Marine Physical Laboratory of the Scripps Institution of Oceanography University of California, San Diego

Progress Report: Potential Impact of Mid-Frequency Active Sonar on Whales from Passive Acoustic Monitoring Data

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14. ABSTRACT
Passive acoustic monitoring (PAM) provides extensive datasets to examine the behavioral response of cetaceans to anthropogenic sound. Broadband passive acoustic monitoring permits the recording of the full range of cetacean sounds as well as signals produced by the Navy and other anthropogenic sources. We have been collecting broadband PAM data in the Southern California (SOCAL) region since 2006. Within this dataset are many instances of anthropogenic sound as well as cetacean presence at the locations of naval training.
We present progress on the development of methods to investigate the potential impacts of sonar and other anthropogenic activities on calling animals. The basis for this effort is previously collected PAM data from four sites in the years 2006 to 2015. Recording effort at these sites varied between 674 and 2,284 days per site, resulting in 19 years of cumulative acoustic recording during 79 instrument deployments and 227 TB of acoustic recordings. As part of the work in this progress report, automated routines have been established and/or modified to detect and classify acoustic signals of blue whales (Balaenoptera musculus) and Cuvier's beaked whales (Ziphius caviostris) as well as Mid-Frequency Active (MFA) sonar pings and explosions. This allows analysis based on individual calls or events: B and D blue whale

calls, beaked whale frequency-modulated (FM) echolocation pulses, MFA sonar pings, and explosions. We completed data preparation for these four sites within the funding period.
We are in the process of addressing source to receiver range ambiguity. Beaked whales have a narrow detection range of <2 km around the sensor yet blue whales can be heard over several tens of km. We will reduce detection range for blue whale B calls to a range of approximately 5 km by selecting for yet to be determined high received level calls. Blue whale D calls on the other hand, with lower source levels and of higher frequency, already have a smaller detection range of about 10 km. Range of the MFA sonar source can be estimated assuming a nominal source level of 235 dBrms re 1 μPa @ 1 m.
Two statistical approaches will be explored for the analysis of impact of sonar: multi-spatial convergent cross mapping and generalized estimating equations (GEEs). During this funding period we investigated the GEE approach in more detail. Multi-spatial convergent cross mapping will be studied in a future funding period.

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Executive Summary

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I. INTRODUCTION

The potential for anthropogenic sound, such as Mid-Frequency Active (MFA) sonar, to disrupt activities of marine mammals is an issue of concern to the Navy (NRC, 2003). Early studies of anthropogenic impact have relied on visual methods, documenting disturbance by observing an absence of whales near a sound source, whales travelling away from a sound source, or whales acting in an unusual manner while exposed to a man-made sound. More recently, attaching electronic tags to the animals during controlled exposure experiments (CEE) has allowed more detailed measures of individual's reaction to disturbance (Tyack *et al.*, 2011; DeRuiter *et al.*, 2013; Goldbogen *et al.*, 2013).

Passive acoustic monitoring (PAM) is an alternative approach to examine the behavioral response of marine mammals to anthropogenic sound. Acoustic recorders are used to document both the production of sound by the animals, and the presence of the potentially disturbing anthropogenic sound. PAM data overcome several of the limitations of CEE, such as the availability of realistic sound sources, the relatively small sample sizes on a limited range of species, and the specter of possible research effects. To date, we have barely scratched the surface of the PAM data that are available for behavioral response research. Melcon *et al.* (2012) analyzed data from one species (blue whale, *Balaenoptera musculus*), one call type (D call) at one site in Southern California (site M; Figure 1), covering a single season over a period of two years; their results suggest that naval sonar may suppress blue whale vocal activity at received levels of >120-130 dB re: 1μPa.

The purpose of this effort is to expand the analysis of behavioral impact of sonar using PAM data collected in the Southern California (SOCAL) region to four strategic sites where there are long-term recordings and different historic levels of MFA sonar detections. A major advantage of these long-term data sets is the large sample size for signals of interest. There have been 100,000s of sonar pings recorded during these deployments. Their received levels at the recorders range from ~100 dB re: 1μPa up to 165 dB re: 1 μPa, thus providing a broad range of intensities to assess sonar impacts opening the possibility for the development of dose response curves.

The goal of this study is to examine existing PAM data for acoustic behavioral response of blue whales and Cuvier's beaked whales (*Ziphius caviostris*) to sonar operations in an area of frequent naval activity. The relationship between MFA sonar and the acoustic behavior of whales is complex and requires inclusion of other potentially relevant variables, such as explosions or ship noise. Additionally, a statistical approach is needed that can account for natural temporal and spatial variability in call densities, *e.g.*, caused by species or population level variability in seasonality, habitat preference, behavioral context of calling, and individual variability. In this report, we document the progress made during the third year of work on data preparation, defining methods and signal parameters to be used in statistical analysis, and first model results.

II. METHODS

A. Acoustic data collection

Since 2006, high-frequency acoustic recording packages (HARPs) have been deployed across the Southern California Bight, the continental shelf region between Point Conception and the Mexican border. This area includes the Southern California Offshore Range Complex, a zone of frequent naval training exercises, with San Clemente Island as a focal point for much of this activity. HARPs recorded underwater sounds from 10 Hz up to 100 kHz, covering all cetacean and anthropogenic signals of interest. Four sites (designated E, H, M, and N) were chosen for the MFA sonar impact analysis (Figure 1) because of their high (H, N), medium (M), or low (E) numbers of MFA sonar detections and intensities and location near SOCAL naval operations areas (Figure 2) (*e.g.*, Debich *et al.*, 2015). Previous ONR-funded work showed that blue whale calls are regularly detected at these sites using PAM (Širović *et al.*, 2015) and they are within primary habitat for Cuvier's beaked whales in SOCAL (Baumann-Pickering *et al.*, in prep.).

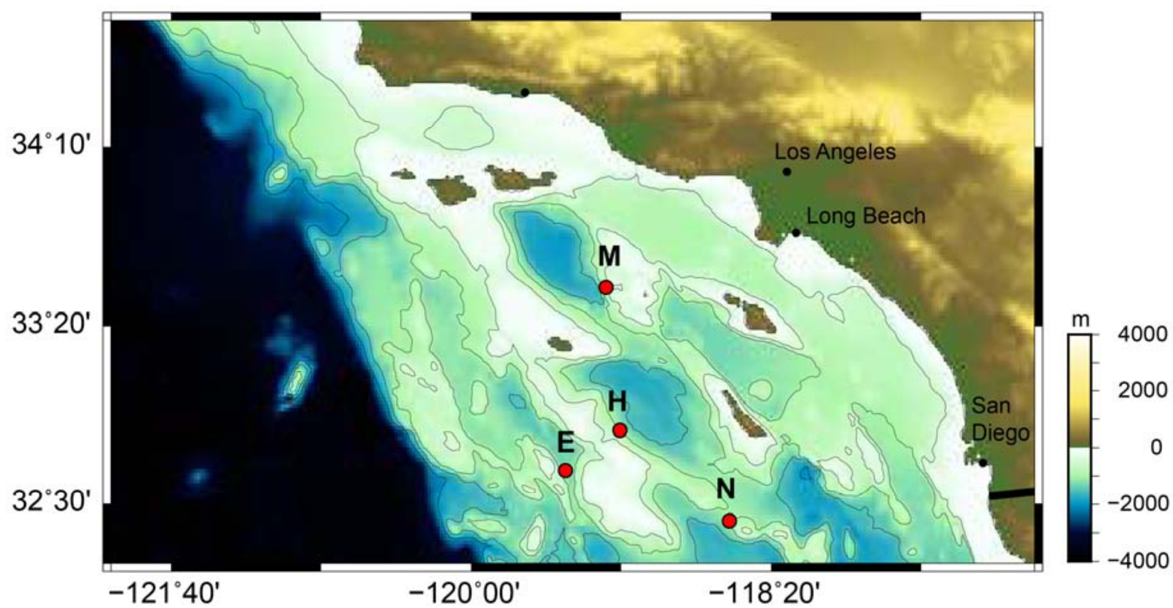

Figure 1. Locations of acoustic recorder deployments off Southern California used in this study.

B. Acoustic signal extraction

Acoustic signals were extracted with automated routines to minimize bias known to occur when multiple human analysts annotate acoustic data manually. This processing allowed a very fine granularity of acoustic detections including individual click level for beaked whales, single calls for blue whales, and single ping events for MFA, providing detailed signal parameter descriptions to be computed, in addition to allowing the evaluation of impact at a variety of time scales.

