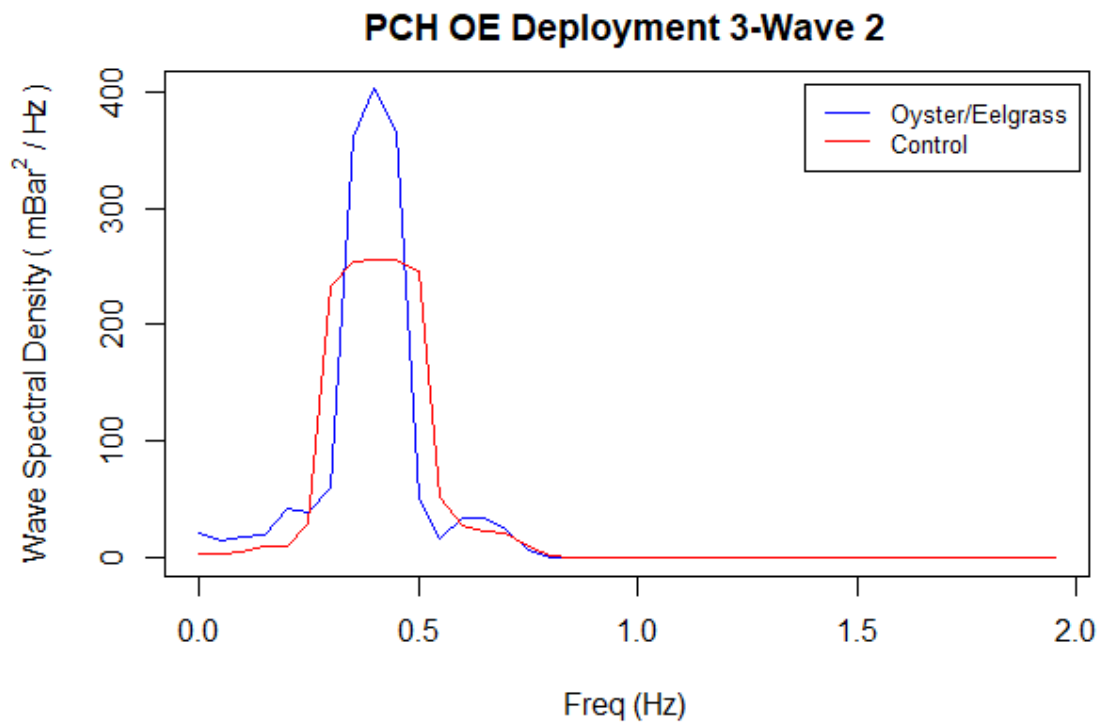


Figure C134. FFT of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

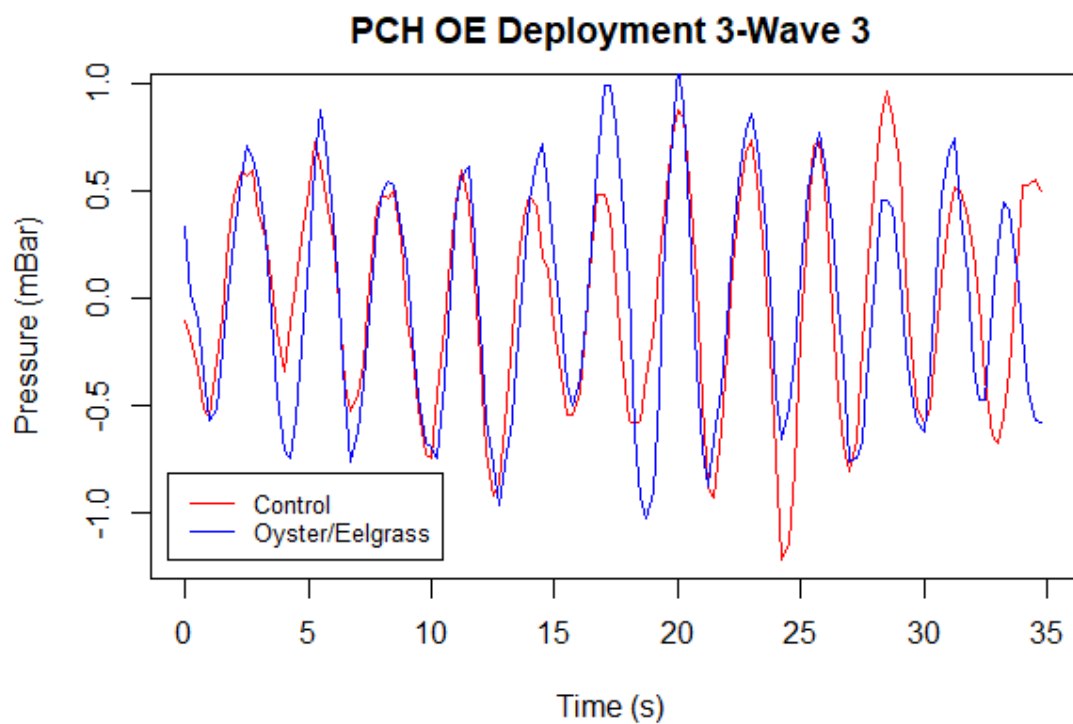


Figure C135. Progression of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

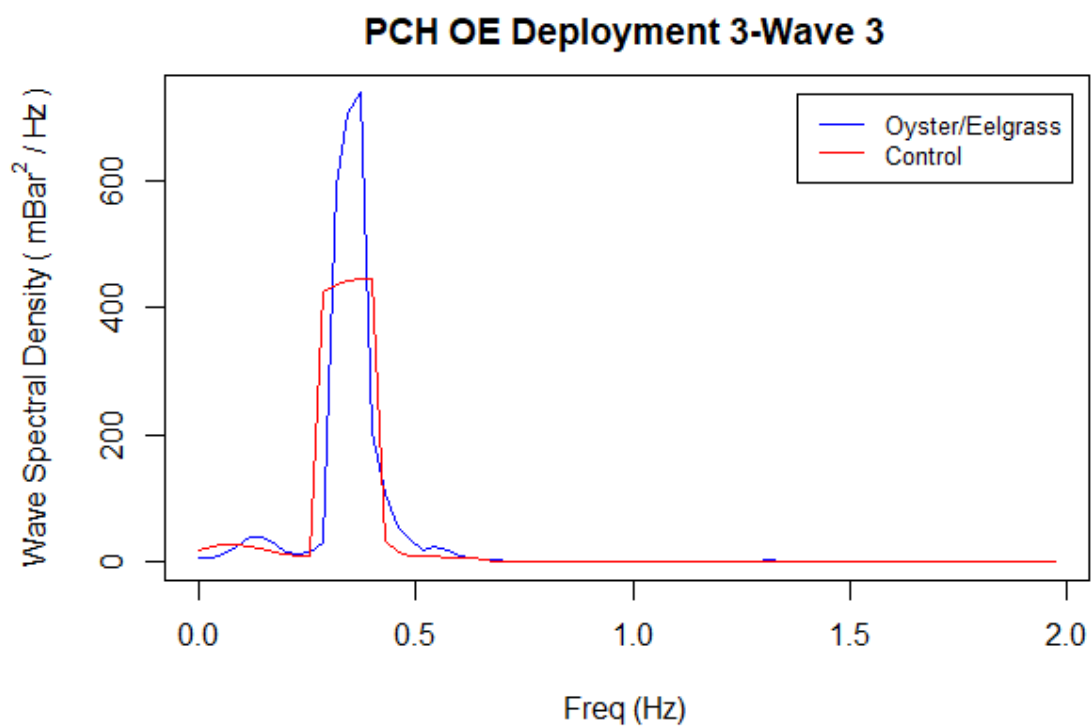


Figure C136. FFT of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

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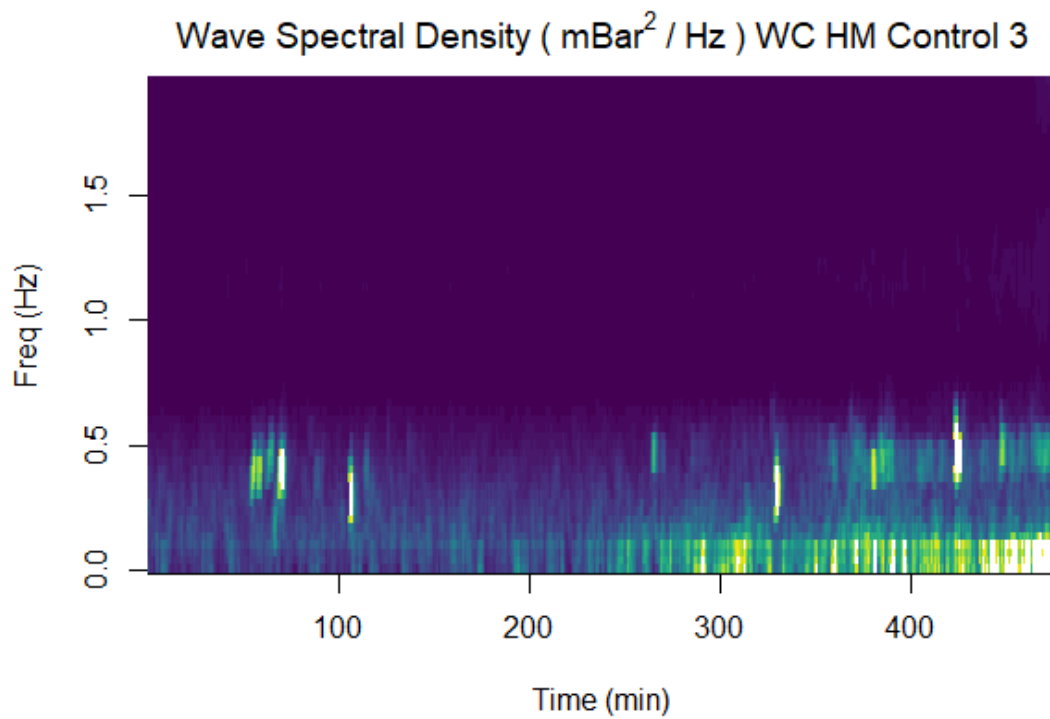


