Vocal Behavior of Blue Whales: The A-call

Mackenzie Perillo, University of California – Los Angeles

Mentors: John Ryan and Danelle Cline

Summer 2021

Keywords: Bioacoustics, Machine Learning, Passive Acoustic Monitoring (PAM)

ABSTRACT

A cacophony of sound resonates throughout the ocean generated by a diverse mix of geophysical, biological, and anthropogenic sources. Studying ocean soundscapes has become increasingly important, as human activity and climate change progressively threaten the health of marine mammal populations that depend upon sound for communication, navigation, and survival. Of these marine mammal populations, blue whales (*Balaenoptera musculus*) are particularly vulnerable to changes in oceanic soundscapes due to their endangered status. This study examines the behavioral ecology of northeastern Pacific blue whales via a population-level analysis of their vocal behavior. Specifically, in this study, we examine the variation in the abundance of the blue whale A-call over time and quantify the correlation of the A-call with a different type of vocalization made by blue whales, the B-call. This is accomplished by using long-term, continuous acoustic hydrophone data of one blue whale song season (June 2017-March 2018), coupled with signal processing and machine learning methods. Our preliminary results suggest that A and B-call vocalizations are tightly correlated, with similarly patterned frequency rates on daily and seasonal time scales. In addition, our preliminary results suggest a seasonal variation in the ratio of A-calls to B-calls, with a significant ratio peak of A-calls to B-calls in November.

INTRODUCTION

Blue whales (*Balaenoptera musculus*) have faced extinction in recent history due to commercial whaling; although populations have recovered somewhat, blue whales remain an endangered species and continue to face anthropogenic threats induced by commercial shipping activity and volatile environmental and oceanic conditions associated with global climate change (McDonald et al., 2009; Melcón et al., 2012; Guilpin et al., 2020). Anthropogenically sourced factors have influenced the largest threats to blue whales: increases in commercial shipping and oceanic noise input have caused increasing whale ship strike events and impair blue whales' ability to communicate with each other, navigate their environment, and carry out necessary behaviors for survival (Melcón et al, 2012). Gaining a better understanding of how blue whales use and produce sound in certain contexts can help us to understand their life processes and ultimately aid in forming comprehensive conservation strategies, minimizing anthropogenically sourced threats and accounting for dynamic environmental conditions.

Blue whales are the largest animal species living on Earth and produce calls with sound waves that penetrate vast amounts of ocean water due to the powerful, low frequency nature of their calls (ranging from 10 Hz - 100 Hz) (McDonald et al., 2006; Balcazar et al., 2015). Blue whale populations can be distinguished and differentiated from each other by regionally specific call types and patterns; literature currently recognizes 10 regional and acoustically unique populations of blue whales (McDonald et al., 2006; Ferris et al., 2011; Balcazar et al. 2015). This study examines the acoustic dialect of the eastern North Pacific blue whale population, specifically the blue whale population that migrates seasonally between the central coast of California and the Pacific coast of Central America.

Eastern North Pacific blue whales produce songs and sounds that are composed of four different calls: the A-call, the B-call (including different harmonic sequences), the C-call, and the D-call (McDonald et al., 2006; Oleson et al., 2007). Male blue whales combine A, B and C calls in different sequential quantities and patterns (with the A-call always initiating the song sequence) in order to produce songs that have been previously associated with reproductive behavior; while D calls occur separately (by both males and females) and have been associated with foraging behavior (McDonald et al., 2006; Oleson et al., 2007; Melcón et al., 2012; Oestreich et al., 2020). Of the three different song components, the B-call is both the most common and highest amplitude call. The call index (CI) is a metric of blue whale song intensity, and essentially, is a measure of the abundance of blue whale B-calls over time. By analyzing the ratio of CInight:CIday, Oestreich et al. established that an acoustic signature of population-level behavioral change from foraging to migration exists in the patterned, annual and seasonal changes of this ratio (Oestreich et al., 2020). While the temporal intensity of blue whale B-calls (and associated song intensity) has commonly been used to study blue whale presence, behavior, and location (Stafford et al., 1998; Wiggins et al., 2005; Oleson et al., 2007; Sirovic et al., 2015), few studies have examined the temporal patterns in A-call production in this population and associated biological implications (Lewis et al., 2018).

Passive acoustic monitoring (PAM) is a method of using underwater audio recordings to explore the sources of sound and analyze various acoustic energy occurrences. With continuous recording on long timescales, ocean soundscapes captured via PAM can be used to decipher and study different marine species' vocal behaviors, and how these behaviors change over time, and in response to different environmental and anthropogenic factors. Understanding the role of environmental conditions and the impact of human sourced acoustic inputs on an animal's behavioral ecology and life processes is fundamental in creating conservation strategies and regulating human actions in order to minimize harm to oceanic ecosystems and the life that exists within them. Understanding the biological effects of human-sourced acoustic inputs becomes more critical in the context of endangered blue whales due to the unique and fundamental role that sound has in the behavior, communication, and survival tactics of blue whales.