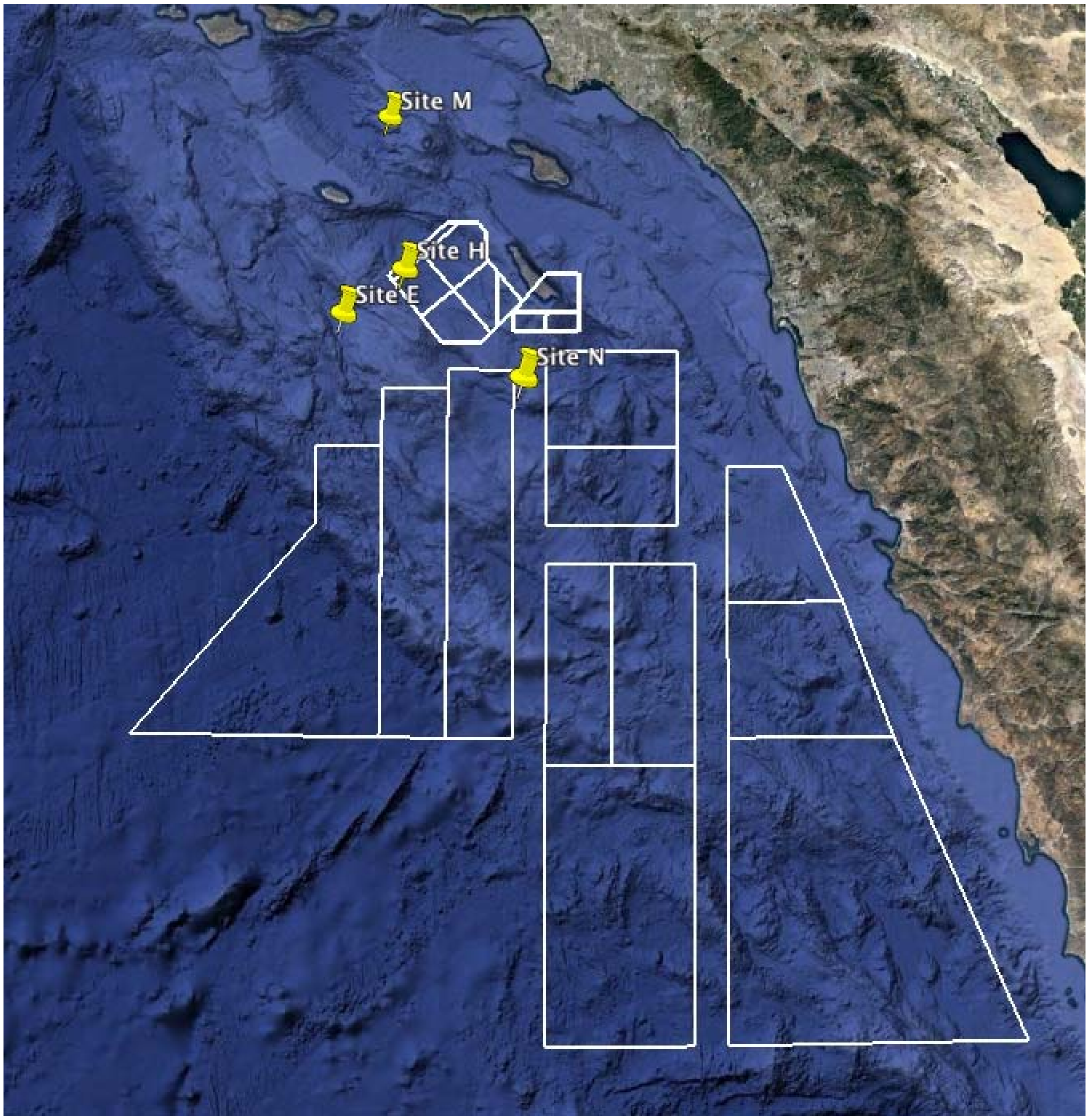

Figure 2. Acoustic recording sites shown relative to SOCAL range op areas (white).

1. Cetacean signals

Blue whale B calls (Širović *et al.*, 2015) and Cuvier's beaked whale echolocation click encounters (Baumann-Pickering *et al.*, in prep.) recorded through the end of 2012 were processed previously under ONR grants. Additional years of data were analyzed as a part of this project's effort and for Cuvier's beaked whale density estimation effort also supported by U.S. Pacific Fleet (Hildebrand *et al.*, 2016). Also, blue whale D calls were added to the effort.

Blue whale B and D calls

Blue whale B calls were automatically detected using spectrogram correlation (Mellinger and Clark, 2000). This method cross-correlates a time-frequency kernel representation of a call with a spectrogram of the recording; a detection event occurs when the correlation value exceeds the specified threshold for a specified duration, in the case of this detector, 5 s. The performance of the automatic detector is affected by seasonal and inter-annual shifts in call frequency (McDonald *et al.*, 2009) and seasonal changes in call abundance (Širović, 2016). To account for these changes and keep rates of missed and false calls as consistent as possible, multiple kernels and thresholds were used for each year and site. In general, the average recall of the detector was above 80% across all sites (Širović *et al.*, 2015).

To achieve a more complete view of blue whale calling behavior, an effort to detect blue whale D calls was also expended for this project. To automatically detect these, a generalized power-law (GPL) detector (Helble *et al.*, 2012) was adapted by modifying the detection parameters including the frequency space over which the detector operates. A unique feature of the GPL detector is that it performs well on non-stereotypical calls, such as D calls. The detector was fine-tuned to perform at less than 9% missed call rate. This resulted in a high false positive rate and a manual verification process permitted analysts to review and verify or reject detections with the assistance of a tool that presented time-condensed spectrograms with detections annotated. Through this process, only true calls remain in the dataset for subsequent analysis.

Cuvier's beaked whale FM pulses

Beaked whales are known to produce frequency-modulated (FM) echolocation pulses that are distinguishable to the species or FM pulse type level (Baumann-Pickering *et al.*, 2013). Beaked whale encounters (with silent periods between bouts of FM pulses separated by one hour or more) were initially automatically detected and then classified to the species or signal type level with an analyst-assisted software (Baumann-Pickering *et al.*, 2013), eliminating false encounters. The rate of missed encounters for this detector has been shown to be approximately 5% in SOCAL recordings. All Cuvier's beaked whale acoustic encounters were reviewed in a second analysis stage to remove false detections of individual FM pulses and provide a consistent detection threshold. FM pulse detections occurred when the signal in a 10 – 100 kHz band exceeded a detection threshold of 121 dB pp re: 1μPa. FM pulses within the acoustic encounters were manually reviewed using comparative diagnostics that included long-term spectral average, received level, and inter-pulse interval of individual FM pulses over time, as well as spectral and waveform plots of selected individual signals. Within each encounter, false detections were removed by manual editing, for instance, when spectral amplitude, inter-click interval, or waveform indicated the detections were from vessels, sonars, sperm whales or delphinids. In addition, this step provided another check on beaked whale species classification and remaining misidentified or false encounters were corrected or removed.

2. Anthropogenic signals

Mid-Frequency Active (MFA) Sonar

Automatic detection of MFA sonar was implemented using a modified version of the *silbido* detection system (Roch *et al.*, 2011) designed for characterizing toothed whale whistles. The algorithm identifies peaks in time-frequency distributions (*e.g.,* spectrogram) and determines which peaks should be linked into a graph structure based on heuristic rules that include examining the trajectory of existing peaks, tracking intersections between time-frequency trajectories, and allowing for brief signal drop-outs or interfering signals. Detection graphs are then examined to identify individual tonal contours looking at trajectories from both sides of time-frequency intersection points. ONR-funded modifications to the published system consisted of a noise regime change detection system, and statistical analyses of graphs and tonal contours for characteristics that removed 57% of the false positives with negligible impact on detected calls (MacFadden, 2015).

For MFA sonar detection, parameters in *silbido* were adjusted to detect tonal contours ≥ 2 kHz (in data decimated to a 10 kHz sample rate) with a signal to noise ratio ≥ 5 dB and contour durations > 200 ms with a frequency resolution of 100 Hz (Figure 3). The primary MFA sonar in use by the United States Navy, the AN/SQS-53C, is operated on surface ships and generates tones and sweeps having typical durations of 0.5 to 2 s with frequencies near 3.5 kHz, at nominal root-mean-square (rms) source levels of 235 dB_{rms} re 1 μPa @ 1 m (United States Navy, 2008). This type of sonar dominates the data set used in this study; however, the filtering process and signal data rate in this detection process excluded a number of lower or higher frequency MFA sonar signals.