Figure C137. Wave spectral density over duration of full deployment at Westcliff High Mini control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

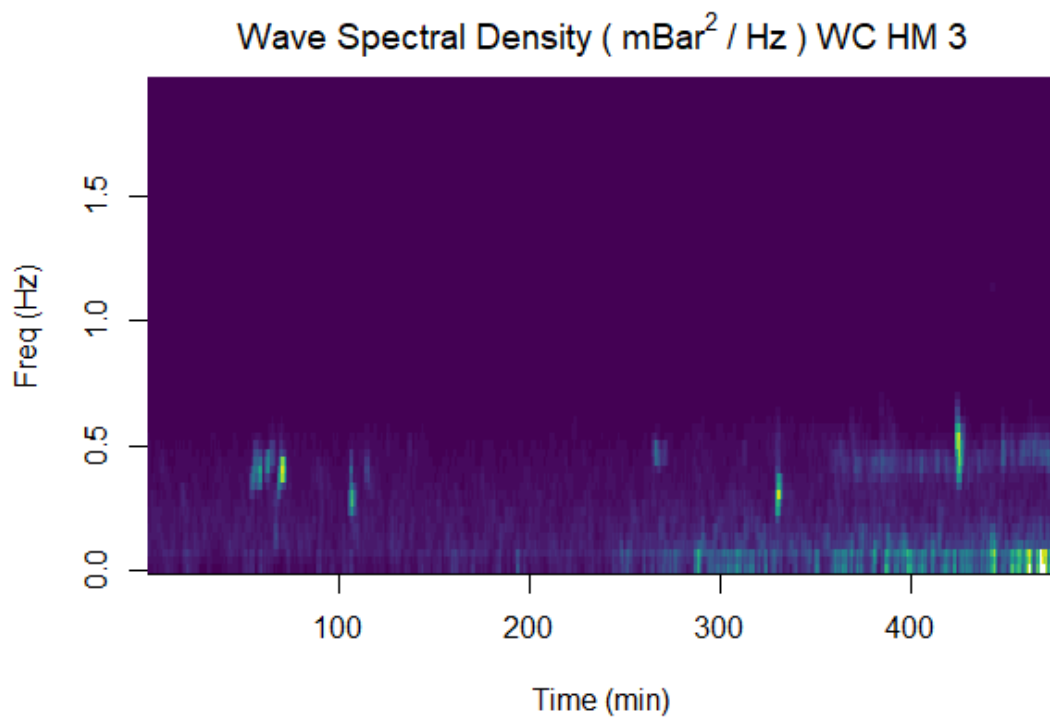


Figure C138. Wave spectral density over duration of full deployment at Westcliff High Mini logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

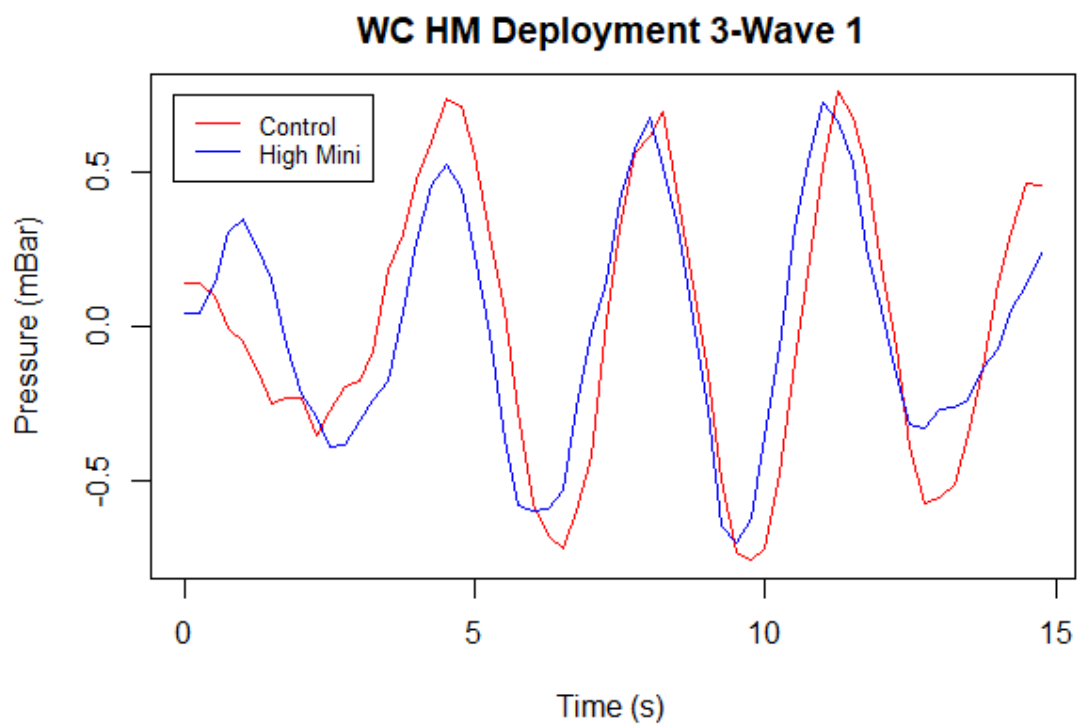


Figure C139. Progression of wave 1 over time at High Mini and High Mini control logger.

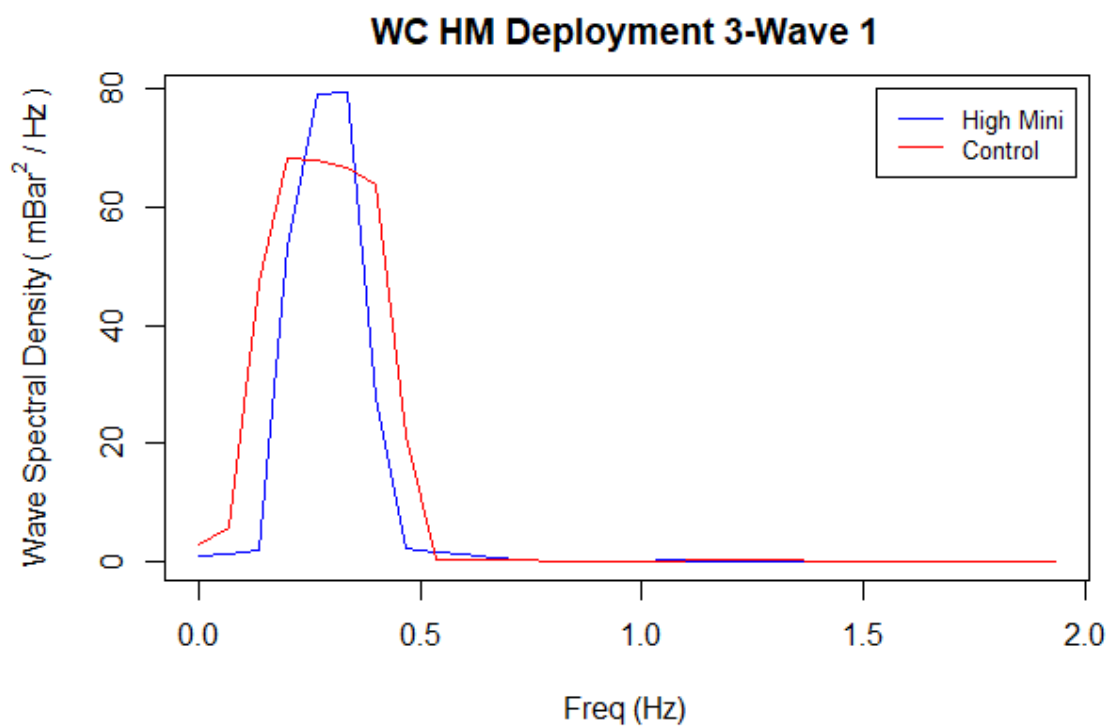


Figure C140 FFT. of wave 1 over time at High Mini and High Mini control logger.