In this study, we used a hydrophone stationed at the Monterey Accelerated Research System (MARS) cabled observatory, located just offshore of Monterey Bay, CA (36°42.75'N, 122°11.21'W; depth 891 m) in order to collect continuous, passive acoustic data (Ryan et al., 2016). This project has three goals:

1. To examine the temporal (seasonal to daily time scales) patterns in the frequency and abundance of A-call production of northeastern Pacific blue whale populations;
2. To analyze potential relationships of the timing and abundance of blue whale A-calls to previously studied temporal patterns in blue whale B-call intensity in the northeastern Pacific Ocean;
3. To assess the differences in machine learning methods versus manual statistical analyses: analyzing the potential differences in respective reported quantity of blue whale A-calls and diagnosing the causation of potential discrepancies.

MATERIALS AND METHODS

I. DATA COLLECTION

In this study, all of the acoustic data that we analyzed were captured by a hydrophone, stationed at the Monterey Accelerated Research System (MARS) cabled observatory, located at (36°42.75'N, 122°11.21'W; depth 891 m) (Figure 1) (Ryan et al., 2016). We initially started the data collection process by establishing the boundaries of the time period that we were going to focus our analysis on; we did this by examining seasonal distributions of blue whale song intensity, measured by the metric of B-Call Index (CI), over the continuous span of six years of acoustic data from MARS (Figure 2). Due to the extraordinarily high CI that we observed in November of 2017, we decided to focus on the complete northeastern Pacific blue whale song season that included the time period from June 2017- March of 2018.

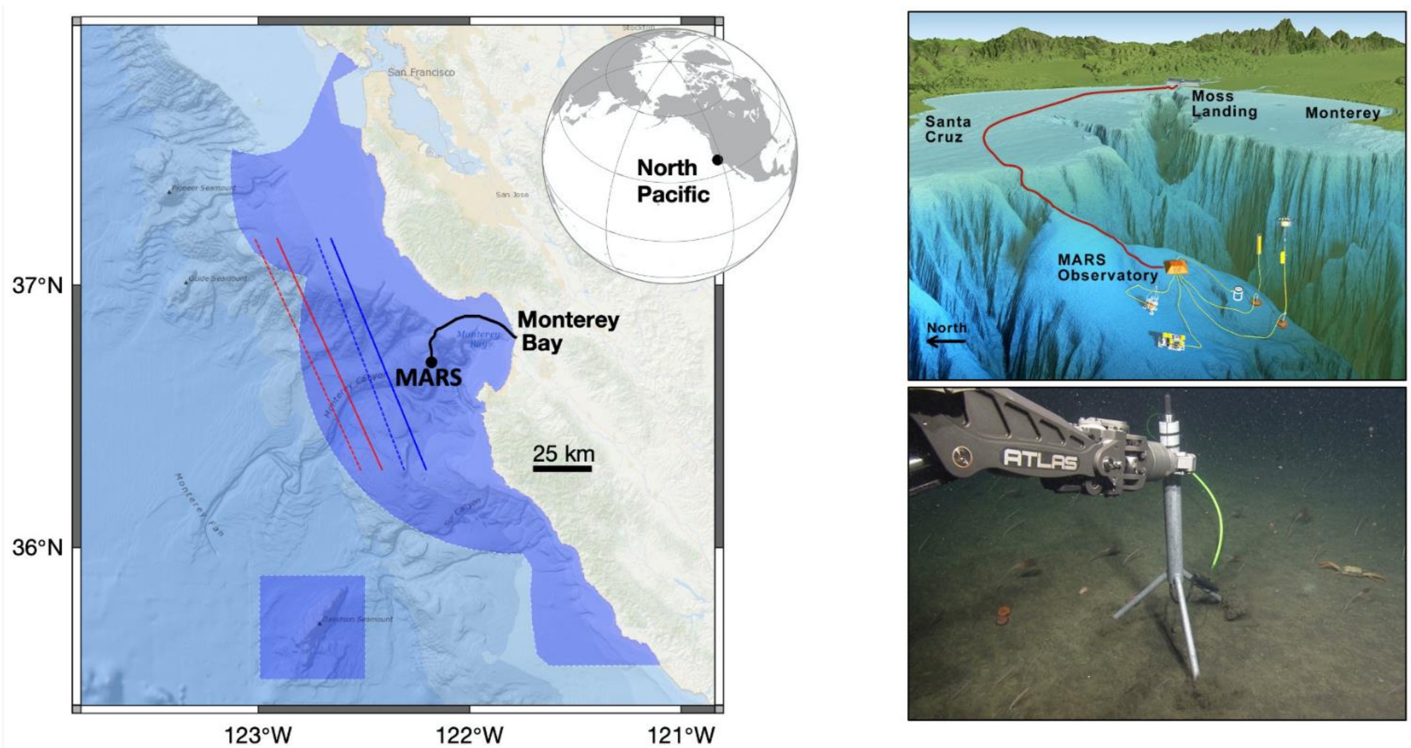

Figure 1. *Left: Location of the Monterey Accelerated Research System (MARS) cabled observatory. Top Right: Underwater topography and visual depiction of the hydrophone set up at MARS. Bottom Right: A picture of the hydrophone that is stationed at MARS, the hydrophone that was used to collect data in this study*