In the frequency range between 2 and 4.5 kHz, the detector frequently triggered on noise produced by instrument disk writes that occurred at 75 s intervals. Over several months, disk write detections dominated the detections, but they were eliminated using an outlier test. Histograms of the detection start times, modulo the disk write period, were constructed and outliers, as identified by a non-parametric outlier test (Emerson and Strenio, 1983), were discarded. This removes some valid detections that occurred during disk writes, but as the disk writes and sonar signals are uncorrelated, this process is expected to only have a minor impact on analysis. As the detector did not distinguish between sonar and other tonal signals within the operating band, analysts manually examined detection output. The manual examination was performed using a graphic user interface that displayed 30-min panels showing long-term spectral average, received level, and inter-detection interval of individual detections. Analysts would accept or reject contiguous sets of detections based on those displayed characteristics.

Detections were compiled into MFA sonar events, defined as MFA sonar detections separated by more than 5 min. For each event, start and stop times, minimum, maximum, start and end frequencies were saved, as well as peak-to-peak (pp) received level (RL, in dB) and sound exposure level (SEL). Additionally, cumulative sound exposure level (CSEL) was calculated for each ping over the entire duration of the MFA sonar event (Southall *et al.*, 2007).

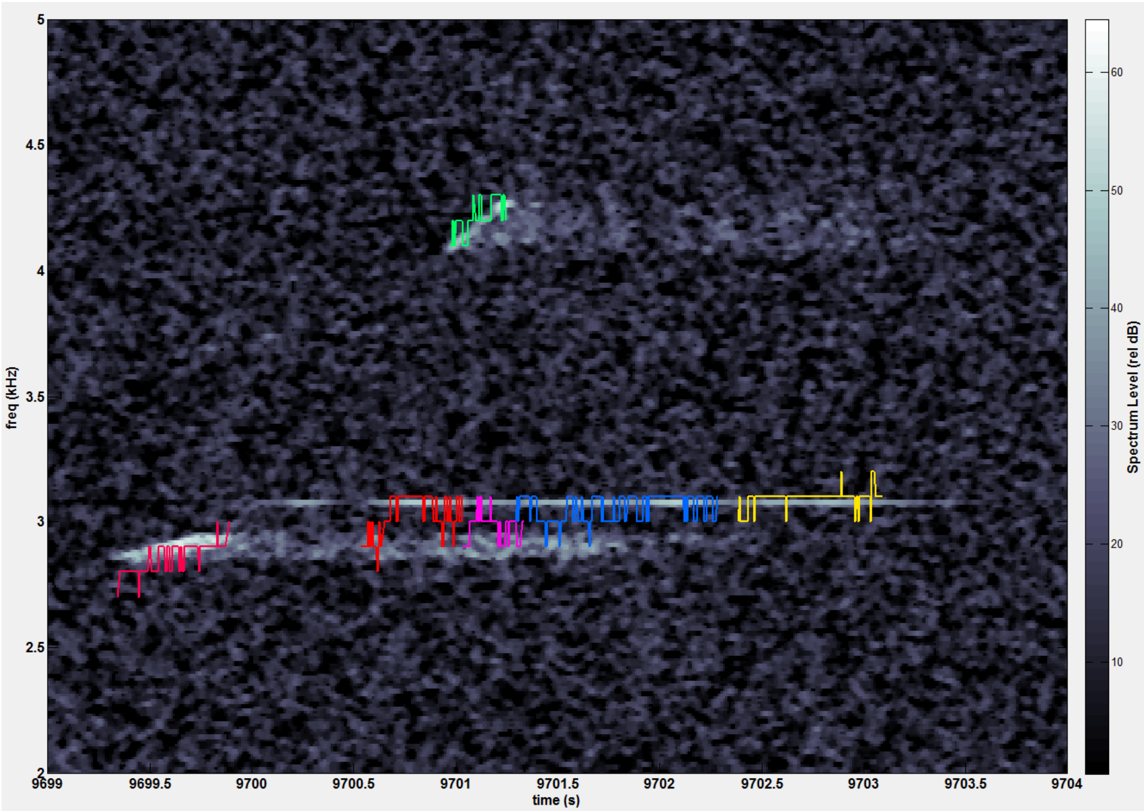

Figure 3. MFA sonar detections. Detections (colored lines) are shown over a gray scale spectrogram. Detector has a 100 Hz resolution, while spectrogram is plotted with 10 Hz resolution. The MFA sonar pings are in general well detected, however some are fragmented, for instance, with multiple segments covering the long ping.

Explosions

Effort was also directed toward finding explosive sounds in the data including military explosions, shots from sub-seafloor exploration, and seal bombs used by the fishing industry (Figure 4). Explosions were detected automatically using a matched filter detector on data decimated to 10 kHz sampling rate. Explosions have energy as low as 10 Hz and often extend up to 2,000 Hz or higher, lasting for a few seconds including the reverberation. The time series was filtered with a 10^{th} order Butterworth bandpass filter between 200 and 2,000 Hz. Cross correlation was computed between 75 seconds of the envelope of the filtered time series and the envelope of a filtered example explosion (0.7 s, Hann windowed) as the matched filter signal. The cross correlation was squared to 'sharpen' peaks of explosion detections. Regions containing candidates for detections are identified by a using a dynamic threshold of the cross correlation.

The median cross correlation of 75 s data frames was computed and regions that exceeded the coefficient median by 3×10^{-6} were identified for further analysis. Consecutive explosions had to be separated by at least 0.5 seconds to be detected. A 300-point (0.03 s) moving average energy across the detection was computed. The start and end defining the potential explosion were determined when the energy was more than 2 dB above the median energy across the detection. Peak-to-peak (pp) and rms RL were computed over the potential explosion period. To be classified as an explosion, the region had to be louder than the background noise before and after the detection region as well as meet constraints on the duration. Specifically, the explosion onset had to be 4 dB PP and 1.5 dB rms above the preceding region, offset had to be 4 dB PP and 1.5 dB rms, and the duration was required to be 0.03 to 0.55 seconds. The thresholds were evaluated based on the distribution of histograms of manually verified true and false detections. A trained analyst subsequently verified the remaining potential explosions for accuracy.

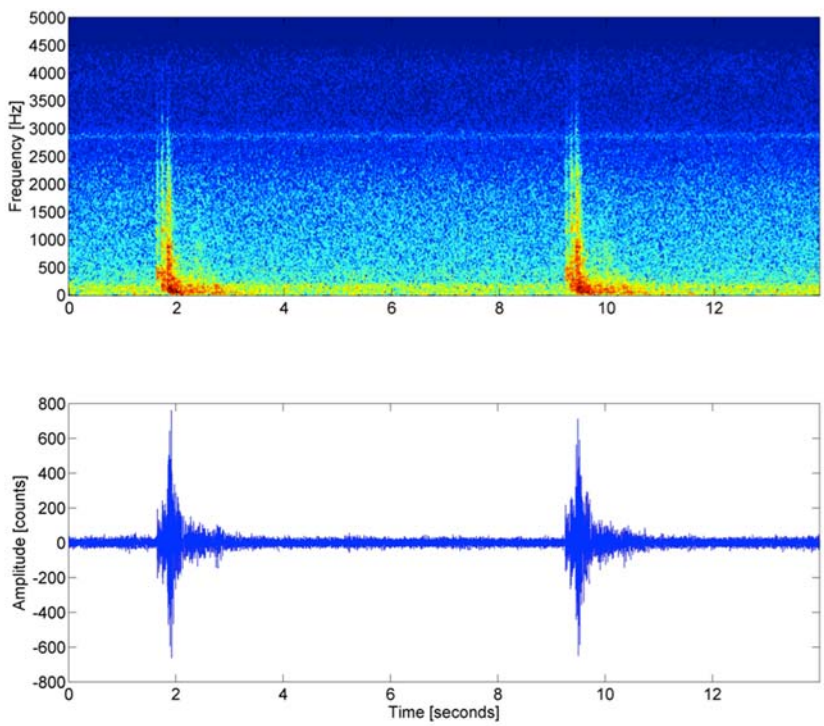

Figure 4. Two explosions, most likely seal bombs, are shown as (above) spectrogram, and (below) time series.

3. Low-frequency noise

Ambient noise is one of the known factors affecting the detectability of a signal, especially in low-frequencies (Širović, 2016). Therefore, we are including a noise variable to models investigating the relationships between blue whale calling and sonar. Noise was calculated first as 5 s spectral averages calculated with 1 Hz resolution and then averaged over 1 min intervals. This calculation was performed for all deployments over the two frequency bands over which detection was performed: 43-49 Hz for blue whale B calls, covering the main energy of the B call third harmonic, and 35-90 Hz for blue whale D calls.

C Statistical analysis

1. General approach

After exploring different statistical frameworks, we decided to focus our analysis efforts on two different approaches to test their applicability to this problem: multi-spatial convergent cross mapping and generalized estimation equations (GEEs).