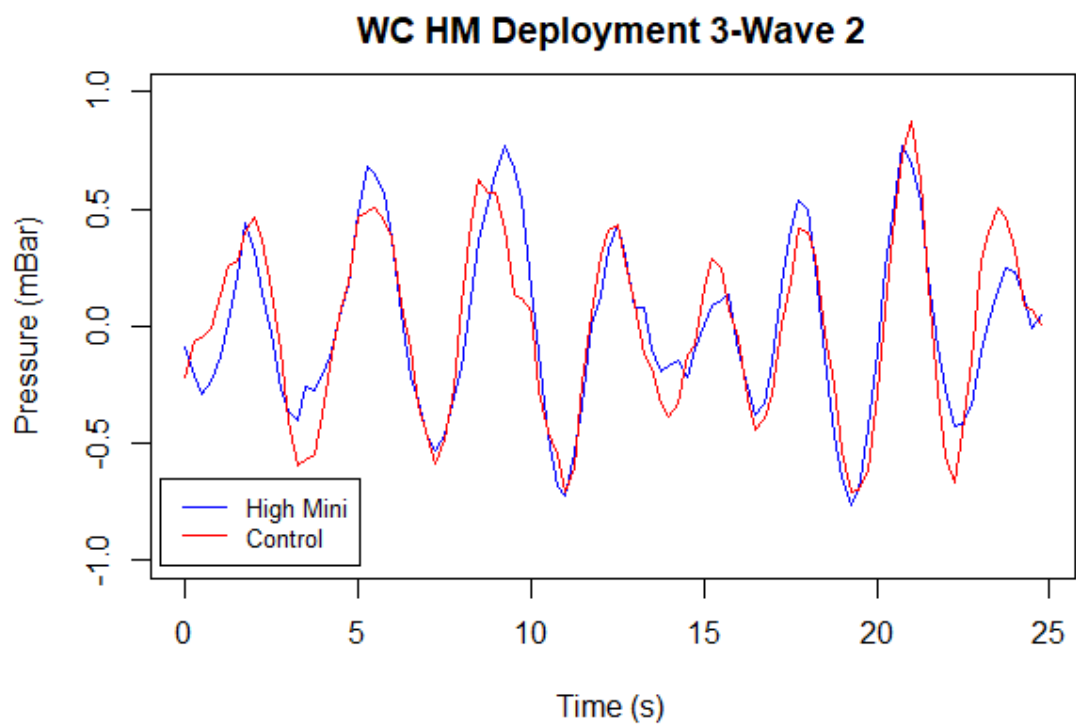


Figure C141. Progression of wave 2 over time at High Mini and High Mini control logger.

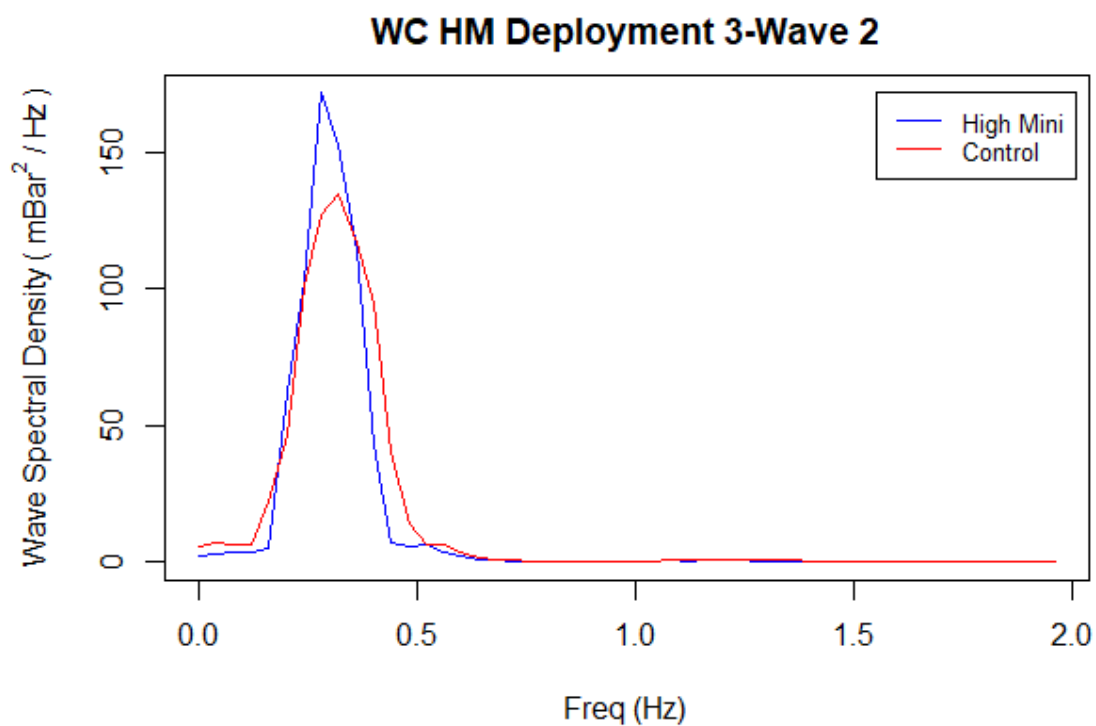


Figure C142. FFT of wave 2 over time at High Mini and High Mini control logger.

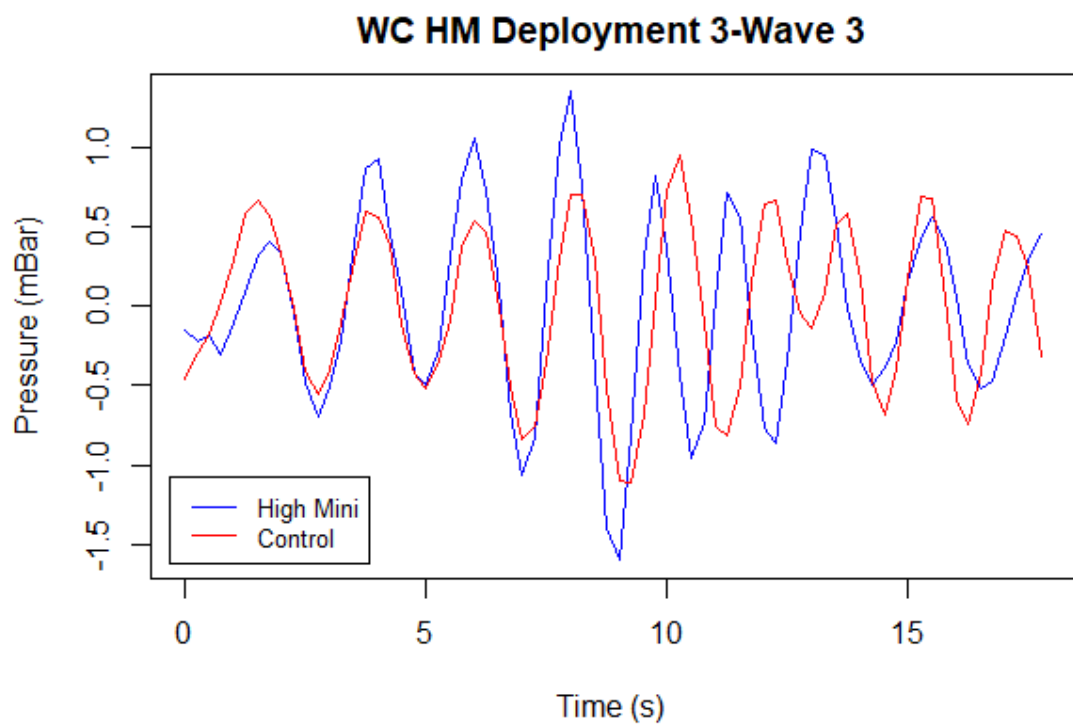


Figure C143. Progression of wave 3 over time at High Mini and High Mini control logger.