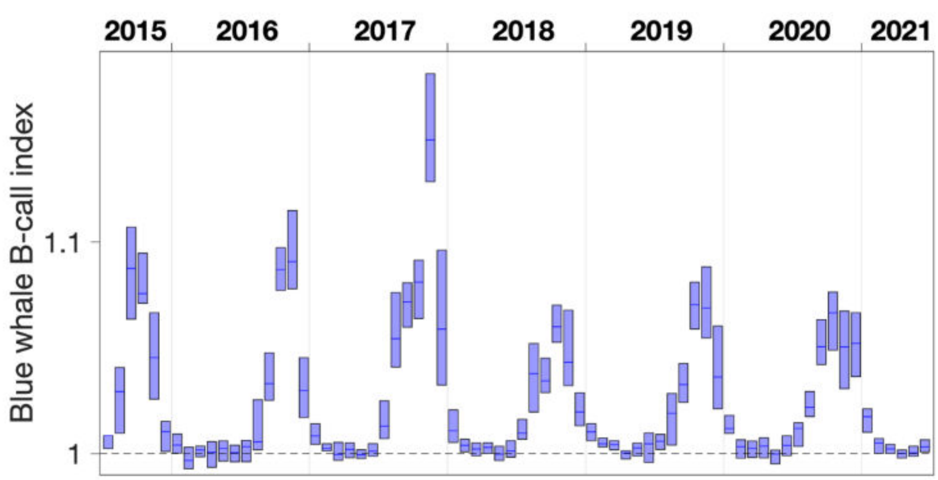

Figure 2. *Monthly binned averages of blue whale B-call Index over the span of July 2015-June 2021.*

II. A-CALL DETECTION

The continuous sound recordings from this time period were converted into spectrograms, or visual representations of sound energy occurrences, in Raven Pro v1.5.0 (The Cornell Lab of Ornithology Center for Conservation Bioacoustics, 2017). We then applied two different Band Limited Energy Detectors (BLED), with pre-programmed parameters (Figure 3) tuned to define occurrence of sound energy within a specified A-call frequency range, determined from examination of many examples from MARS recordings. After the BLEDs were applied, we had a compilation of all of the total possible occurrences of blue whale A-calls in our specified time range, including many false positive detections (due to the tuning of the BLED detectors to ensure that we did not have a data set missing any A-calls that occurred). The total quantity of BLED detections from June 2017-March 2018 includes 302,002 detections.

	Blue A 1	**Blue A 2**
FFT window size (samples)	512	512
Overlap (%)	95	95
Min Freq (Hz)	70	70
Max Freq (Hz)	95	95
Min Duration (s)	9.984	9.984
Max Duration (s)	40.064	40.064
Min Separation (s)	1.024	1.024
Min Occupancy (%)	20	30
SNR Threshold (dB)	4	1
Block Size (s)	60.032	29.952
Hop Size (s)	19.968	1.024
Percentile	50	60

Figure 3. *BLED parameters.*

III. MACHINE LEARNING CLASSIFICATION AND VERIFICATION

A. Classification

To assess how closely each detection resembled a true blue whale A-call, and the associated probability that the detection is a real blue whale A-call, each BLED detection was denoised and converted into a spectrogram image with a range of 70-100 Hz and a 25 second window. We then trained a convolutional neural network model called EfficientNetB0 to recognize a blue whale A-call with a training data set of manually labeled spectrogram images (2982 true examples and 1361 false examples of a blue whale A-call detected by the BLED were used) (Tan and Le, 2019). The machine learning classifier achieved 91.5% accuracy after training. We then input the 302,002 spectrogram images to be processed by the machine learning classifier, which assigned two scores to each image: a True A-Call Score and a False A-Call Score. The True and False A-Call scores for each image summed to equal 1, with a score close to 1 indicating high confidence of the machine learning that the corresponding spectrogram image matches the category of the assigned score: for example, a spectrogram image with a True A-Call Score of .9 and a False A-Call Score of .1 indicates that the machine learning classifier has a high confidence that the spectrogram image is a true blue whale A-call.

B. Manual Threshold Verification

With a scored set of 302,002 total possible blue whale A-call detections, we established a minimum True A-Call Score that signified the threshold of a complete set of BLED detections that are true blue whale A-calls. We established the minimum threshold by manually counting the number of A-calls visible in a spectrogram on a number of different days in a variety of different months. We then compared manual daily A-call counts to the different quantities of BLED detections that were classified as true A-calls under a range of different True A-Call Score minimum thresholds (.1-.9). We established a threshold minimum True A-Call Score of .8, as the manual counts of daily A-calls best matched the quantity of BLED detections that were classified by the machine learning as having a True A-Call Score of .8 or higher.