Multi-spatial convergent cross mapping, an extension of convergent cross mapping, is a test for causal associations between pairs of processes represented by time series. It is based on non-linear state space reconstruction where causality can be distinguished from correlation even in the presence of process noise and observation error (Sugihara *et al.*, 2012; Clark *et al.*, 2015; Ye *et al.*, 2015). This technique has shown to be useful for testing causality in systems where experiments are difficult (Clark *et al.*, 2015) and thus seems ideally suited to this problem.

In comparison, GEEs are used to estimate parameters of generalized linear models that have unknown correlations between outcomes. Their strength lies in that they can be used with repeated measurements over space and time and they provide the estimate of the average response of the population (Zeger *et al.*, 1988). Here we are presenting preliminary results from GEE modeling as that was our primary focus during this funding year. In this approach, the response variable was related to explanatory covariates describing time of day and season, sonar presence and characteristics of the sonar signal. The GEE framework allows for the covariates to have a nonlinear relationship with the response variable and can accommodate autocorrelation inherent to the time-series nature of the data.

As a first approach, we focused on a single site, SOCAL N, and limited the response variables to the presence of 1) blue whale D calls and 2) beaked whale clicks in 1-min segments. To eliminate potentially confounding issues in responses among different species, we conducted the analysis separately for these two signal types.

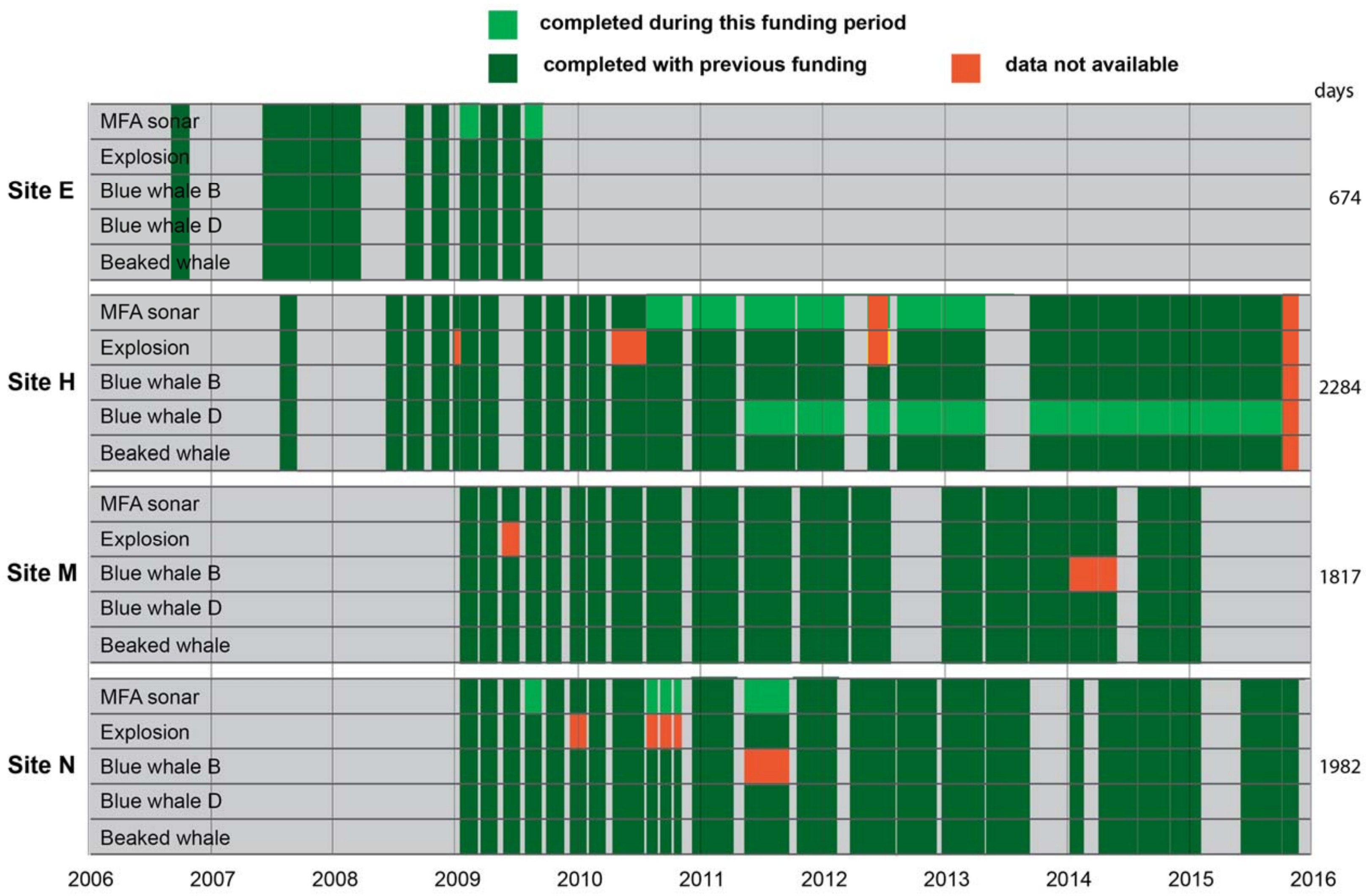

Figure 5. Finalized analysis for MFA sonar, explosions, blue whale B and D calls, and Cuvier's beaked whales over 19 years of cumulative acoustic recordings from 4 sites, collected between 2006 and 2016, comprising 227 TB of data in 79 deployments. Gray areas show time periods of no data. Total number of days with available data listed on the right for each site.

2. Data formatting

For GEE analyses, we elected to discretize the data into 1-min segments as the individual observation units as opposed to individual detections. There was unequal effort for detections of blue whale D calls, Cuvier's echolocation clicks, MFA sonar and calculations of low-frequency noise. This is due to slight differences in data availability (Figure 5, Table 1).

***Table 1**. Summary of blue whale D call and beaked whale echolocation click data from site N.*

	Blue whale	**Beaked whale**
1-minute segments	2,428,745	2,414,275
Segments with call/click-presences	18,029	15,708
Mean number of calls/clicks in each segment given presence (SD)	1.27 (0.63)	34.73 (45.39)
Segments with presence of sonar	167,173	166,205
Years	2009 - 2015	2009 - 2015

3. Response variables

The response variable was defined as presence of a cetacean signal in a 1-minute segment. We used a binary response variable which was equal to 1 (presence) for those 1-min segments during which at least one cetacean signal was detected and 0 (absence) for those during which no signal was detected. This was done separately for blue whale D calls and beaked whale clicks (Table 1).

4. Explanatory covariates

The explanatory covariates for the GEE (Table 2) were defined to capture the potential effects of sonar on the response variable in various ways, *e.g.*, the amount of sonar over a short or longer time period, the variability in sonar, the recovery time since sonar stopped. Non-sonar related variables such as time of day, date or year were included to account for natural variability in the response.

***Table 2**. Explanatory covariates for the GEE included in the analyses of the blue whale D call and the beaked whale click data.*

Covariate	**Short name**	**Description**	**Calculation details**	**Notes**
Sonar presence	*spres*	Binary (1/0): Presence/ absence of sonar pings	0 if no sonar in that 1-min segment, 1 if at least 1 sonar ping	Tested as a covariate and used as dummy variable in interaction terms
Sonar lag	*sonarlag*	Integers: number of 1-min	Each 1-min segment = 0 where *spres* = 1 (see above); otherwise as lag in minutes	

		segments since last sonar ping	since last 1-min segment with sonar. Periods after no sonar effort are NA until first sonar ping	
Peak-to-peak received level	*maxpprl*	Maximum ppRL per 1-min segment.	0 if no pings, if multiple pings fall in 1-min segment, result is the maximum	To accommodate 1-min segments without pings we used interaction with *spres*
Sound exposure level (SEL)	*cumsel*	Cumulative sound exposure level in dB for 1-min segment	Adding up values (SEL) from different pings in the same 1-min segment: bels= SEL/10 intensity=10^bels cumsel = 10 * log10 (sum(intensity))	for 1-min segments without pings we used interaction with *spres*
Proportion of sonar	*sprop*	Proportion of 1-min segment with sonar	Sum of duration of all sonars (secs) that fall within 1-min segment / 60 secs	
Noise measurement	*RLD_dB*	Received level within the frequency band of blue whale D calls	Provided in 1-min segments	Only considered for blue whale data
Day-night	*DN*	Binary (1=day, 0=night)	Using sunrise and sunset information	
Minutes-since-sunrise	*MSR*	Length in minutes since sunrise	Integers: 0 for 1-min segment in which sunrise occurred	
Minutes-since-sunset	*MSS*	Length in minutes since sunset	Integers: 0 for minute in which sunset occurred	
Julian date	*jd*	Date in integers	Consecutive day of year: 1-365	
Year	*year*	Year of recording		
Cumulative				
Sonar presence over 1 hour	*spres.1hr*	Binary (1/0): Presence/absence of sonar pings	0 if no sonar in the preceding 60 and current 1-min segments, 1 if at least 1 sonar ping	Only used for interactions with other cumulative terms
>1 sonar ping over 1 hour	*scount2plus.1hr*	Binary (1/0): Presence/absence of sonar pings	0 if 0 or 1 sonar ping detected in the preceding 60 and current	Only used for interactions