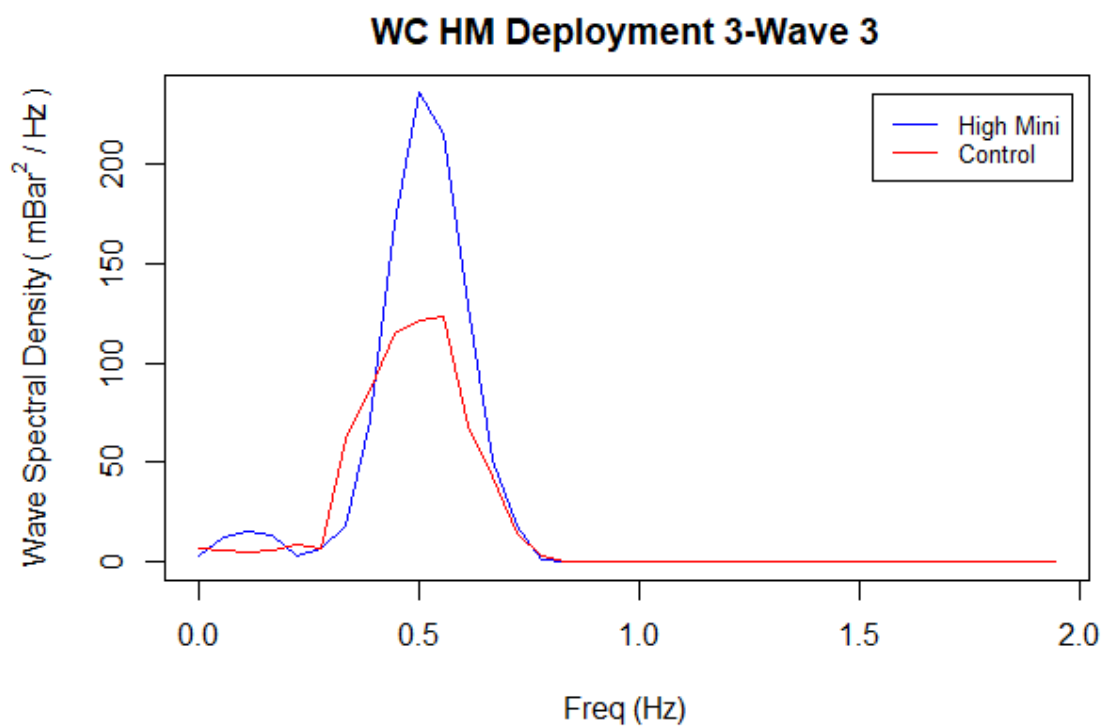


Figure C144. FFT of wave 3 over time at High Mini and High Mini control logger.

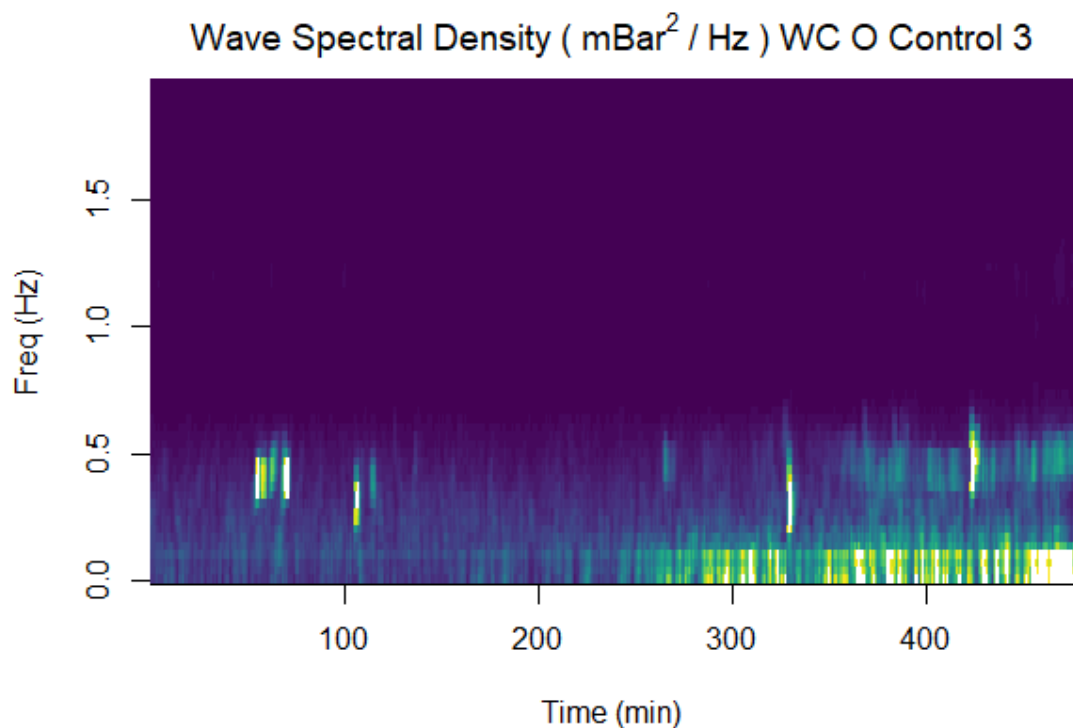


Figure C145. Wave spectral density over duration of full deployment at Westcliff Oyster control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

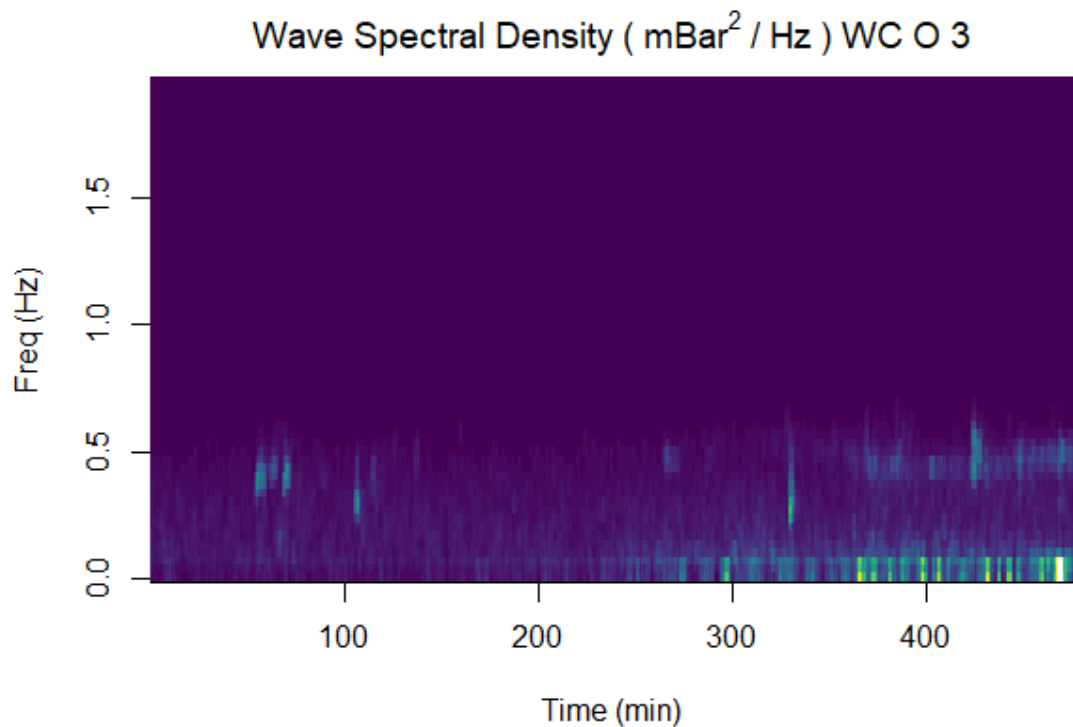


Figure C146. Wave spectral density over duration of full deployment at Westcliff Oyster logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

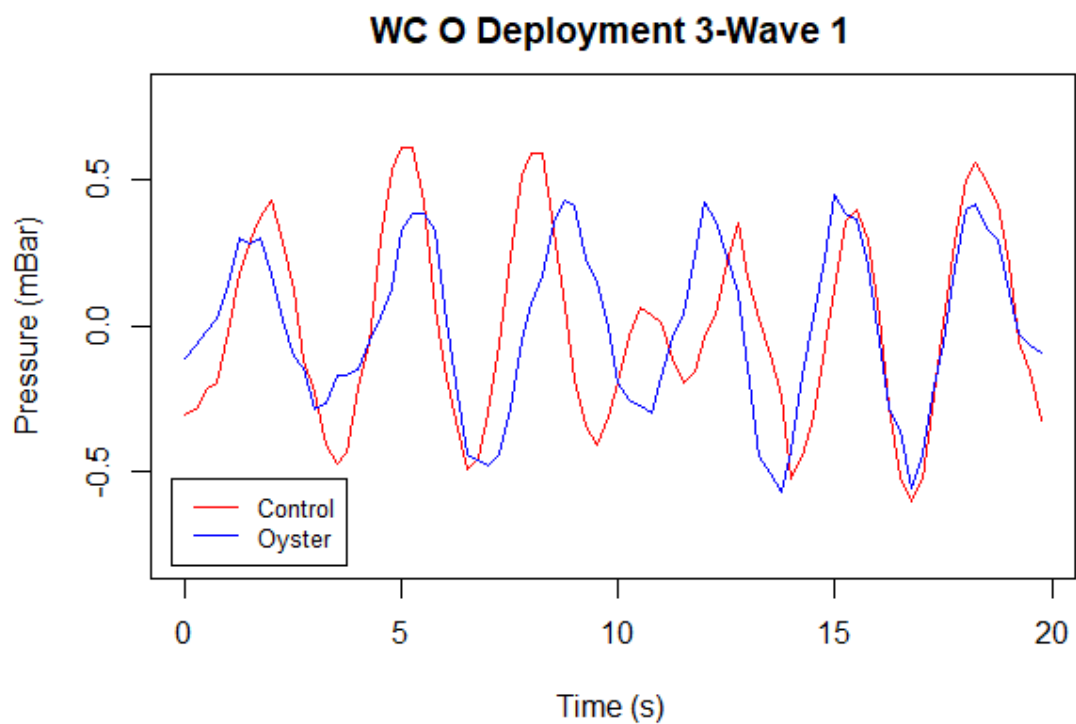


Figure C147. Progression of wave 1 over time at Oyster and Oyster control logger.

