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Determining temporal recording schemes for underwater acoustic monitoring studies

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DETERMINING TEMPORAL RECORDING SCHEMES FOR UNDERWATER ACOUSTIC MONITORING STUDIES

by

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ABSTRACT

Soundscape Ecology, the physical combination of sounds at a particular time and place, is a rapidly growing field. As acoustic technology advances, several possible future uses of passive acoustic monitoring (PAM), such as biodiversity counts and monitoring of habitat health, are being explored. This thesis is divided into two chapters; each is a stand-alone paper. The first chapter provides a review of soundscape ecology, ambient sound, current recording methods and data analysis used in PAM studies, and identifies several major future recommendations for the field. One of these recommendations is to standardize recording methods and indices used during analysis in long-term studies. The second chapter analyzes a 55-minute continuous recording on a coral reef in Tunicate Cove, Belize in 1996 by Professor P. Lobel. This recording was then subsampled with several intermittent recording schedules to explore the amount of acoustic information lost as periods of active and inactive recording vary. The continuous recording consisted of a high frequency band (3-4 kHz), which may correspond to abiotic sounds, and a low frequency band (0.1-0.5 kHz), which generally corresponds to biotic sounds. Two recording schedules, 30 seconds every 4 minutes and 2 minutes every 10 minutes, were significantly correlated with the continuous recording. The statistical significance of the other five recording schedules varied among the three parameters tested in this study (average power (dB), average entropy, and aggregate entropy).

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Chapter 1: The Current State of Soundscape Ecology in Underwater Habitats

Introduction

Soundscape ecology is an emerging field of research broadly defined as the physical combination of sounds at a particular time and place (Pijanowski et al., 2011; Schafer, 1977). The soundscape of a particular habitat consists of abiotic sounds, such as wind and rain (geophony); biotic sounds, which are sounds produced by living organisms (biophony); and man-made sounds, including seismic exploration, shipping, dredging, and sonar navigation (anthrophony) (Krause, 1987; Pijanowski et al., 2011). Acoustic habitats can convey important information about an ecosystem such as flora and fauna composition, environmental conditions, and habitat quality (Staaterman et al., 2013).

However, over the past few decades, the contribution of anthrophony in the oceans has increased drastically and raised concerns about its interference with biological behavior, such as masking animal communication and impeding larval settlement (Jolivet et al., 2016; Lillis et al., 2013, 2014, 2016; Lobel, 2005, 2009; Vermeij et al., 2010). In order to best regulate these man-made sounds in the oceans, we need a better understanding of the acoustic complexities that interact to create unique soundscapes. An effective method to monitor the soundscapes of different habitats is through long-term passive acoustic monitoring (PAM). The use of omni-directional hydrophones allows researchers to record all sounds at a particular location, including the ambient, or background, sound. Many studies have begun exploring the potential that long-term PAM has to serve as a low-field labor intensive and cost effective tool to monitor health and biodiversity of remote marine ecosystems (Au et al., 2012; Bertucci et al., 2015; Butler et al., 2016; Lammers et al., 2008;

Rossi et al., 2017; Staaterman et al., 2017; Sueur et al., 2008b). **This paper provides a review of ambient sound and soundscape ecology, current recording and sampling methods used in long-term PAM, parameters and metrics used in acoustic data analysis, and future recommendations for the field.**

Ambient Sound and Soundscape Ecology

In water, sound propagates omni-directionally and moves at a speed four and a half times faster in saltwater than through air. Acoustic cues play important roles in animal communication including species identification, mate selection, timing of insemination, and larval settlement (Lillis et al., 2014; Lobel, 1992; Vermeij et al., 2010). Evolution of acoustic communication during speciation may also be influenced by the ambient sound, or background sound, of a habitat. Acoustic signals have also been found to potentially play a role in speciation. One study found that the sounds of closely-related species of a well-studied family of soniferous fishes, Damselfish, have evolved differently when home ranges do not overlap geographically (Parmentier et al., 2009). These differences in acoustic signatures are likely due to varying abiotic factors in the ambient sound.

Ambient sound can also convey important information about habitat quality to individuals. Parmentier et al., 2015 found that some species of coral reef fishes are even attracted to certain reef sounds and repelled by others. Wenz, 1962 concluded that ambient noise in the ocean is primarily made up of three overlapping components: turbulent-pressure fluctuations, wind, and traffic noise – which describes low frequency background noise produced by ships from a great distance and is not readily recognizable as produced by ships. However, ambient sound is comprised of the geophony, biophony, and anthrophony together. The interaction of all of these sounds creates a distinct soundscape in different habitats and even in distinct parts of the same habitat. Biological sounds are, however, much more difficult to generalize than abiotic sounds because they vary much more in frequency, time, and location. Structurally complex and diverse habitats that have undergone regime shifts to less complex habitats have been found to be directly correlated with a decrease in biological sounds in at least one study (Rossi et al., 2017). Mean sound levels may also increase with coral cover due to higher biodiversity found on reefs with higher coral cover (Bertucci et al., 2015). Studies have also shown that soundscapes can be used to estimate biodiversity in terrestrial ecosystems (Pieretti et al., 2011; Sueur et al., 2008b) and this hypothesis has recently been extended into the marine realm (Pieretti et al., 2017; Rossi et al., 2017). Based on preliminary studies demonstrating that sound intensity is higher on healthy reefs than degraded ones (Piercy et al., 2014), soundscapes and ambient sound have the possibility to serve as a monitoring tool for ecosystem health.