			1-min segments, 1 if more than 1	with variability terms
Cumulative SEL_dB over 1 hour (unweighted)	*cumsel.1hr*	Same as *cumsel* above except over 60 minutes		for 1-min segments without pings in previous 60 minutes we use interaction with *spres.1hr*
Cumulative SEL_dB over 1 hour (weighted)	*cumsel.1hrw*	Lag is time lag in minutes between sonar pings and 1-min segment. Using exp(-lag*3/60) as a weight ensures that after 60 minutes weight is negligible	bels <- SEL/10 intensity <- 10^bels intensity.weighted<-intensity*exp(-lag*3/60) cumsel.1hrw <- 10 * log10(sum(intensity.weighted))	for 1-min segments without pings in previous 60 minutes we use interaction with *spres.1hr*
Variability				
Standard deviation of SEL_dB (unweighted)	*sdsel.1hr*	Standard deviation of all SEL values that occurred within the last hour (each with equal weight)	sd(SEL of pings that fall within 60 minutes before respective 1-min segment)	for 1-min segments with 0 or only 1 ping in previous 60 minutes we use interaction with *scount2plus.1hr*
Standard deviation of SEL_dB (weighted)	*sdsel.1hrw*	Standard deviation of all SEL_dB values that occurred within the last hour (weighted by time lag)	weighted sd(SEL of pings that fall within 60 minutes before respective 1-min segment) using sqrt(Hmisc:wtd.var()). Same lag-based weighting as applied to individual SEL values for calculating *cumsel.1hrw* where 1-min segments with greater lag contribute less than 1-min segments with smaller lags.	for 1-min segments with 0 or only 1 ping in previous 60 minutes we use interaction with *scount2plus.1hr*
Standard deviation of *sprop* over 1 hour	*sdsprop.1hr*	Standard deviation of *sprop* over 60 minutes		

5. Methods for generalized estimating equations

Modeling approach for GEEs

The relationship between the coefficients and the response (presence of calls or clicks) is modeled using a logit-link function that can be expressed as

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k,$$

where p is the probability of presence, 1-p is the probability of absence, and β represent the intercept and coefficients associated with the k covariates x.

We fitted GEEs using the *geeglm* function of the *geepack* package in R (Halekoh *et al.*, 2006). We added smoothing terms of 3 to 5 degrees of freedom using the *bs* function of the *splines* package. We used the default correlation structure 'independence' where correlated observations were grouped using a block identifier (argument *id* from the *geeglm* function). Each block consisted of consecutive observations of 1-min segments. The size of the blocks was determined using the *acf* function from the *stats* package. This function estimates the autocorrelation between consecutive residuals for various lags. We chose sizes of 20 and 41 for the blue whale and beaked whale models, respectively.

Model selection for GEEs

Our methods for selecting the final model included three main steps: 1) elimination of collinear covariates; 2) stepwise backwards selection based on marginal *p*-values; and 3) stepwise backwards selection by inspecting 95% confidence intervals around partial fit plots.

To test for collinearity, we used variance inflation factors (VIF) which can be measured using the *vif* function from the *car* library in R. We excluded all covariates that scored VIFs > 10 (Fox and Monette, 1992). To test VIFs, we began with a full model (with all candidate explanatory covariates from Table 2) and eliminated one covariate at a time, always the one with the highest VIF, until VIFs of all covariates were <10.

We used *p*-value based backward model selection where we started with the model we arrived at after eliminating collinear covariates (see first step) and omitted one covariate at a time, testing whether this improved the model. For this test, we used the marginal *p*-values associated with an *F*-test statistic which tested whether each covariate in the model was important given that the other covariates were already in the model. These *p*-values were calculated with the *getPvalues* function from the *MRSea* package (Scott-Hayward *et al.*, 2013).

Partial fit plots were created using a modified version of the *runPartialPlots* function from the *MRSea* package which uses parametric bootstrapping of model coefficients to create confidence intervals around the partial fit. During this step we eliminated covariates which exhibited 95% confidence intervals around their partial fits that were wide enough to fit a straight horizontal line within the bounds of the confidence limits through the entire range of observed covariate values. This was an indication that the respective covariate potentially had no effect on the response.

III. PRELIMINARY RESULTS

A. Acoustic signal extraction

The recording effort at sites E, H, M, and N from 2006 to 2015 varied between 674 and 2,284 days per site, cumulatively resulting in 19 years of recordings and 227 TB of acoustic data over 79 instrument deployments. The automated signal detection process generated millions of counts. The complete data analysis required a total of ~1,100 days of computing time and ~300 person-days of manual editing, not including the upkeep of computing infrastructure or potential trouble-shooting of computing irregularities. We have finalized detection and classification analysis for this project during this funding period (Figure 5, Table 1).

A potential advantage of controlled exposure experiments over PAM impact analysis approaches is the precise knowledge of the location of the source and the animal being studied. This can be addressed in a PAM impact analysis by using received sound level as a proxy for the range between the sensor and the sonar. If we assume a nominal source level of 235 dB_{rms} re 1 µPa @ 1 m (United States Navy, 2008 ,Vol. 2), sonar can be detected at a large distance (~20-50 km). Likewise, it is possible to estimate the animal range from the sensor using received level and other call characteristics, such as source level and frequency content. The detection range to Cuvier's beaked whales is generally small based on the high-frequency content of the signal (<2 km, Hildebrand *et al.* 2015). The identified blue whale D calls were estimated to be within 10 km of the recorder. Future analysis will quantify the range ambiguity for both beaked and blue whales more precisely.

In the case of blue whale B calls, detection range still needs to be restricted to calls with high RLs and hence animals close to the sensor within similar distances as animals producing D calls. By limiting the range to detected animals, we can limit the sonar-animal range ambiguity to a few kilometers. In the case of a sonar detection that is much farther away from the recorder than the animal, the RL at the recorder can be used as a proxy for the RL at the animal. The preliminary statistical model results are currently focused on blue whale D calls.

B. Statistical analysis

1. Data exploration

We explored the relationships between presence of blue whale D calls and beaked whale clicks, respectively, and each of the candidate explanatory covariates (Figure 6 and 7).

Blue whale D calls and beaked whale clicks were present throughout all years 2009 to 2015. For beaked whales, 2009 and 2010 showed particularly high densities of 1-min segments with click detections (Figure 7). Both blue whales and beaked whales showed a seasonal pattern in acoustic occurrence (Figures 6 and 7); however, the blue whale D call data revealed stronger seasonality within a given year, with low densities of call detections in early months of the year and highest in the summer (as shown in Širović *et al.*, 2015). Cuvier's beaked whales had a higher presence as the intervals of sonar use (*sonarlag*) increased (Figure 7).