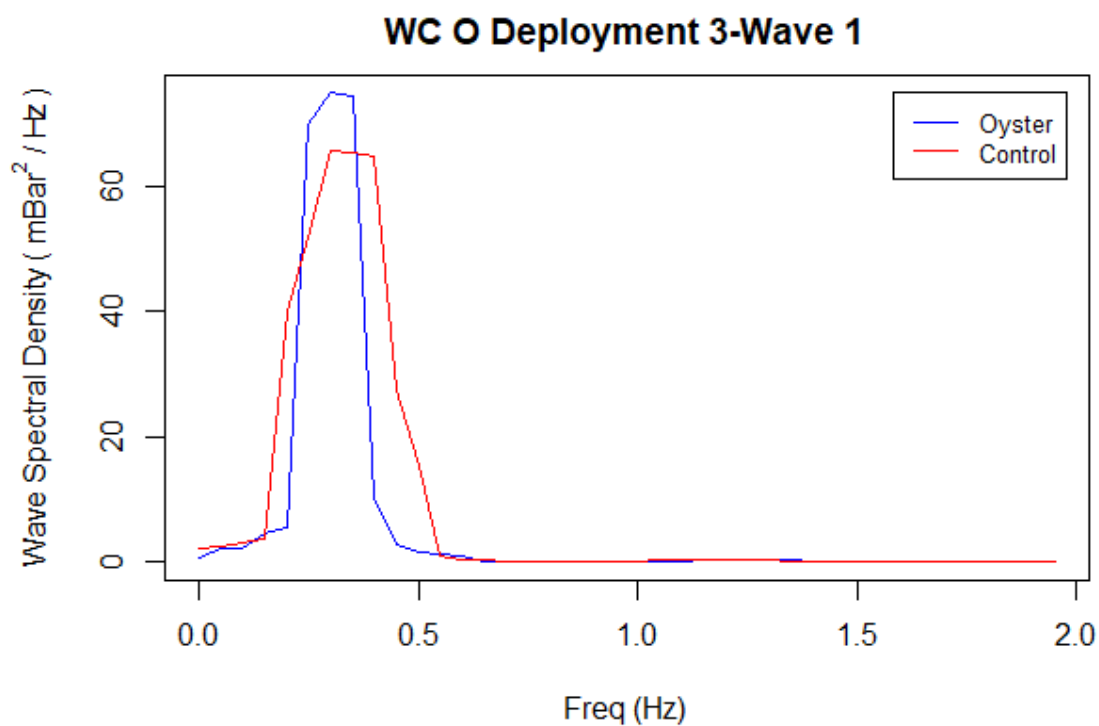


Figure C148. FFT of wave 1 over time at Oyster and Oyster control logger.

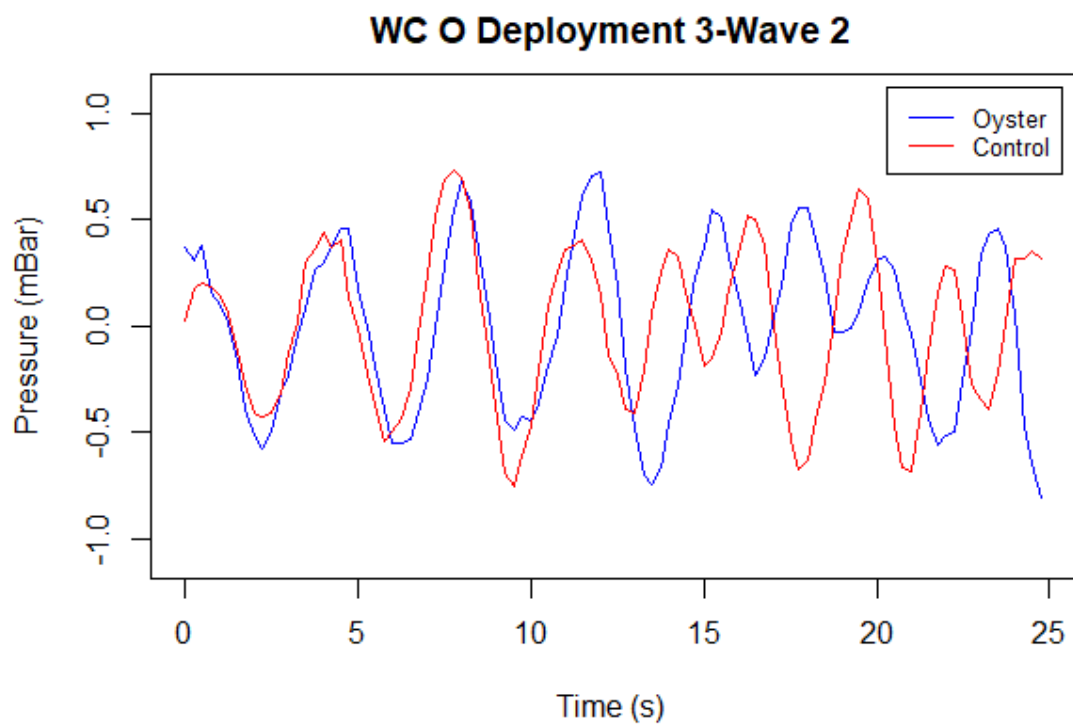


Figure C149. Progression of wave 2 over time at Oyster and Oyster control logger.

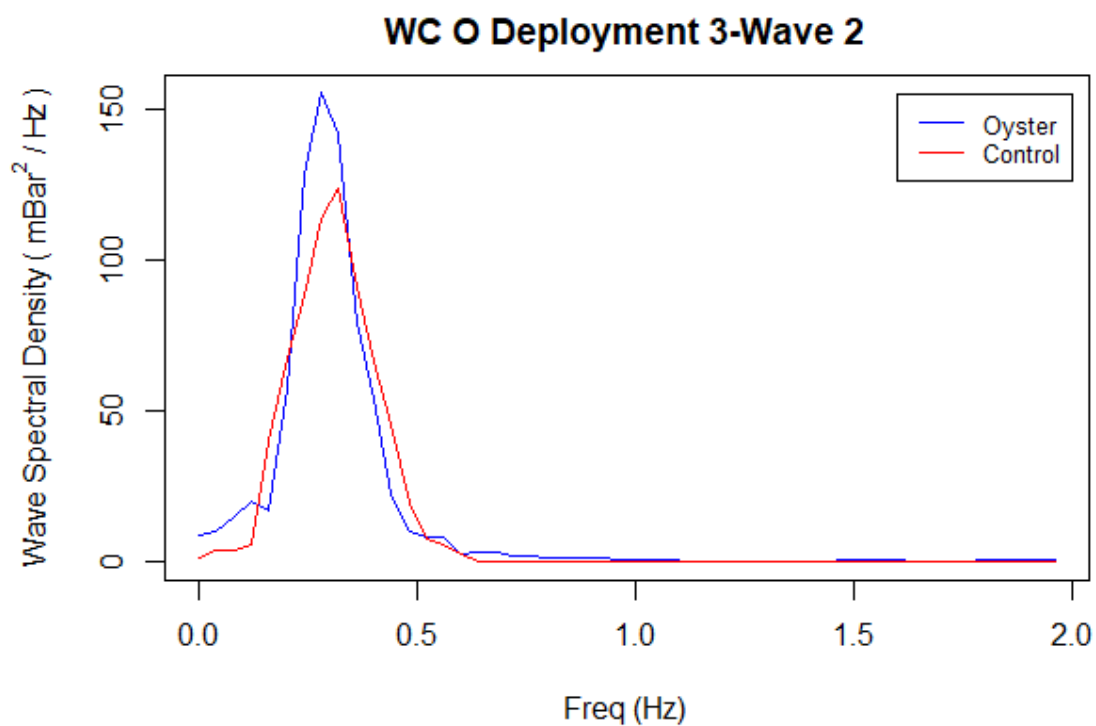


Figure C150. FFT of wave 2 over time at Oyster and Oyster control logger.