Current Long-Term Passive Acoustic Monitoring Methods

Acoustic technology has advanced significantly in recent years. Omni-directional hydrophones with high sensitivities, automatic acoustic recorders, and associated hardware are capable of collecting a wide range of acoustic data and currently only limited by battery life and memory storage. Hydrophones are produced with a wide range of recording sensitivities and need to be calibrated to the appropriate sensitivity depending on the target sound source(s). In general hydrophone sensitivities being used in the field range from -

156 to -193 dB re: V/ µPa. Studies that have not been able to calibrate their hydrophone systems have shown the importance of doing so when recording long-term (Curtis et al., 1999). All of this technology allows researchers to collect data at regularly scheduled intervals, independent of previously limiting factors such as weather and study site depth.

Different sources of sounds are produced over a wide range of frequencies. In general, the sound of wind and breaking waves correlate to the wide frequency band of 0.1 – 20 kHz with a peak from 200 – 2,000 Hz (Curtis et al., 1999). Shipping noise is generally in the 30 – 100 Hz band and typically about 10 dB above other background noise (Curtis et al., 1999). The peaks in rainfall sound occur in the 15 – 20 kHz range and generally last over longer periods of time at a fairly steady rate (Haxel et al., 2013). In terms of biotic sound production, most studies find the loudest contributors to the overall soundscape are snapping shrimp, which can sometimes drown out other biotic sounds in recordings (Au et al., 2012). Fishes and whales tend to dominate sound production at lower frequencies (<500 Hz) and invertebrates dominate the higher frequencies (2.5 – 15 kHz) (Radford et al., 2011). However, biotic sounds show high variability between times of day, month, year, and lunar cycle (Staaterman et al., 2014). Such a wide range of frequencies demonstrates the difficulties in capturing and distinguishing between different sources of sounds in an overall soundscape.

Since many long-term PAM projects are using recording rates based off the desired length of study, battery life, and data storage capabilities of their hydrophones and acoustic recorders, there has been no common framework among studies. Recording rates used in recent studies range have been highly variable and are summarized in Table 1.1. A wide range of frequency rates have been used during recording as well, ranging from 2 kHz to 250 kHz (Table 1.2). However, studies have yet to be performed to test for the accuracy of non-continuous acoustic data in underwater studies. Testing current methodologies and assumptions is an important step in any emerging field to create a common framework.

Data Analysis

Acoustic Parameters and Measurements

There are also a very wide variety of parameters used in the analysis of data across studies. Across a total of 60 studies looked at for this review, 34 different metrics and/or indices were used when analyzing acoustic data. Power spectral density, or the strength of the variations in energy as a function of frequency, is the most readily used during the analysis of acoustic data (Au et al., 2012; Bertucci et al., 2015; Brown et al., 2016; Butler et al., 2016; Gavrilov & Parsons, 2014; Kaplan et al., 2015; Lillis et al., 2013; Locascio & Burton, 2015; Merchant et al., 2015; Pieretti et al., 2017; Radford et al., 2011; Rossi et al., 2017; Staaterman et al., 2013, 2014, 2017; Stanley et al., 2017; Wiggins et al., 2016). Sound pressure level (SPL), or root mean square (RMS) - SPL, are the next most frequently used parameters (Au et al., 2012; Curtis et al., 1999; Fisher-pool et al., 2016; Haxel et al., 2013; Kaplan et al., 2015; Lammers et al., 2008; Lillis et al., 2014, 2016; Locascio & Burton, 2015; Merchant et al., 2015; Rossi et al., 2017; Staaterman et al., 2014; Stanley et al., 2017; Vermeij et al., 2010; Wiggins et al., 2016). Many studies choose a small number of parameters to focus on during analysis, while some analyzed up to ten different parameters (Stanley et al., 2017). There is still discussion about

Recording Rate	Paper(s)
30 seconds every 4 minutes	Heenehan et al., 2017
12 seconds every 5 minutes	Staaterman et al., 2013, 2014
20 seconds every 5 minutes	Rowell et al., 2012
30 seconds every 5 minutes	Wall et al., 2017
10 seconds every 10 minutes	Locascio & Burton, 2015
1 minute every 10 minutes	Staaterman et al., 2017
2 minutes every 10 minutes	Lillis et al., 2016
30 seconds every 15 minutes	Lammers et al., 2008
150 seconds every 15 minutes	Depraetere et al., 2012
1 minute every 20 minutes	Kaplan et al., 2015
10 minutes every 1 hour	Radford et al., 2011
1 hour every 3 hours	Benoit-Bird et al., 2001
Continuously for 24 – 48 hours	Au et al., 2012; Jolivet et al., 2016; Pieretti et al., 2017; Staaterman et al., 2017

Table 1.1: Recording rates used in various underwater Soundscape Ecology and/or long-term Passive Acoustic Monitoring publications.