All BLED detection spectrogram images with a True A-Call Score of .8 or higher signified all of the blue whale A-calls recorded by the hydrophone that occurred during our selected time frame. 71,142 of the original 302,002 detections had a True A-Call Score of .8 or higher, comprising 21.56% of the total BLED detections.

IV. ANALYSIS

With a finalized set of blue whale A-calls, which we were confident encompassed the entirety of the A-calls that were produced between June 2017 and March 2018, we could conduct an analysis on the temporal variation of A-call vocalizations and the potential correlation of these data to the temporal patterns described previously for B-call vocalizations. Using the A-call data we collected and processed in this study and the B-call data previously collected and analyzed by Oestreich et al., various statistical analyses were conducted in R v 3.6.3 (Oestreich et al., 2020; R Core Team, 2020). Days of acoustic data that were compromised by missing a period of recording were excluded from the analysis of A-calls and B-calls. For each unit of time that was used to analyze the quantity of A-calls, we normalized the A-call count by calculating an A-call rate. For a daily analysis, we divided the total number of calls by the total number of hours of recording time (resulting in a total number of A-calls per day). For a diel and monthly analysis, we divided the total number of A-calls occurring during a specific time of day over the span of one month by the total number of days of recording time that occurred during a specific time of day, over the span of one month (resulting in total number of A-calls per day, divided into three subcategories specifying what time of day: day, night, dusk/dawn). Normalization was necessary for analysis; by calculating a rate as opposed to quantity of A-calls in a given time, the differences in recording time within specified time categories did not mask the level of A-call occurrence in these given times.

Specifically, we analyzed the total A-call Count, the A-call rate (calls/day), and the B-call Index in regards to time of day (based on solar elevation), to month, and to each other using R packages “ggplot2” (Wickham, 2016), “tidyverse” (Wickham et al., 2019), “patchwork” (Pederson, 2020) , “ggpubr” (Kassambara 2020), and “padr” (Theon, 2020; R Core Team 2020).

RESULTS

I. SEASONAL TIMESCALES

Intensity of the B-call index and the occurrence of A-calls showed similar patterns between June 2017 and March 2018: both B CI and A-call rate approach no activity near the ends of the blue whale song season in June and March, and both have a minor peak in September and a major peak in November, with a decrease in abundance in between these peaks in October (Figure 4).

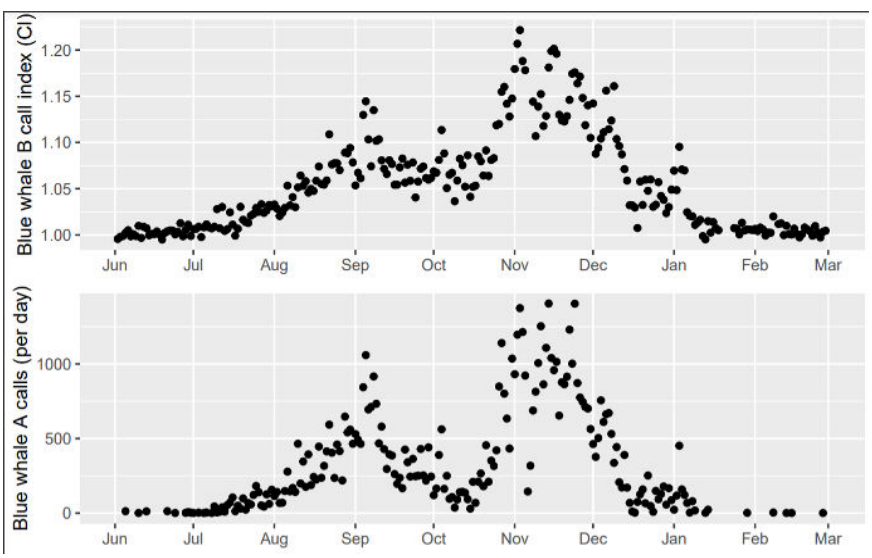

Figure 4. *Top) The daily blue whale B-call Call Index (CI) for every day of sufficient recording data in the span of time from June 2017-March 2018. Bottom). The total quantity of blue whale A-calls per day for every day of sufficient recording data in the span of time from June 2017-March 2018.*

A-call abundance and B CI are strongly associated with each other, quantitatively correlated with an R^2 value of 0.84, meaning that 84% of the variation in the daily A-call rate can be predicted by variation in the B-call CI (Figure 5).