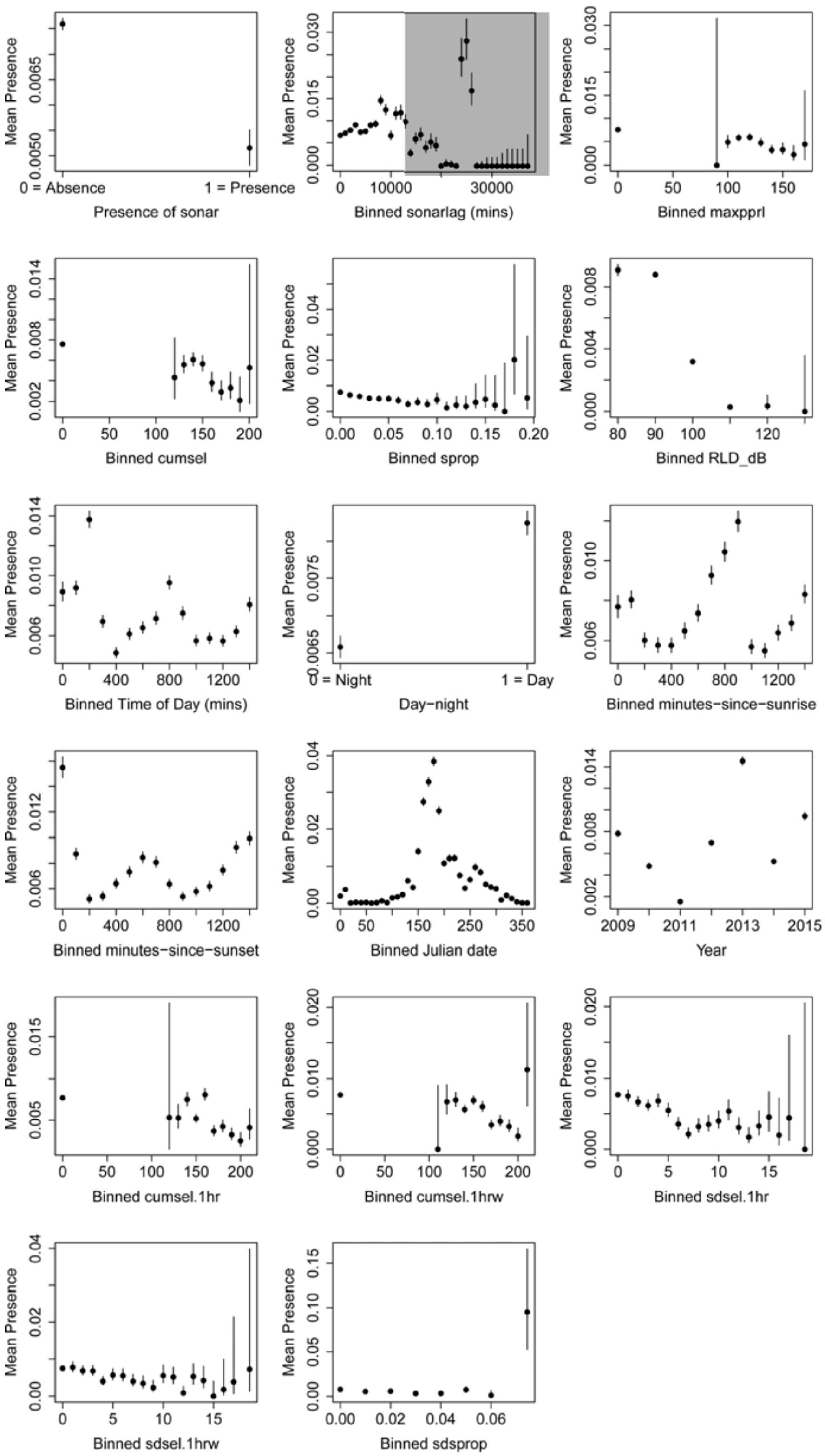

***Figure 6*. Mean presence and 95% CI of blue whale D calls in 1-min segments against potential explanatory variables (Table 2). Gray shaded area in *sonarlag* (top center) indicates outlier values.**

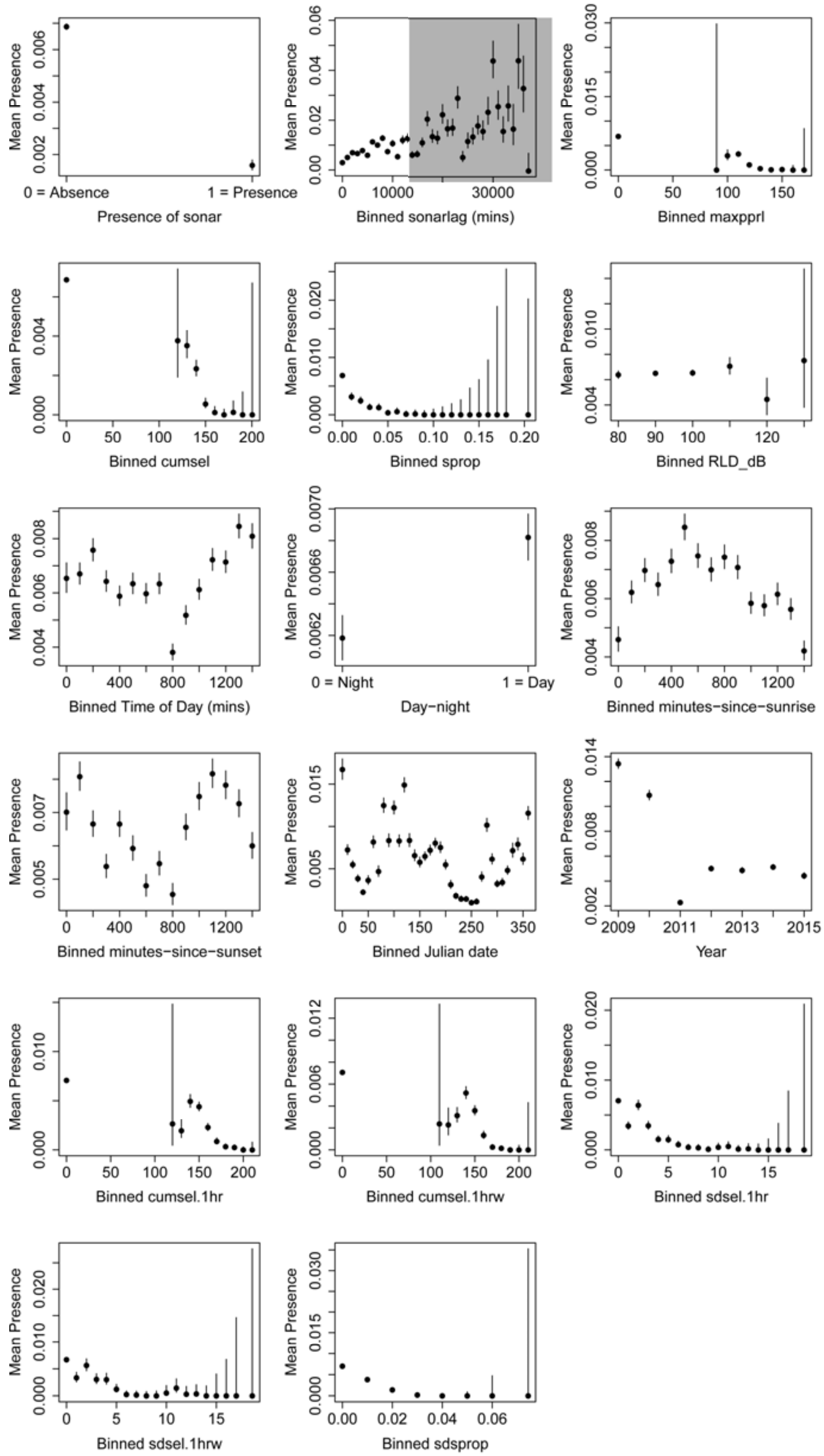

***Figure 7*. Mean presence and 95% CI of beaked whale clicks in 1-min segments against potential explanatory variables (Table 2). Gray shaded area in *sonarlag* (top center) indicates outlier values.**

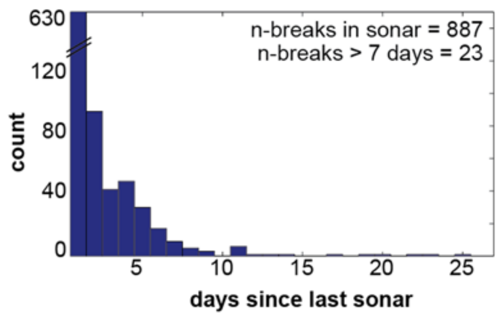

***Figure 8*. Histogram of number of days since last sonar event.**

When exploring MFA sonar data going into the *sonarlag* calculation, we find that 70% of sonar data shows a gap of 1-day or less, *i.e.* day-to-day continuous sonar use; 26% of gaps are 2 to 7 days long. Only 3% of gaps between sonar were longer than 7 days (or ~10,000 minutes). Looking at the acoustic presence of animals during those longer gap times it is apparent that seasonality strongly shapes the observations in *sonarlag,* particularly for blue whales but also for beaked whales.

These longer gaps need to be considered as outliers in future analysis (Figure 8). We will consider eliminating data points > 10 days.

2. GEE modeling

Model summary

For presence of blue whale D call models, we identified several covariates as collinear including sound exposure level (*cumsel*), weighted cumulative SEL_dB over 1 hour (*cumsel.1hrw*), sonar presence (*spres*), day-night (*DN*) and peak-to-peak received level (*maxpprl*). The covariates retained in the best fitting model included the factor covariate *year* as well as the continuous covariates Julian day (*jd*), sonar lag (*sonarlag*), proportion of sonar (*sprop*), ambient noise (*RLD_dB*) and standard deviation of *sprop* over 1 hour (*sdsprop.1hr*) (Table 3, Figure 9). Factor covariates are generally fitted by first defining a base level (usually the first level in numerical or alphabetical order, here *year* = 2009). This base level forms part of the intercept estimate against which other levels (here years 2010-2015) are contrasted. The coefficients of the remaining years represent how these years contrasted against the intercept. For the blue whale models, 2009, 2011 and 2013 were the three years with the highest estimated presences.

The partial fit plots revealed: highest probabilities in detecting blue whale D calls were in mid-July to early-August (the vicinity of *jd* = 200). With increase in *sonarlag* the probability of detecting blue whale calls increased, with increase in background noise measured in *RLD_dB* the probability of detecting blue whale D calls declined.