Recording Frequency Rate	Paper(s)
2 kHz	Haxel et al., 2013; Stanley et al., 2017; Wiggins et al., 2016
20 kHz	Staaterman et al., 2013
44.1 kHz	Vermeij et al., 2010
96 kHz	Lillis et al., 2016; Rossi et al., 2017
250 kHz	Parks et al., 2014

Table 1.2: Recording frequency rates used in various underwater Soundscape Ecology and/or long-term Passive Acoustic Monitoring publications.

whether one number, or index, can fully describe a soundscape. As the field continues to grow, it is recommended that studies continue to use multiple parameters, each of which provides details about different aspects of a soundscape. All of these small details can be analyzed together to gain a richer understanding of individual soundscapes. Determining which indices provides the most accurate description of the acoustic data remains one of the major challenges in soundscape ecology.

Several measurements, including power spectral density (PSD) and spectral entropy (H), can be quickly calculated in bioacoustics software, such as RavenPro (Bioacoustics Research Program, The Cornell Lab of Ornithology, Ithaca, NY) and Avisoft SASLab Pro (Avisoft Bioacoustics, Germany). These quick calculations can be especially useful when analyzing larger data sets. Power spectral density estimates how the power of a signal is distributed over frequency, instead of time, and is generally used to characterize broadband random signals. In Raven, average PSD is calculated by summing the square magnitudes of the Fourier coefficients across time and frequency and dividing by the product of the selection duration and selection bandwidth; resulting in a measurement in decibels (dB). The spectral entropy calculated in Raven is affected by the signal, begin/end times, low/high frequencies, window size, Discrete Fourier Transform (DFT) size, and overlap. This measure has a low value for signals with a similar type of distribution of energy over a spectral slice. The average entropy measurement computes the entropy of each spectral frame and averages those measurements, while the aggregate entropy corresponds to the overall disorder in a sound.

Acoustic Indices

In general, there are two major groups of acoustic indices: with-in group (α) and between-group (β) indices (Sueur et al., 2014). With-in group indices are useful in comparing all aspects in the same group; with a group being defined as “a sample unit as a site, a habitat, or a time event” (Sueur et al., 2014). Between-group indices are useful in determining how acoustically different multiple acoustic communities are. Depending on the specific research question, it may be necessary to assess indices from both groups to gain a full understanding of the acoustic landscape.

Several new indices are being tested to measure the evenness of an acoustic space (acoustic entropy index (H)) (Sueur et al., 2008b), the dissimilarity between two communities (acoustic dissimilarity index (D)) (Depraetere et al., 2012; Sueur et al., 2008b), acoustic richness of a community (acoustic richness (AR)) (Depraetere et al., 2012; Sueur et al., 2008b), and degree of complexity (acoustic complexity index (ACI)) (Pieretti et al., 2011). Indices such as AR, ACI, and H are considered α indices and the D index is in the β group. Most studies testing the robustness of these indices were performed in terrestrial ecosystems; the data of which is not directly comparable to data from underwater acoustics. Therefore, these studies should also be conducted in marine ecosystems.

Each of these indices has different advantages and drawbacks. Acoustic entropy (H) is the product of both spectral and temporal entropies and results on a scale of 0 to 1, with 0 indicating more pure tones and 1 indicating random noise. The H index can provide interesting information regarding species richness in a habitat. Sueur et al, 2008 demonstrated the use of this index by comparing the sounds of a degraded forest to those of a healthy forest in coastal Tanzania. Their study found that H values were significantly higher in the healthy forest than in the degraded forest. However, if a few species dominate the habitat acoustically then diversity will be shown to be low through this index alone. There is also some error with this index in areas with an overall low number of species because variability decreases in these communities. Abiotic and anthropogenic noise can also reduce the reliability of this index (Sueur et al., 2008b). In order to account for the false high values generated from geophony and anthrophony, Depraetere et al., 2012 elaborated upon the H index to create the acoustic richness (AR) index.