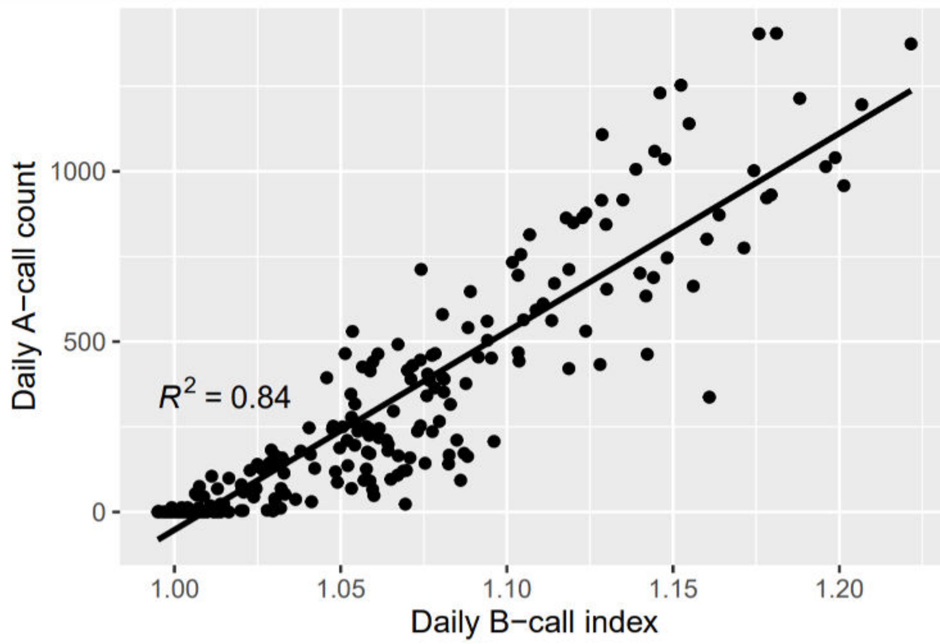

Figure 5. *Relationship of the calculated daily B-call index to the daily A-call count recorded by the hydrophone stationed at MARS, with a calculated R^2 value of 0.84.*

While A-calls and B-call CI are found to be strongly associated with each other overall, the A-call rate was relatively low compared to the B-call call index during October 2017. In this time period, the median quantity of A-calls per day showed a significant decrease as opposed to the median quantity of A-calls in the months preceding and following October 2017 (Figure 6). By comparing the monthly median quantity of each metric of blue whale A-calls and B-call CI, seasonal patterns and anomalies are drawn out: November 2017 is an outlier of the selected time period, as the median quantity of both daily A-call count and B-call CI have a significantly high value for each respective metric (Figure 6). Particularly, when directly compared to each other, the ratio of the median value of daily A-calls to the median daily B-call CI, November 2017 exceeds any other month by at least two times the next highest monthly ratio (Figure 7).

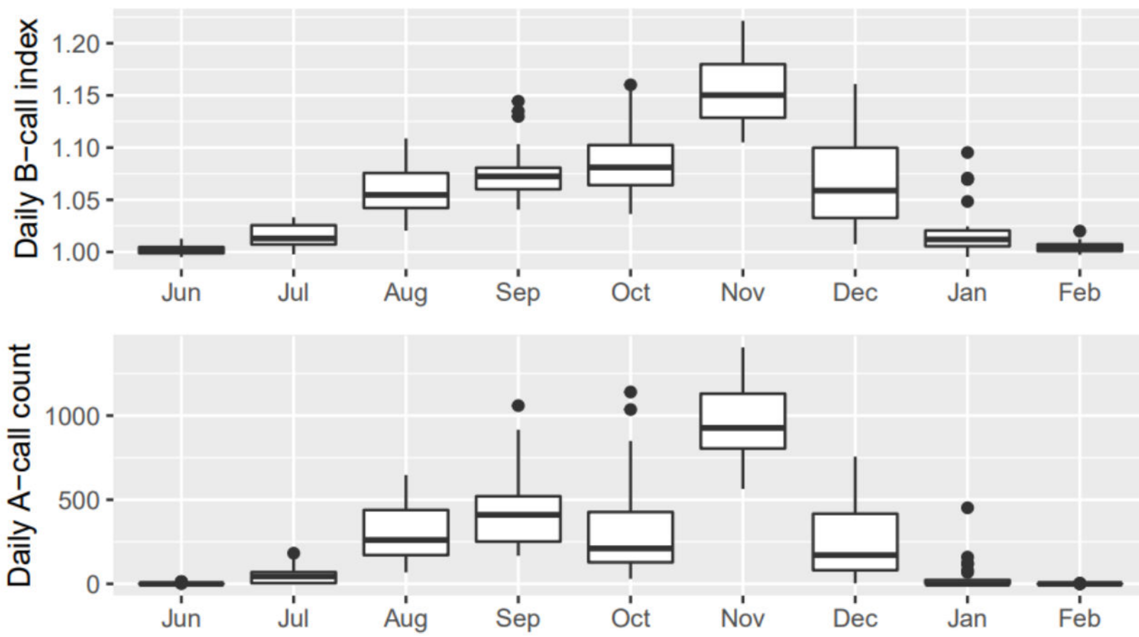

Figure 6. Top) *Monthly binned statistics of the average daily B-call index over the span of time from June 2017-March 2018. The bottom, middle, and top lines of the boxes mark the 25th, 50th, and 75th percentiles of daily CI values from each month, respectively. The span of the vertical black line for each month marks the minimum and maximum value of the daily B-call CI, with the dots indicating outliers.* Bottom) *Monthly binned statistics of the average daily A-call count over the span of time from June 2017-March 2018. The bottom, middle, and top lines of the boxes mark the 25th, 50th, and 75th percentiles of daily A-call count values from each month, respectively. The span of the vertical black line for each month marks the minimum and maximum quantity of the daily A-call count, with the dots indicating outliers.*