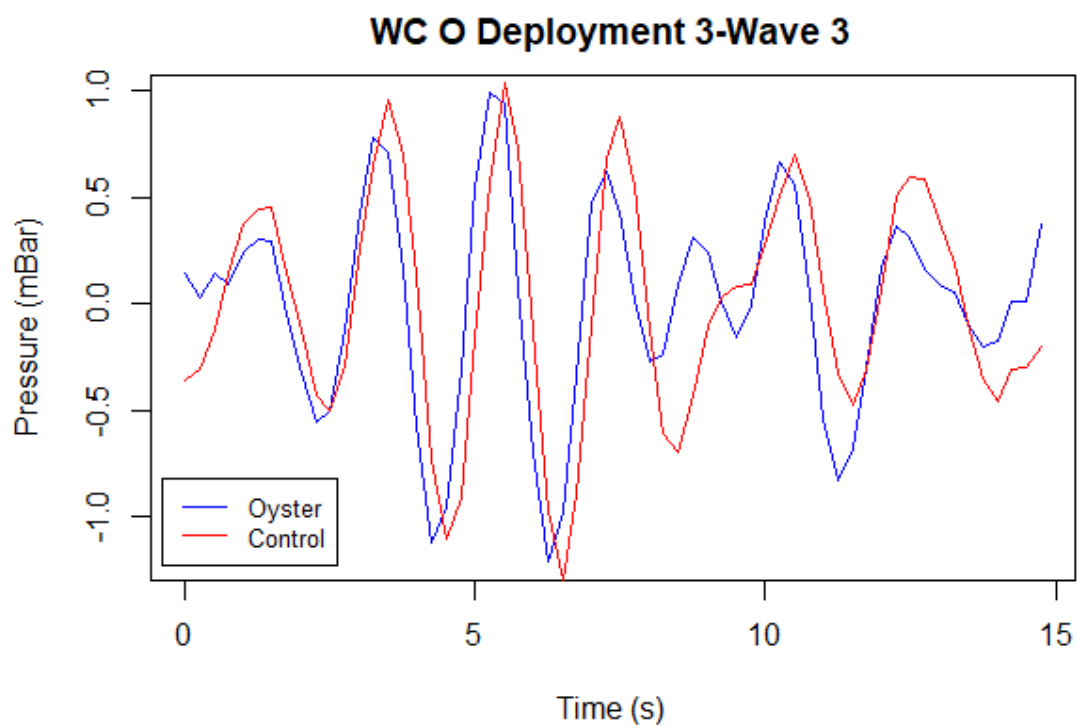


Figure C151. Progression of wave 3 over time at Oyster and Oyster control logger.

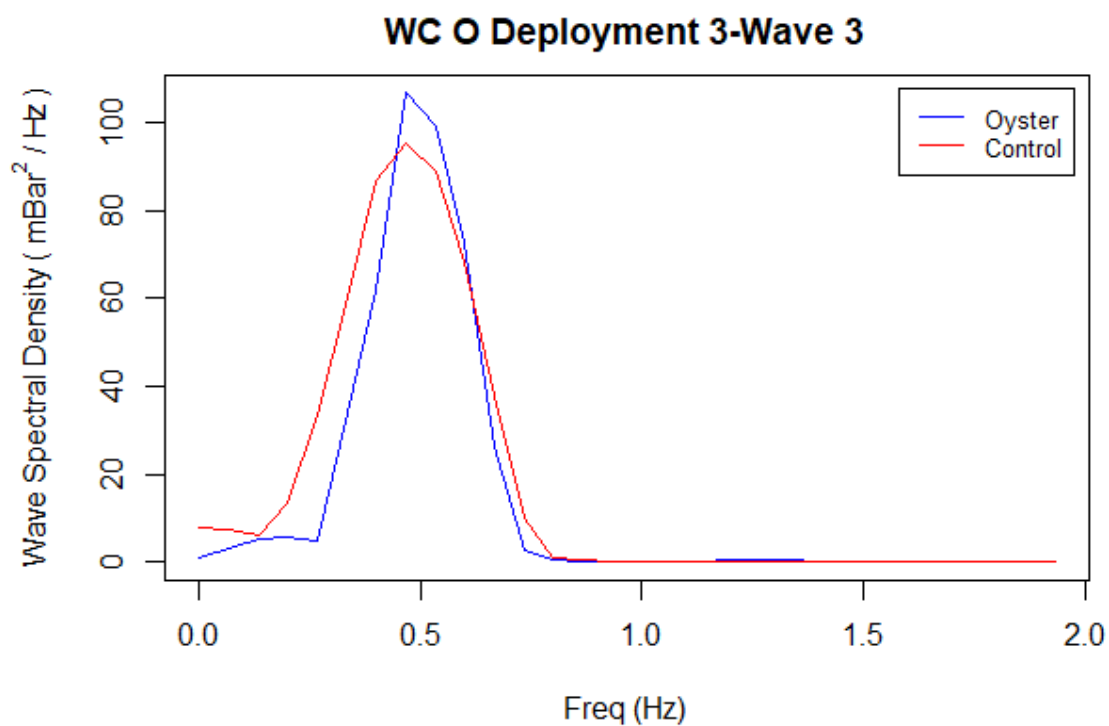


Figure C152. FFT of wave 3 over time at Oyster and Oyster control logger.

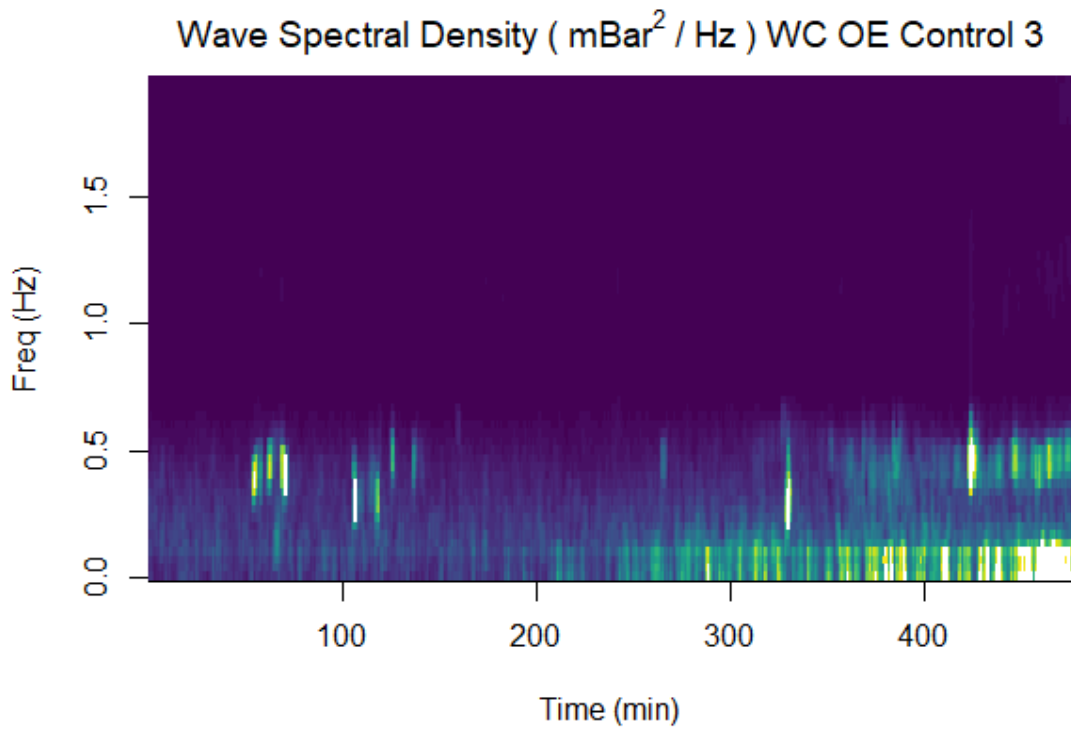


Figure C153. Wave spectral density over duration of full deployment at Westcliff Oyster/Eelgrass control logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