Sueur et al, 2008b also tested the acoustic dissimilarity index (D) in their acoustic comparison of two Tanzanian forests. The D index estimates the compositional dissimilarity between two communities and takes into account both temporal and spectral acoustic data (Sueur et al., 2008b). The acoustic dissimilarity index compares two signals of the same duration, at the same frequency. This number will increase as the number of unshared species between chorus pairs increases. Therefore, this index could be used to infer differences between community compositions. D values in this study showed differences between the healthy and degraded forests based on the finding of a linear increase in D values with the number of unshared species between the two communities. Comparably to H index, if a couple of species are more widespread and dominate the area acoustically, then the D index will be low. Both the D and H indices can be used to infer differences between communities.

The most widely used of these newer indices is the acoustic complexity index (ACI) (Butler et al., 2016; Kaplan et al., 2015; McWilliam & Hawkins, 2013; Pieretti et al., 2011;

Pieretti et al., 2017; Pijanowski et al., 2011; Staaterman et al., 2014, 2017; Sueur et al., 2014; Towsey et al., 2014a, 2014b). Pieretti and Morri, 2011 developed the ACI with the goal of producing a fast and direct quantification of acoustic sounds by focusing on intensity. The creation of this index was based off of the observation that many animal sounds have varying intensities compared with the relatively constant intensity of human generated noise (Pieretti et al., 2011). The ACI index basically calculates the absolute difference between two adjacent values of intensity in a single frequency bin then adds together all intensities in the first temporal step of a recording. Although this index was created for and tested in terrestrial habitats, several studies have extended these efforts to the marine realm (Butler et al., 2016; Kaplan et al., 2015; McWilliam & Hawkins, 2013; Pieretti et al., 2017; Staaterman et al., 2014). Studies have concluded that this index is better suited for soundscapes with constant intensities, possibly such as those dominated by snapping shrimp. The calculations are also very time consuming and may not be well suited to monitoring of repeated recording sessions (McWilliam & Hawkins, 2013). As with the other indices mentioned, ACI may overlook finer details when there is one dominant, soniferous species and should, therefore, be considered along with other parameters.

Acoustic Statistical Software

Several open access statistical software routines have been created to allow future researchers to more easily calculate some of these newer indices. Notable routines are available in Matlab (The Mathworks, Inc., Natick, MA, USA) and R (R Foundation for Statistical Computing) including: PAMGuide (Merchant et al., 2015), CHORUS (Gavrilov

& Parsons, 2014), SoundEcology (Villanueva-Rivera & Pijanowski, 2014), and Seewave (Sueur et al., 2008a). Each package includes code to calculate different indices. Although none are yet fully integrated, each has unique benefits and drawbacks; see below.

PAMGuide includes code for both Matlab and R to calculate broadband sound pressure level (SPL), PSD, 1/3-octave band levels (TOL), and waveforms. The CHORUS package includes code to calculate PSD, compose long-term average (LTA) spectrograms, and has an automatic detection function that can currently detect two whale calls and allows for easy addition of automatic detectors. Villanueva-Rivera and Pijanowski, 2014 created the Soundecology package in R with code to measure the ACI and D indices. Pieretti and Morri, 2011 also developed a plug-in soundscape meter for Wavesurfer (v.1.8) to calculate the ACI index. Both the H and D indices can be computed through R functions in the free package Seewave and can be used relatively easily by non-scientists for biodiversity estimation (Sueur et al., 2008a). Depending on the aim of a study, multiple software packages may need to be used to calculate every desired metric.

Future Recommendations for the Field

As a still relatively new field, soundscape ecology has advanced greatly in recent years with the number of scientific publications increasing mainly within the past 10 years (Fig. 1.1). However, there is still a great deal that is unknown about quantifying acoustic signals and how to quantitatively compare data. Across dozens of studies from the past 10 – 15 years, most researchers recognize a handful of recommendations as imperative next steps; these are detailed below. As many of these limitations and issues are solved, soundscape ecology can fulfill some of its wide-scale applications such as monitoring the health of remote habitats.

In order to accurately describe biodiversity of any habitat through acoustics and monitor the impacts of anthropogenic noise, the detection and documentation of fish sounds and hearing sensitivities is imperative (Kaplan et al., 2015; Locascio & Burton, 2015; Radford et al., 2011; Staaterman et al., 2013, 2014; Vermeij et al., 2010; Wall et al., 2017). Fully understanding the hearing sensitivities of soniferous fishes is also imperative in the understanding of their communication (Mann et al., 2007). Most abiotic and anthropogenic sounds can be easily generalized by source and frequency range. However, biological sounds tend to be less predictable and many remain un-described. Currently, only the acoustic signatures of marine mammals (Gavrilov & Parsons, 2014; Morisaka et al., 2005) and a handful of fish species have been described (Lobel et al., 2010; Lobel & Mann, 1995; Locascio & Burton, 2015; Mann & Lobel, 1997; Mosharo & Lobel, 2012; Ripley & Lobel, 2004; Rowell et al., 2012; Tricas & Boyle, 2014; Tricas & Webb, 2016). This process requires the use of directional hydrophones coupled with video recordings of the target species in order to confirm that a sound matches with an individual fish behavior (Kovitvongsa & Lobel, 2009; Lobel, 2002). As the acoustic signatures of more species are documented, the automatic detection features of many bioacoustics software can be updated. Automatic detection of biological sounds will allow for simpler and faster analysis of large acoustic data files. Documenting the sounds species produce as well as the hearing sensitivities will allow for better regulation of human-produced sounds in the ocean.