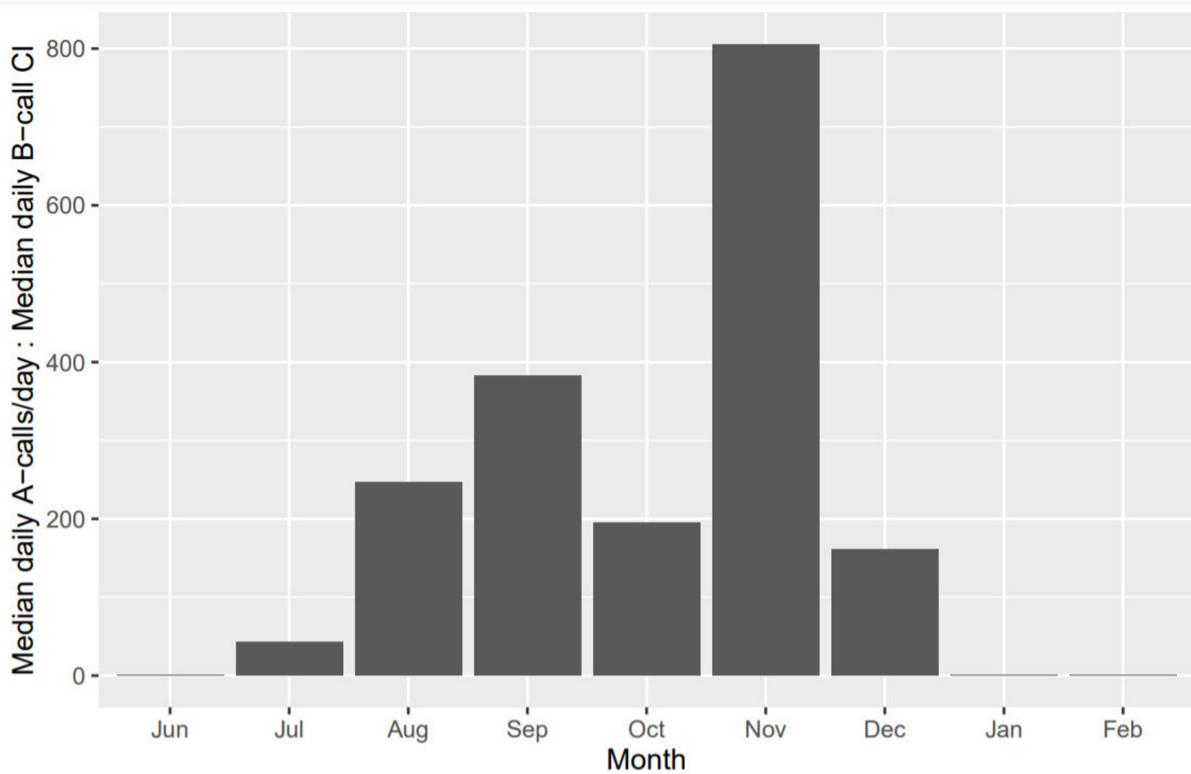

Figure 7. *Monthly binned ratio of the average median value of A-call rate (A-calls per day) to the average median value of the daily B-call CI.*

II. DIEL VARIATION IN THE A-CALL

Overall, between June 2017 and March 2018, the highest rate of A-call production occurred during the night (480 calls/day) and the lowest rate of A-call production occurred during the day (300 calls/day). The rate of A-call production occurring at dusk/dawn, overall, was in between the day rate and the night rate, with a value of 420 calls/day (Figure 8).