However, both *sonarlag* and *RLD_dB* will need to be reconsidered. We showed in Figure 8 that *sonarlag* >10,000 min results from only 3% of sonar data and should likely not be integrated into the model. The probability of detecting blue whale calls diminishes with increased background noise levels (*RLD_dB*) due to masking. Hence, in future evaluations we will consider marking background noise levels >110 dB as off-effort periods.

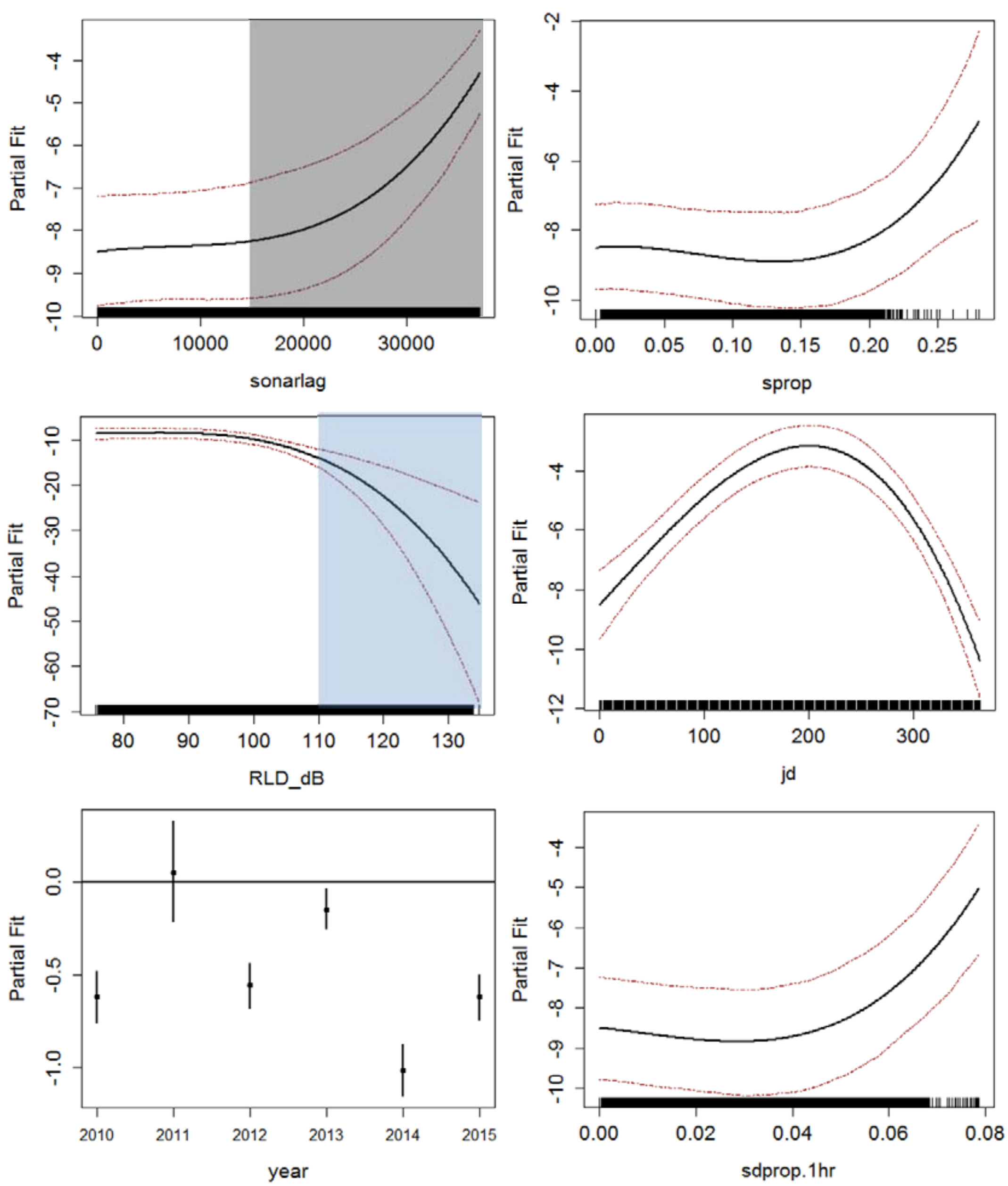

***Figure 9*. Partial fit plots for presence model for blue whale D calls (note that the partial fit is given on the scale of the logit-link function, see above). Vertical lines (rug) at the inside of the x-axis show locations of observed covariate values. The covariates retained in the final model were *sonarlag*, *sprop*, *RLD_dB*, *jd*, *year* and *sdsprop.1hr*. Gray shaded area in *sonarlag* (top left) indicates outlier values. Blue shaded area in *RLD_dB* shows levels where signal masking is apparent.**

Table 3**. Models for the presence of blue whale calls: parameter estimates (MLE) on the logit-link scale and standard errors (SE) from best fitting models with significance codes (SC) related to* p-values *(1 ' ' 0.1 '.' 0.05 '*' 0.01 '**' 0.001 ''). For polynomial splines, coefficients are given for the three B spline bases.*

Coefficient	**MLE**	**SE**	**SC**
Intercept	-8.50	0.64	***
bs(sonarlag)1	0.40	0.23	.
bs(sonarlag)2	-0.69	0.52	
bs(sonarlag)3	4.19	0.38	***
bs(sprop)1	0.35	0.48	
bs(sprop)2	-2.59	1.19	*
bs(sprop)3	3.63	1.24	**
bs(RLD_dB)1	-0.22	1.63	
bs(RLD_dB)2	4.53	3.74	
bs(RLD_dB)3	-37.59	11.79	**
bs(jd)1	4.63	1.24	***
bs(jd)2	10.04	0.32	***
bs(jd)3	-1.90	1.02	.
as.factor(year)2010	-0.62	0.07	***
as.factor(year)2011	0.05	0.14	
as.factor(year)2012	-0.56	0.06	***
as.factor(year)2013	-0.15	0.06	**
as.factor(year)2014	-1.02	0.07	***
as.factor(year)2015	-0.62	0.06	***
bs(sdprop.1hr)1	-0.32	0.34	
bs(sdprop.1hr)2	-1.45	0.73	*
bs(sdprop.1hr)3	3.50	0.54	***

For beaked whale presence of click models, we identified several covariates as collinear including sound exposure level (*cumsel*), weighted cumulative SEL_dB over 1 hour (*cumsel.1hrw*), sonar presence (*spres*) and day-night (*DN*). The final model for the presence of beaked whale clicks contained the factor covariate *year* as well as the continuous covariates *jd* and *sonarlag* and the interaction term for standard deviation of SEL over the preceding hour with presence of sonar ping over 1 hour (*scount2plus.1hr:sdsel.1hr*) (Table 4, Figure 10). Here, the highest presences were estimated for years 2009 and 2010, while the lowest presences were estimated for 2011. Presence of beaked whales fluctuated throughout the year with highs in the winter and late spring (see partial plot for *jd* in Figure 10). The partial plot for the interaction term revealed that presence of clicks decreased with increasing values of covariate *sdsel.1hr*. The best fitting model predicted that the probabilities of detecting beaked whale clicks increased with increasing *sonarlag*. Probability of presence increased until about 7 days (or 10,000 minutes) and then level out. The further increase at about 2.5 weeks (or 25,000 minutes) is, similar to blue whales, likely due to outliers and will need to be reevaluated.