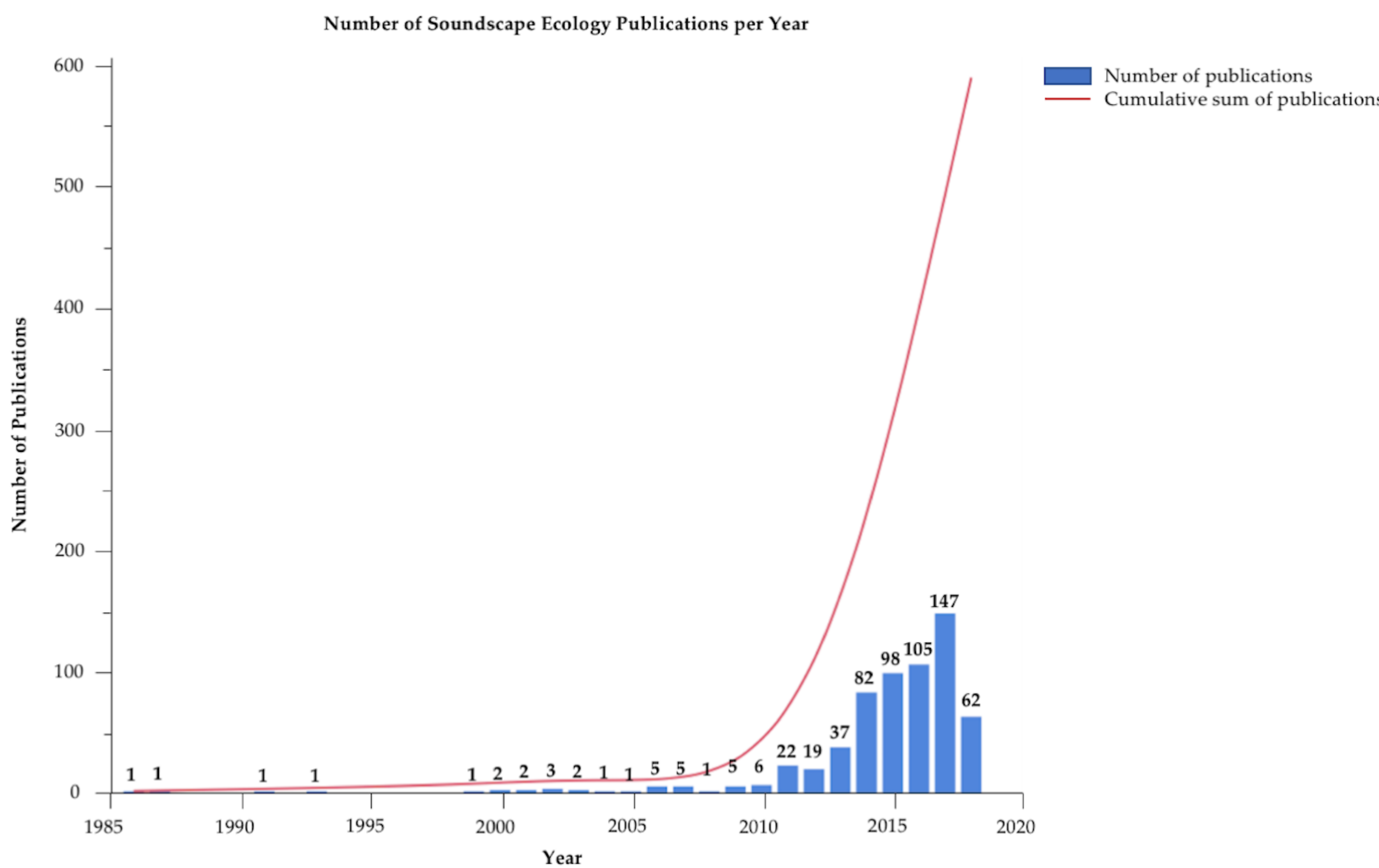

Figure 1.1: Number of Soundscape Ecology scientific papers published per year.