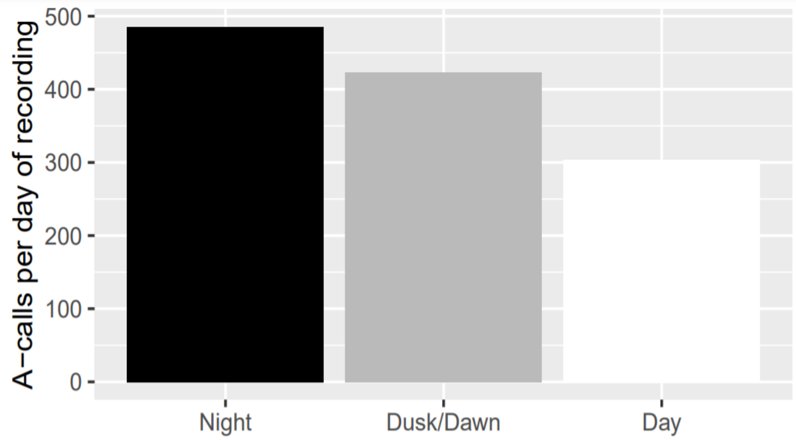

Figure 8. *Average A-call rate over the span of time from June 2017 - March 2018 that occurred during a specific time of day : night, dusk/dawn, and day.*

When broken down into monthly and diel timescales, the proportion of the A-calls produced during the day was the lowest for the months (August, September, and November) with the greatest total amount of song (Figure 9). Particularly, in the anomalous month of November, the large majority of A-calls were produced at night, dusk, and dawn, in comparison to the rate of A-calls that were produced during the day.

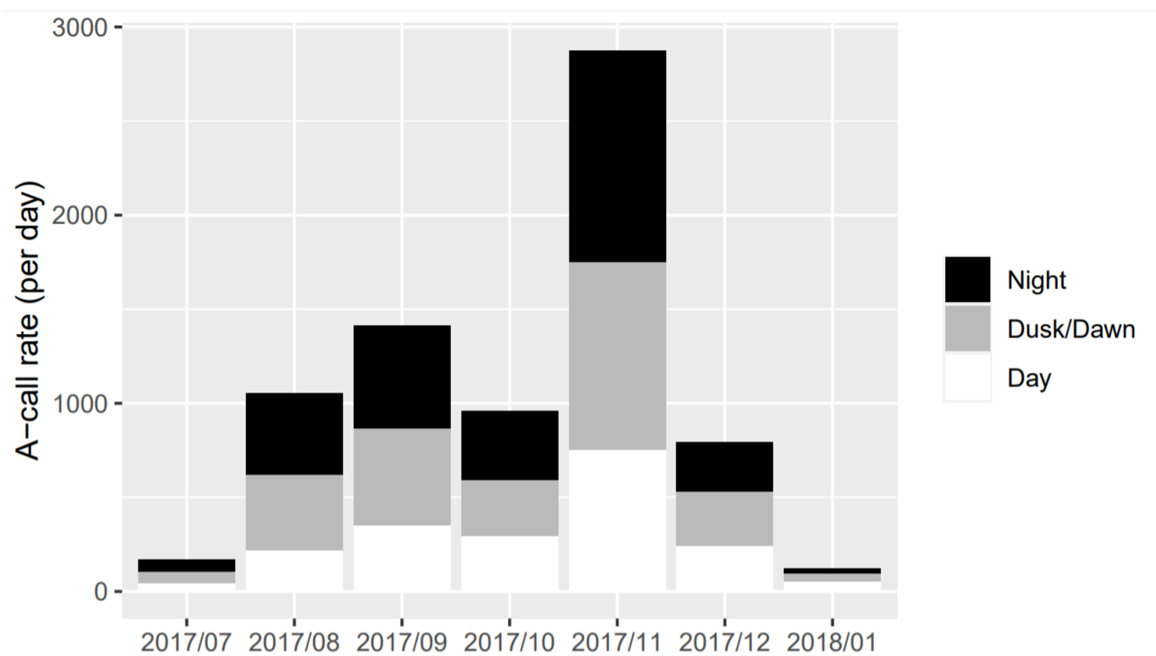

Figure 9. *Monthly binned average A-call rate over the span of time from June 2017 - March 2018, represented by each complete vertical bar. The white, grey, and black components of the bar quantifies the A-call rate that occurred during a specific time of day : night, dusk/dawn, and day, respectively, per month.*

DISCUSSION

Few studies have focused on the vocal behavior of blue whales off central California, however, the seasonal distribution of song production that we see observed in this study is consistent with previous studies on blue whale vocal behavior in this region. Blue whale song (phrases of A, B, and C-call) behavior begins to increase in July, peaking in November with the most activity, and decreasing to no activity again in February (Oestreich et al., 2020). The initial seasonal increase in vocalizations (summer) is attributed to a behavioral change in regionally present blue whales, whereas the seasonal decrease in vocalizations (late winter) is attributed to regionally present blue whales migrating out of range of the hydrophone's recording radius (Figure 2).

The observed seasonal distribution of blue whale vocalizations off southern California is similar to that off central California in regard to the pattern of an annual increase and decrease in vocalizations, though the peak of song production off southern California occurs in September as opposed to November (Širovic er al., 2015; Lewis et al., 2018; Oestreich et al., 2020).

June 2017-March 2018 was an extraordinary northeastern Pacific blue whale song season, displaying the highest song production recorded in the last 6 years of continuous acoustic data recorded at MARS. While this vocal activity is thought to have resulted from a surge in the regional blue whale population during this time period, a metric to quantify population size was not included in our study.