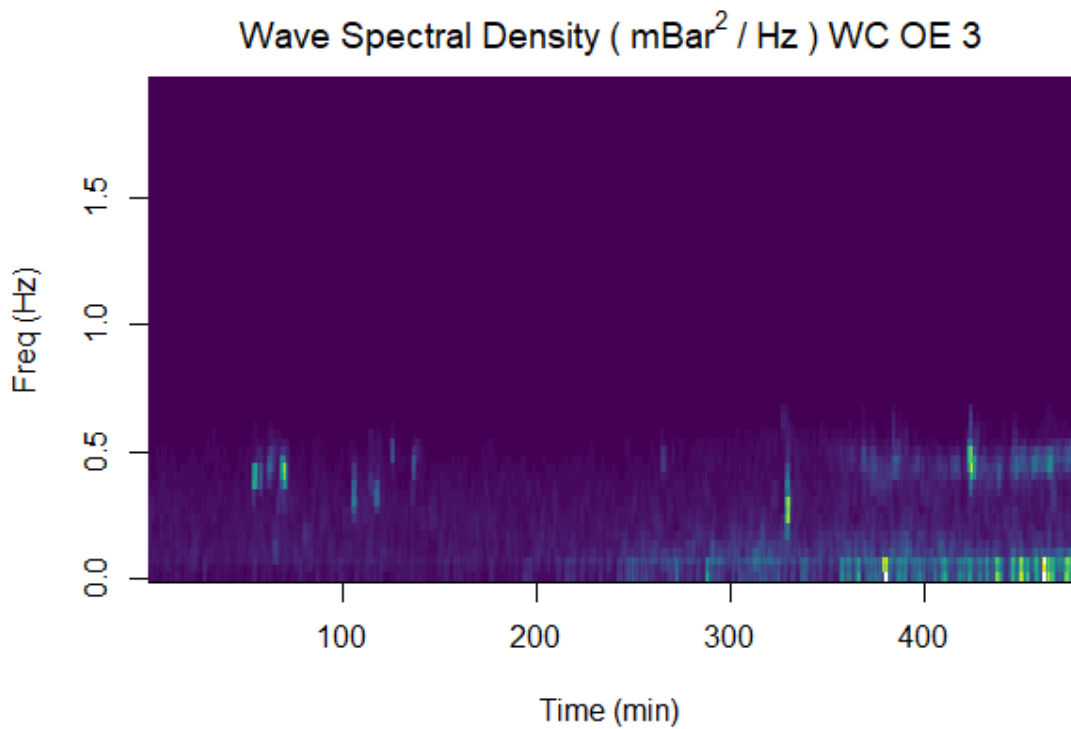


Figure C154. Wave spectral density over duration of full deployment at Westcliff Oyster/Eelgrass logger. Boat wakes are indicated by bright white “chirp” signals between 0.05-1 Hz.

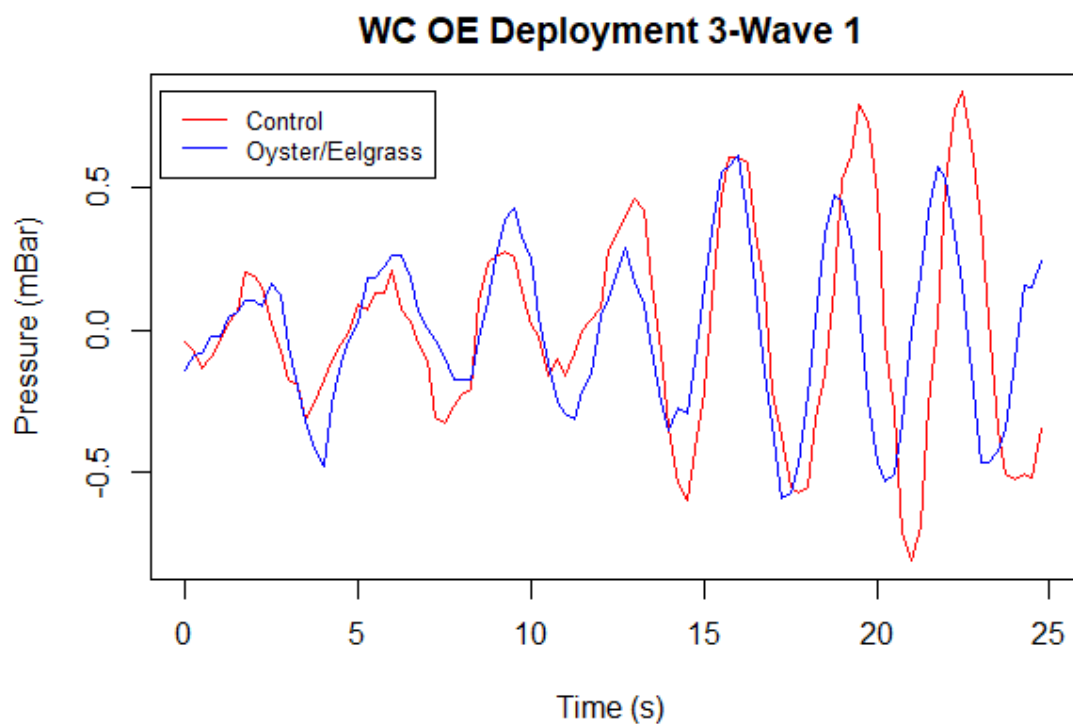


Figure C155. Progression of wave 1 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

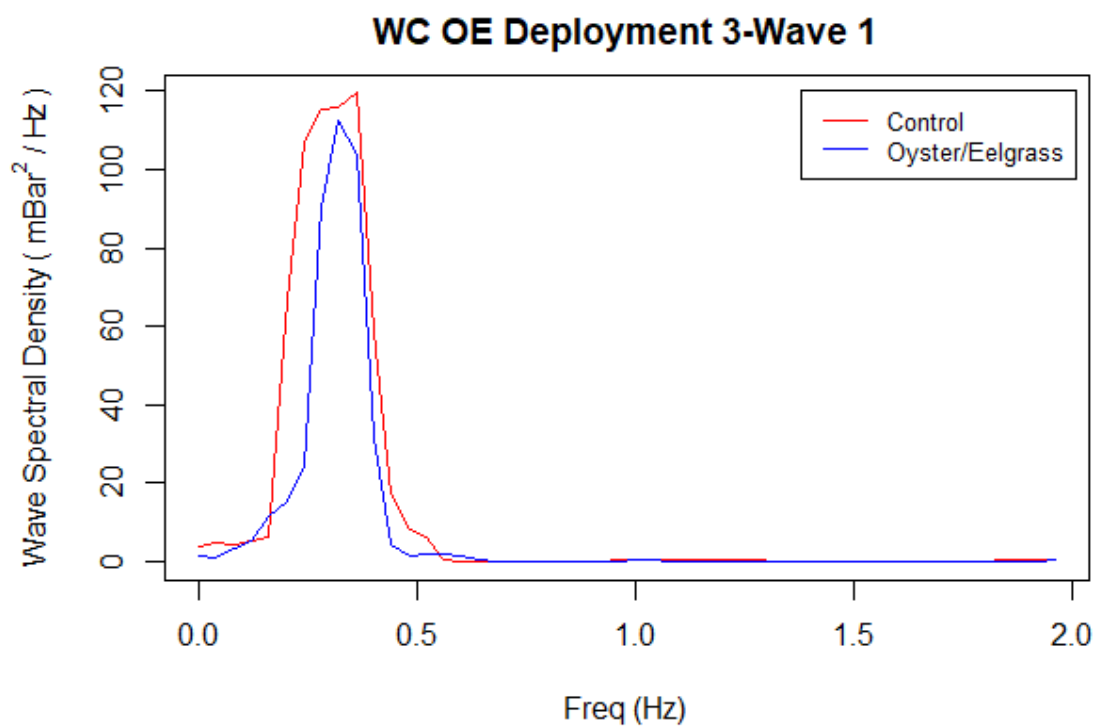


Figure C156. FFT of wave 1 over time at Oyster and Oyster control logger.

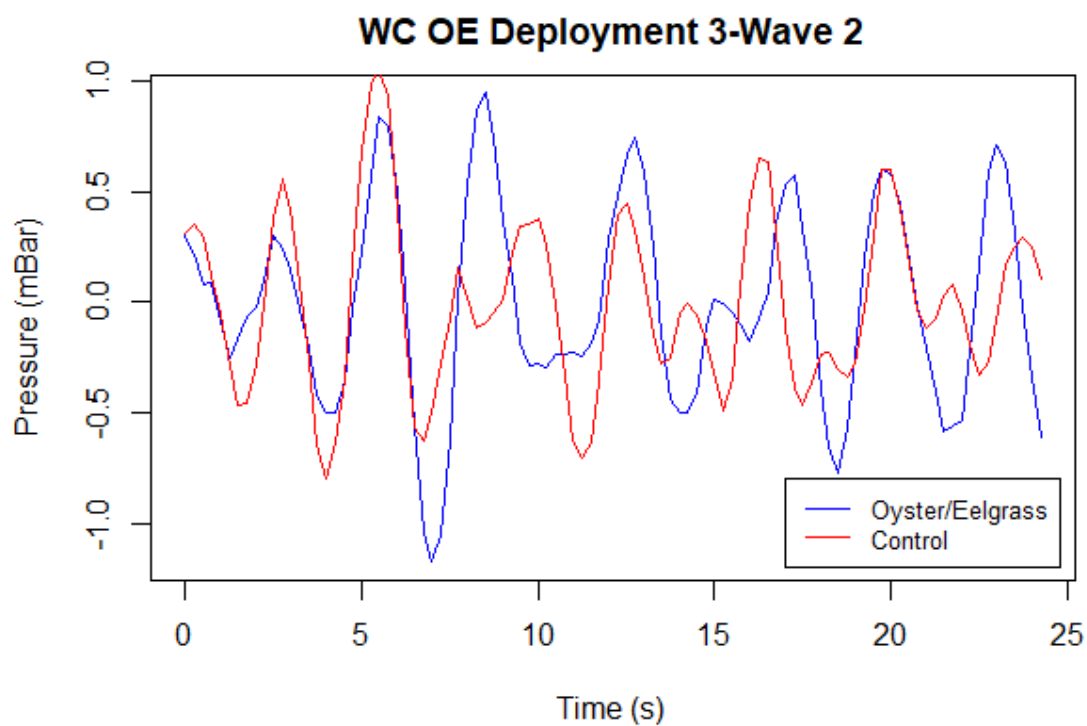


Figure C157. Progression of wave 2 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