Directional hydrophones can also be useful in determining the source of a sound (Blumstein et al., 2011; Dushaw et al., 2009; Pieretti et al., 2017). However, most studies currently use omni-directional hydrophones, which are capable of picking up sounds from every direction. Localizing the sources of sounds can be applied to studies about population distribution and individual counts (Blumstein et al., 2011). Many current studies also generalize entire acoustic habitats from single point recordings. However, multiple hydrophones in varying arrays can ground truth patterns and aid in determining whether single point recordings give an accurate representation of an entire soundscape (Rowell et al., 2012). Terrestrial acoustic studies have used directional arrays in order to localize specific species and individuals as well as to reduce the number of differences detected in the recordings (Blumstein et al., 2011; Frommolt & Tauchert, 2014; Wang et al., 2003). The feasibility of directional arrays to localize sound sources and ground truth single point recordings is the next phase to be tested in marine habitats.

An integral part of any emerging field is to establish a common framework so that data become comparable among studies. In acoustics, this includes the standardization of sampling/recording methods, metrics, and indices used in data analysis, visualization tools, sensor calibration, and to ground truth current methods (Blumstein et al., 2011; Brainard & Bainbridge, 2010; Hatch et al., 2016; Haxel et al., 2013; Kaplan et al., 2015; Merchant et al., 2015; Og˜uz, 1994; Parks et al., 2014; Pijanowski et al., 2011; Rowell et al., 2012; Staaterman et al., 2014; Sueur et al., 2008b; Wall et al., 2017). With such a wide variety of recording rates used in the field, it is more difficult to compare data and results across studies. However, as more studies set long-term recording goals of several months or more along with limitations of battery life and memory storage, studies are required to forgo continuous recording. This means that scientists must find sampling schemes that maximize recording time in the field while conserving field labor and technological resources. These same sampling schemes must not lose a significant amount of soundscape information. Pieretti et al., 2015 explored this issue in tropical forests with the aim of determining how much acoustic information is lost as the gap in recording time increases. Although the findings of Pieretti et al., 2015 suggest that each location and soundscape require a unique recording schedule; overall, the loss of important information increases significantly with the gap in recording time. Therefore, these findings suggest that it is more important for studies to use a more intense recording regime. This could mean that studies may need to choose a more active recording scheme with a shorter total study period in order to obtain the most accurate acoustic data. To our knowledge, this type of study has yet to be performed in a marine habitat.

A possible future application for soundscape ecology is the use of long-term recordings to monitor the health of vulnerable and remote ecosystems. However, more long-term studies that explore the link between health of an ecosystem and the corresponding soundscape are needed (Lammers et al., 2008; Pieretti et al., 2011; Sueur et al., 2008b). A handful of studies have begun to explore the acoustic differences between a healthy habitat (i.e. forests, seagrass beds, coral reefs, etc.) and one that is degraded (Butler et al., 2016; Piercy et al., 2014; Sueur et al., 2008b). These studies have found preliminary differences in the acoustic signatures of healthy vs. degraded habitats but such differences may just be based upon the variation in biological communities. Playback of healthy habitat sounds has also been shown to attract settlement of coral, mollusk, and coral reef fish larvae (Eggleston et al., 2016; Jolivet et al., 2016; Lillis et al., 2013, 2014, 2016; Vermeij et al., 2010). These early results suggest that underwater acoustic playback has the potential to serve as a way to restore degraded habitats. As there is a decline in many of the worlds important, shallow-water habitats, such as coral reefs and seagrass beds, it is imperative to explore alternative monitoring and restoration methods.

Conclusions

Underwater soundscapes and long-term PAM both have incredible potential in the fields of ecology, behavior, evolution, and conservation biology. Coupled with conventional underwater survey methods, PAM can be used to gain a more accurate understanding of the health, biodiversity, and structure of underwater habitats. Acoustics present researchers the ability to monitor many different groups at the same time, which offers an integrative look at ecosystems overall (Blumstein et al., 2011). Long-term PAM also provides a good opportunity to monitor remote habitats or areas too deep for diving. It is necessary to use acoustic monitoring alongside conventional visual surveys in order to get a complete and accurate view of underwater habitats. As the acoustic community addresses the limitations discussed in this review, the full extent of acoustic monitoring can be realized. We hope that the overview of current methods and data analysis parameters as well as recommendations from recent studies can help to move the field forward and help future studies determine the most important gaps to address.

CHAPTER 2:

Determining Temporal Recording Schemes for Underwater Acoustic Studies

Introduction

Soundscape ecology is an emerging field of research broadly defined as the physical combination of sounds at a particular time and place (Pijanowski et al., 2011; Schafer, 1977). The soundscape of a particular habitat consists of abiotic sounds, such as wind and rain (geophony); biotic sounds, which are sounds produced by living organisms (biophony); and man-made sounds including: seismic exploration, shipping, dredging, and sonar navigation (anthrophony) (Krause 1987; Pijanowski et al., 2011). Acoustic habitats can convey important information about an ecosystem such as flora and fauna composition, environmental conditions, and habitat quality (Staaterman et al., 2013).