Some studies of blue whale song have been conducted off central California, yet, no studies have been conducted on the A-call of blue whales in this region. However, one study using recordings off southern California examined A-calls recorded on tags attached to blue whales (Lewis et al., 2018), rather than continuous PAM as in our study. Studying the same northeastern Pacific population of blue whales as this study, Lewis et al. used tagging data to obtain individually-scaled behavioral data and production of A-calls, B-calls, and D-calls. The seasonal distribution and diel distribution of A-call production rates are consistent across both studies: the highest amount of vocal activity occurs during late autumn and the highest rate of production of song occurs during dawn/dusk and night (Lewis et al., 2018).

Additionally, Lewis et al. found that the majority of sound production of blue whales was associated with a phrase or song, with occurrences of individual A-calls and B-calls bordering phrases very closely (Lewis et al., 2018). In this study, November 2017 was found to have an anomalous ratio of daily A-calls to daily B-call CI (Figure 7); though the placement of the excess number of A-calls was not analyzed in regards to the context of the occurrence of phrases or songs. With the analysis spanning the extent of only one season, it is unknown if the ratio of A-calls to B-calls is always the highest in November, or if the year of 2017 is an anomaly. More research will also need to be done in order to better understand if the extraordinarily high production of A-calls was integrated into songs/phrases, or if these A-calls were individual calls.

The large majority of northeastern Pacific blue whale calls occur during shallow, non-lunging dive behavior (Lewis et al., 2018). Previous literature has examined the temporal variation in regard to the intensity of the B-call, deciphering an acoustic signature that indicates when northeastern Pacific blue whales begin to migrate and change their vocal behavior (Oestreich et al., 2020). While this study did not yet include the analysis of behavioral data, A-call vocalization patterns and the anomalies between months/years of song seasons may have meaningful implications when placed in a behavioral context of blue whales. Expanding our understanding of the vocal behaviors of blue whales can help us to better understand how the sounds that we inject into ocean soundscapes affect the necessary behaviors of populations of blue whales. Delineating behavioral implications of the production of blue whale A-calls can help to better inform conservation strategies, regulations on anthropogenic and oceanic acoustic inputs, and shipping traffic routes and speed limits, in order to reduce the overall harmful effects on this endangered species.

CONCLUSIONS/RECOMMENDATIONS

Although this study is only a preliminary examination, including only one seasonal cycle of blue whale song detection, the correlation between A and B-calls is strong enough to conclude that they are tightly related with each other. We can preliminarily conclude that A-calls may signify a similar behavioral change in blue whales as B-calls do.

However, to expand future research, I propose five aspects of this study that would be beneficial in dedicating more time and thought to.

1) Time scale expansion: The continuous acoustic data that the hydrophone stationed at MARS records currently spans six years and is lengthening with every day. This study only focused on one blue whale song cycle (which happens annually). By extending this study to a length of six years, we will have six blue whale song cycles to analyze; we can determine if the patterns and correlation of A-calls and B-calls are homogenous every song cycle, or if 2017-2018 is a unique cycle.

2) Systematic examination of minimum blue A-call True Score threshold: The methods that we used to establish an accurate minimum threshold for a True A-call score in this study are sufficient enough to validate the results of a pilot study. However, if this study were to be expanded to multiple blue whale song seasons, the minimum threshold for a true blue whale A-call needs to be verified by more extensive statistical analyses under a larger variety of unique daily, environmental conditions.

3) Intricate examination of the idiosyncratic time period of mid-September to mid-October: While A-calls and B-calls are seemingly closely associated with each other, the discrepancy in similarity between the A-call rate and the B CI in the period of September 2017 - October 2017 can be examined with greater detail in the future to understand the extent of this variation in production rates.

4) Incorporation of context and other calls: By including a time-oriented analysis of B-calls, C-calls, and D-calls, we can better understand if the fluctuation in A-call production is associated directly with fluctuations in song production, is related to D-call production, or is an independently fluctuating variable.

5) Collection of behavioral tagging data: Accounting for the timing of individual foraging and migrating behaviors and pairing that data with population-level vocal behavior data collected and analyzed in this study would give behavioral contexts to vocal behaviors. By pairing behavioral data with temporal occurrence of A-calls, the timing of A-calls can be associated with certain behaviors of blue whales.

ACKNOWLEDGEMENTS

Thank you sincerely to John Ryan, Danelle Cline, and William Oestreich for their guidance, mentorship, and inspiration. Thanks to previous MBARI summer interns for leading by example, and to the 2021 MBARI summer interns for fostering growth through support and creative collaboration. I would also like to thank George Matsumoto, Megan Bassett, and Lyndsey Claassen for directing an incredible summer internship experience. Lastly, thank you to the generous support received through a gift from the Dean and Helen Witter Family Fund and the Rentschler Family Fund in memory of former MBARI board member Frank Roberts (1920-2019) and to the support provided by the David and Lucile Packard Foundation.

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