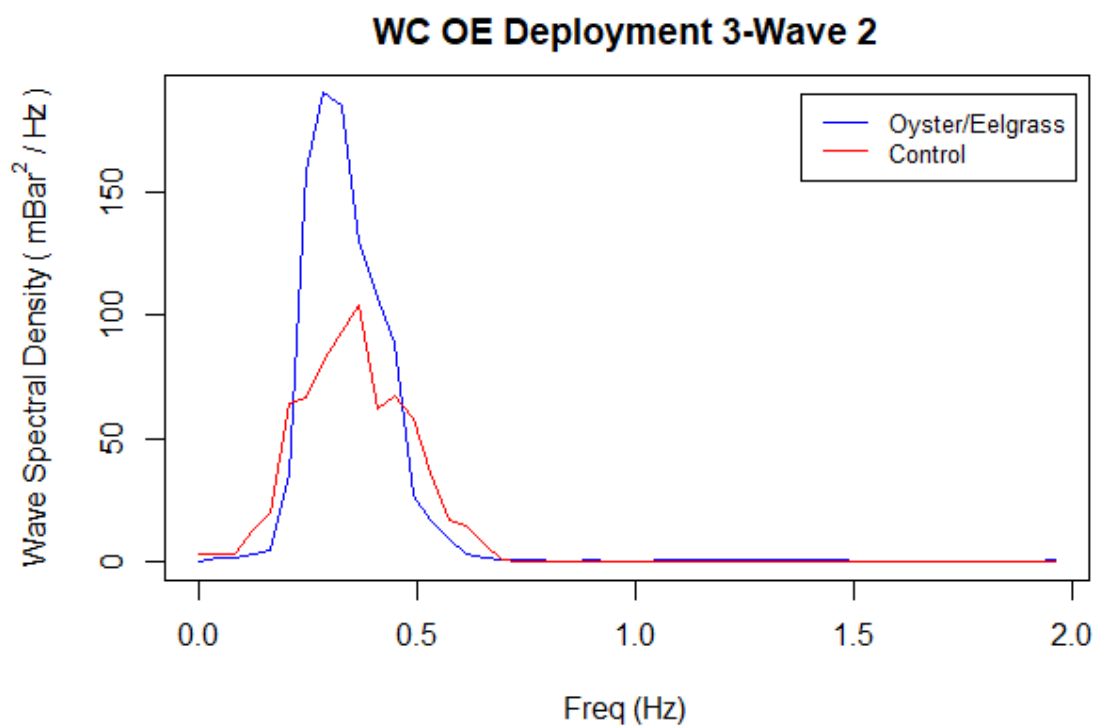


Figure C158. FFT of wave 2 over time at Oyster and Oyster control logger.

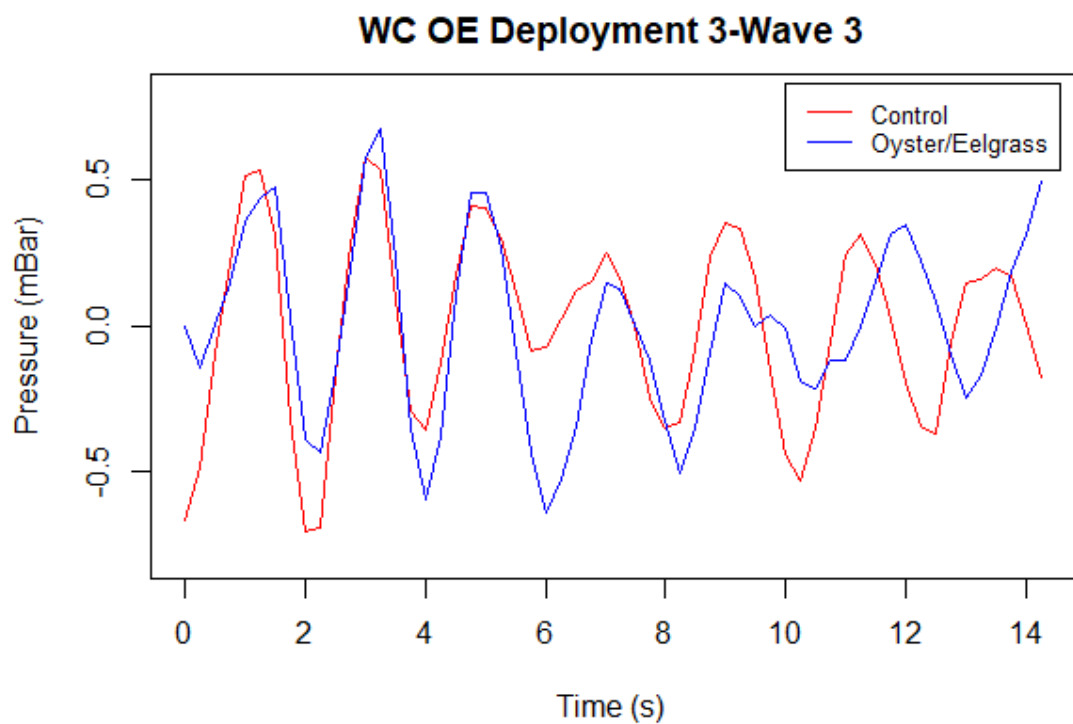


Figure C159. Progression of wave 3 over time at Oyster/Eelgrass and Oyster/Eelgrass control logger.

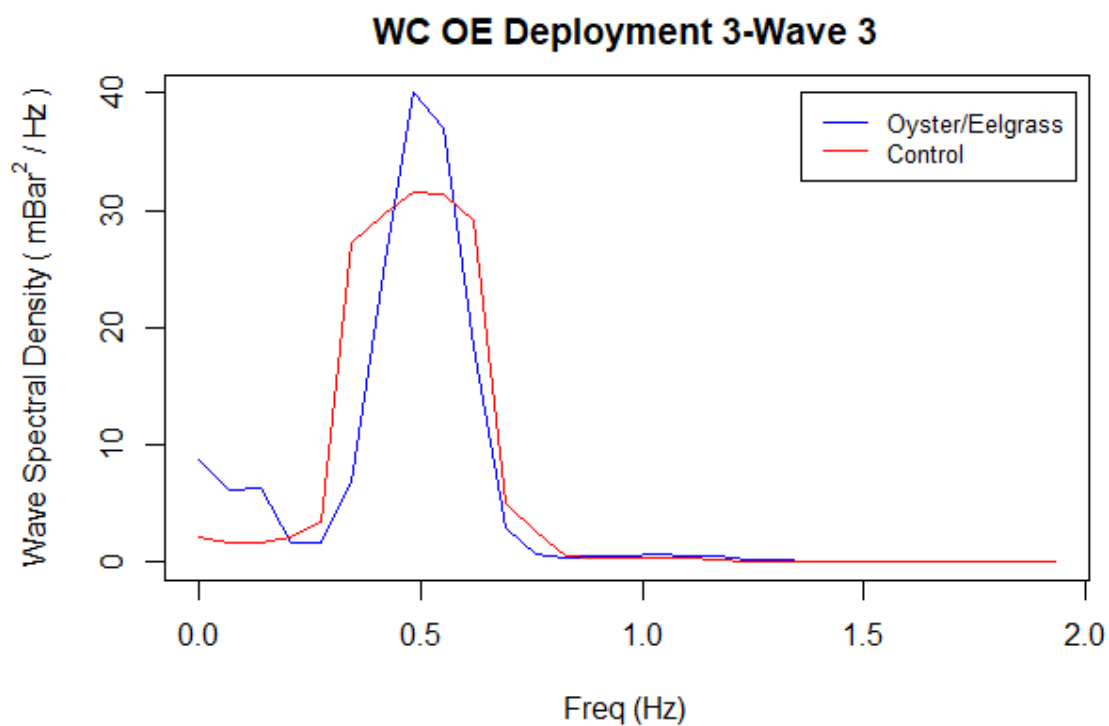


Figure C160. FFT of wave 3 over time at Oyster and Oyster control logger.

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