Acoustics are a very effective form of communication in water. Sound propagates omni-directionally at a speed of roughly four and a half times faster in saltwater than air due to the higher density of water. Acoustic cues play important roles in several aspects of animal communication such as species identification, mate selection, timing of insemination, and larval settlement (Lillis et al., 2014; Lobel, 1992; Vermeij et al., 2010). Bioacoustics, or animal communication, have garnered the majority of scientific attention; however, in recent years, the ambient sound, or background noise, of an environment has been found to be important for an animals' evaluation of habitat quality and conditions.

Characterizing the ambient sound of a habitat is the primary aim of soundscape ecology. Wenz, 1962 concluded that ambient noise in the ocean is primarily made up of three overlapping components: turbulent-pressure fluctuations, wind, and traffic noise –

which describes low frequency background noise produced by ships from a great distance and is not readily recognizable as produced by ships. Although the main contributors to ambient sound, geophony and anthrophony, tend to fall into more predictable frequency ranges, the final contributor, the biophony, varies much more in frequency, time, and location and can, therefore, be much more difficult to generalize over long time frames.

An effective way to capture this acoustic information is through long-term passive acoustic monitoring (PAM). Long-term PAM studies use omni-directional hydrophones with high sensitivities, automatic acoustic recorders, and associated hardware capable of collecting acoustic data and are currently only limited by battery life and memory storage. Long-term PAM has shown promise to serve as a cost-effective and low-field labor intensive method of monitoring the health and biodiversity of remote underwater habitats (Au et al., 2012; Bertucci et al., 2015; Butler et al., 2016; Staaterman et al., 2017). Some studies have even determined that sound intensity tends to be higher on healthy reefs than ones that are degraded (Piercy et al., 2014). However, as an emerging field, soundscape ecology and underwater PAM still face several challenges.

Many of these major challenges are beginning to be addressed; however, studies focusing on the standardization of underwater recording rates and data analysis parameters have yet to be performed. As more studies aim to record for several months or more, recording rates continue to be limited by battery life and memory storage capabilities. These limitations cause studies to have to forgo continuous recordings and choose recording schemes with short periods of active recording and long periods of inactivity. One terrestrial study by Pieretti et al., 2015 sought to determine the exact amount of acoustic information that is lost with different recording schemes in three tropical forests. They concluded that the recording scheme mainly depended on the acoustic complexity of the study site but that, in general, the shortest recording scheme of one minute every five minutes most accurately depicted the total soundscape of these forests. This terrestrial study now needs to be replicated in marine ecosystems. **The main objective of this study is to explore and describe the acoustic information that is lost with various recording schedules at coral reefs.**

Methods and Materials

Study Site

The field recording was made by Dr. Phillip Lobel while SCUBA diving in Tunicate Cove, Belize (16°39.59'N, 88°11.07'W) on the southern Belizean Barrier Reef in 1996 at 11:00 hours (Fig. 2.1). The site mainly consisted of a relatively shallow coral reef in water depths ranging from 3-5m (Fig. 2.2).

Acoustic Recordings and Data Analyses

The field recording was made using a SONY V-9 video camera with a hydrophone (frequency flat response: 10-3000 Hz; sensitivity: -162 dB re: V/µPa) (Bioacoustics Inc., Woods Hole, MA) along with a SONY Professional Walkman (WMDC6) tape recorder with two hydrophones. The hydrophone was buoyed about 0.5 meters above the substrate with a float attached to a boom by cables. The hydrophone was placed roughly in the center

Figure 2.1: Map of Tunicate Cove, Belize showing the approximate location where the acoustic recording was taken by Dr. Phillip Lobel in 1996.

of a coral patch and the SCUBA divers moved away during the recording in order to not disturb any marine life. The total recording was 67 minutes; the first 11 minutes consisted mainly of Dr. Lobel searching for an appropriate site to place the hydrophone and were cut out prior to analysis. The final recording consists of 55 minutes of continuous audio-video recording.

Videotapes were digitized using iMovie HD 6 (Apple Inc., 2006) and saved as a .mov file. The files were saved at sampling rate 44.1 kHz and 16-bit depth. The .mov file was then imported into Raven Pro 1.4 (Bioacoustics Research Program, The Cornell Lab of Ornithology, Ithaca, NY) as a paged sound file in 60 second sections with 10% step increment and 90% page increment (DFT size: 256 samples; Hann window: 256 samples) in order to visualize waveforms and spectrograms and to calculate acoustic measurements. The total 55-minute recording was generated into consecutive 1-second, 10-second, 30-second, and 1-minute selections. Average and peak power spectral density (PSD), average and aggregate entropy (H), root-mean-square (RMS) amplitude, and energy were calculated in Raven for each selection. PSD and RMS were chosen because they are the most commonly used acoustic measurements in the soundscape ecology literature and provide information about the strength of the variations in energy as a function of frequency. The H indices are also relatively common throughout the literature and can provide interesting information about species richness and habitat health (Sueur et al., 2008b).