Table 4. *Models for the presence of beaked whale clicks: parameter estimates (MLE) on the logit-link scale and standard errors (SE) from best fitting models with significance codes (SC) related to* p-*values (1 ' ' 0.1 '.' 0.05 '*' 0.01 '**' 0.001 '***'). The interaction term with dummy variable* scount2plus.1hr *allowed setting the covariate value for* sdsel.1hr *to 0 for those segments where no data existed for the respective covariate. For polynomial splines, coefficients are given for the three (or five) B splines bases.*

Coefficient	MLE	SE	SC
Intercept	-4.10	0.21	***
bs(sonarlag)1	2.09	0.30	***
bs(sonarlag)2	-0.87	0.46	.
bs(sonarlag)3	2.28	0.38	***
bs(jd, degree = 5)1	-4.76	0.79	***
bs(jd, degree = 5)2	8.37	0.99	***
bs(jd, degree = 5)3	-9.56	1.24	***
bs(jd, degree = 5)4	1.99	0.60	***
bs(jd, degree = 5)5	-0.83	0.27	**
as.factor(year)2010	-0.18	0.10	.
as.factor(year)2011	-1.75	0.16	***
as.factor(year)2012	-0.82	0.11	***
as.factor(year)2013	-0.96	0.11	***
as.factor(year)2014	-0.65	0.11	***
as.factor(year)2015	-0.65	0.12	***
scount2plus.1hr:bs(sdsel.1hr)1	1.64	1.41	
scount2plus.1hr:bs(sdsel.1hr)2	-20.95	7.29	**
scount2plus.1hr:bs(sdsel.1hr)3	4.26	1.63	**

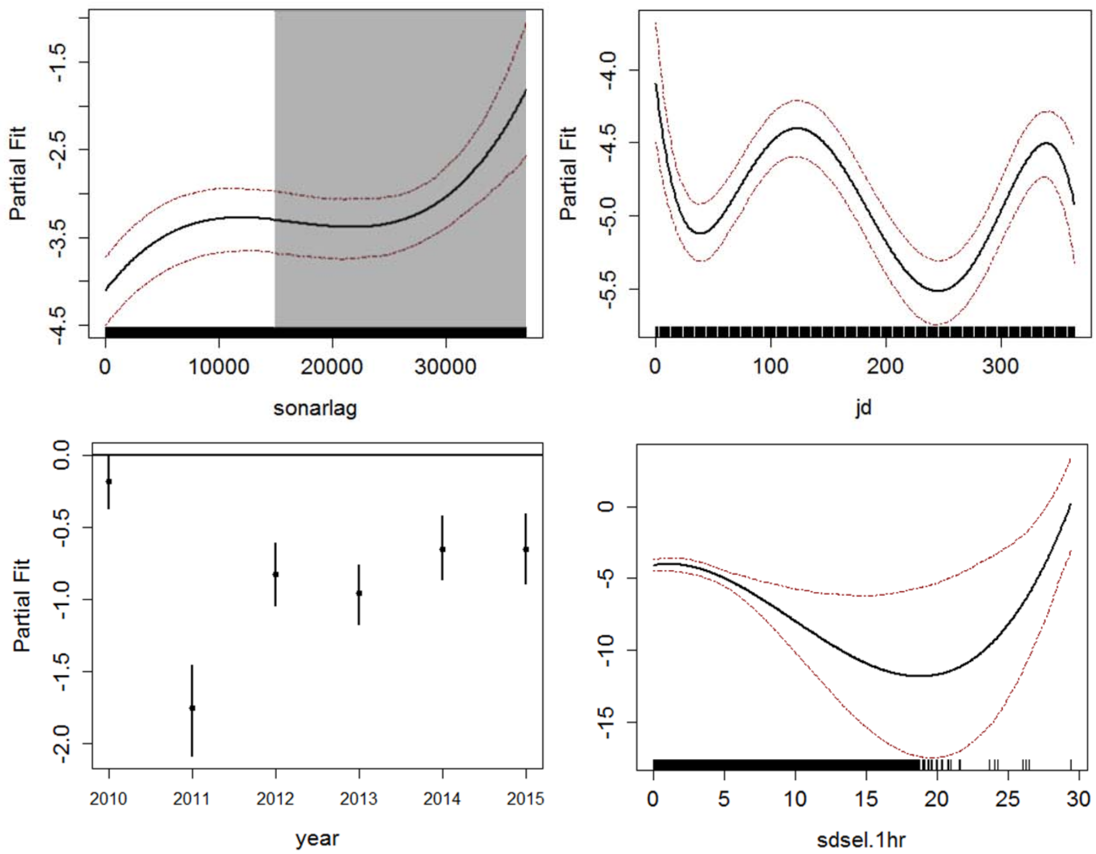

***Figure 10*. Partial fit plots for presence model for beaked whale clicks (note that the partial fit is given on the scale of the logit-link function). Vertical lines (rug) at the inside of the x-axis show locations of observed covariate values. The covariates retained in the final model were *sonarlag*, *jd*, *year* and the interaction term *scount2plus.1hr:sdsel.1hr*. Gray shaded area in *sonarlag* (top center) indicates outlier values.**

Assessing presence of call model assumptions

The estimates of the dispersion parameters provided evidence for overdispersion of the data in the blue whale model (170) but not for beaked whale model (1.07). For both the blue whale D call and beaked whale click models, the pattern of residual means across the range of observed values appeared unstructured, with no increase or decrease in variance.

Assessing model fit

To assess model fit, we split the fitted values of the model into 20 equally sized bins in ascending order of fitted values. We then calculated the means of the fitted values per bin and plotted these against the mean of the corresponding observed values in Figure 10. As expected, there was a random pattern around the line of perfect fit (Figure 11).

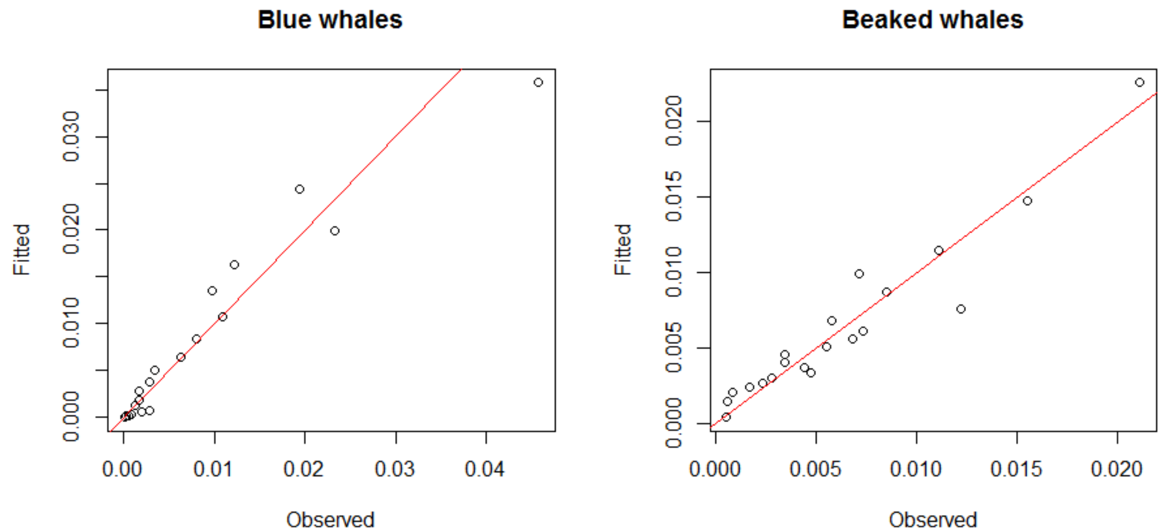

***Figure 11*. Mean observed versus mean fitted values from presence models for blue whale D calls and beaked whale clicks. Note that observations and fitted values were combined into 20 equally sized bins in ascending order of fitted values for which the mean was calculated. The red lines indicate a perfect fit of the model to the observed data.**

An additional method to assess model fit is to compare the predicted presences and absences against the observed presences and absences for each observation. For this purpose, we generated predicted presences using the fitted values of the best model. If, for a given observation, the fitted value was larger than the overall mean of the fitted values, we attributed a presence to the respective record. In the case that the fitted value was smaller than the overall mean of the fitted values, we attributed an absence to the respective record. Overall, the presence models for blue whales and beaked whales predicted 66.16% and 64.03%, respectively, of all observations correctly. A substantial percentage of predictions, however, were false positives (33.84% and 35.97% for the blue whale and beaked whale models, respectively).

IV. CONCLUSION AND NEXT STEPS

Major progress has been achieved on standardized, automated detection of acoustic signals of interest to generate an unbiased dataset with reproducible output. The data assembly is complete. Starting with model development using GEEs, we defined covariates to test the relationship of blue whale D call and Cuvier's beaked whale click presence with MFA sonar parameters as well as covariates describing natural variability.

First models representing results from one site and per signal type, established that inter-annual differences (*year*) and seasonality (*jd*) needed to be included in the models. As expected, the probability of blue whale call D detection declined with increase in background noise (*RLD_dB*) as signals become increasingly masked by noise. We may need to consider marking time periods with background noise levels >110 dB as off-effort.

Most importantly, both species reacted with an increase in detection probability as intervals of sonar use were increased (*sonarlag*). However, this increase needs to be reevaluated, particularly for blue whales and to a lesser degree for beaked whales, as the increase >10 days (or 14,400 minutes) likely is an artefact shaped by unusually long gaps (outliers) and seasonality of acoustic presence. The model also suggested that beaked whales negatively react with a decrease in echolocation to an increase in variations in sonar SEL over the preceding hour (*sdsel.1hr*).

In the next funding period we will continue the development of GEE models for other sites with data. This will allow us to evaluate how consistent is the response by comparing how much difference there is in the results of the selected models at different location. We will also add blue whale B calls to the analysis. In addition, we will be testing the applicability of the multi-spatial convergent cross mapping approach to these questions and our data.

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