Figure 2.2: A portion of a coral reef in Tunicate Cove, Belize, 1996 where the original audio/video recording was taken. The grey line is the boom of the hydrophone used to record.

Statistics

All measurements for each time bin selection and the continuous recording were imported into Microsoft Excel (2016). Initially, all parameters were plotted vs. time (seconds) as scatter plots to compare the general pattern seen in the various size time bins and how they compare to that of the continuous recording. 12 minutes were then randomly selected from the continuous recording to explore how closely the average power (dB) for each selected minute compares to the PSD and standard deviations each averaged from the 10-second (n=6 selections) and 30-second (n=2 selections) time bins.

The next set of methods and analyses were modeled after the study by Pieretti et al., 2015, which investigated the most accurate temporal sampling scheme for passive acoustic studies in tropical rainforests. Non-parametric correlation analyses (Spearman's rho, $p < 0.01$; Kendall's tau, $p < 0.01$) were performed in JMP Pro 13.2.0 (SAS Institute Inc., Cary, NC, USA, 2016) to explore the relationship between the continuous recording and the sub-sampled recording schemes. Recording schemes were chosen based on what has been used in the literature to explore how acoustic data from a continuous recording compares to intermittent recording schemes with periods of "off" time (Table 2.1). Multivariate scatterplot matrices were created in JMP Pro 13.2.0 with lines of best fit and correlation coefficients and univariate simple statistics were calculated. Finally, Spearman's rho and Kendall's tau non-parametric analyses were performed for average power, average entropy, and aggregate entropy.

The recording schedules chosen for simulation were: (1) 30 seconds every 4 minutes; (2) 12 seconds every 5 minutes; (3) 20 seconds every 5 minutes; (4) 30 seconds every 5 minutes; (5) 10 seconds every 10 minutes; (6) 1 minute every 10 minutes; and (7) 2 minutes every 10 minutes. Other recording schedules were excluded based on time constraints of the continuous recording used for analysis.

These recording schedules were simulated by selecting the corresponding seconds or minutes from the continuous recording. A mean of average power, average entropy, and aggregate entropy were calculated for every 4-minutes, 5-minutes, or 10-minutes of the continuous recording and data from the simulated recording, depending on the recording scheme being investigated. This allowed for paired data to be compared in the correlation analyses. It is important to note that these methods resulted in 6 sets of data points for recording schedules (5), (6), and (7); therefore, the small sample sizes may lead to suspect p-values.

Results

Soundscape Characterization

The entire 55-minute recording had an average aggregate entropy of 3.13 ± 0.48, average energy of 120.91 ± 4.24 dB, average peak power of 101.12 ± 2.94 dB, and RMS amplitude of 2877.78 ± 1630.97 (Table 2.2). Overall, PSD and RMS amplitude are higher at the beginning of the recording and gradually decrease before leveling off. The entropy measurements displayed the opposite pattern; starting at lower values then increasing (Fig. 2.3). Two main frequency bands were clearly defined in the visual inspection of the spectrogram: (1) 3 - 4kHz and (2) 0.1 – 0.5 kHz. (Fig. 2.4).

Recording Rate	Paper(s)
30 seconds every 4 minutes	Heenehan et al., 2017
12 seconds every 5 minutes	Staaterman et al., 2013, 2014
20 seconds every 5 minutes	Rowell et al., 2012
30 seconds every 5 minutes	Wall et al., 2017
10 seconds every 10 minutes	Locascio & Burton, 2015
1 minute every 10 minutes	Staaterman et al., 2017
2 minutes every 10 minutes	Lillis et al., 2016
30 seconds every 15 minutes	Lammers et al., 2008
150 seconds every 15 minutes	Depraetere et al., 2012
1 minute every 20 minutes	Kaplan et al., 2015
10 minutes every 1 hour	Radford et al., 2011
1 hour every 3 hours	Benoit-Bird et al., 2001
Continuously for 24 – 48 hours	Au et al., 2012; Jolivet et al., 2016; Pieretti et al., 2017; Staaterman et al., 2017

Table 2.1: Recording rates used in various underwater soundscape ecology and/or long-term passive acoustic monitoring publications.

Average Energy (dB)	Peak Power (dB)	Average Power (dB)	Average Entropy (u)	Aggregate Entropy (u)	RMS Amplitude (u)
120.91 ± 4.24	101.12 ± 2.94	70.39 ± 4.23	2.28 ± 0.25	3.13 ± 0.48	2877.78 ± 1630.97

Table 2.2: Summary of soundscape features of a coral reef at Tunicate Cove, Belize, 1996.

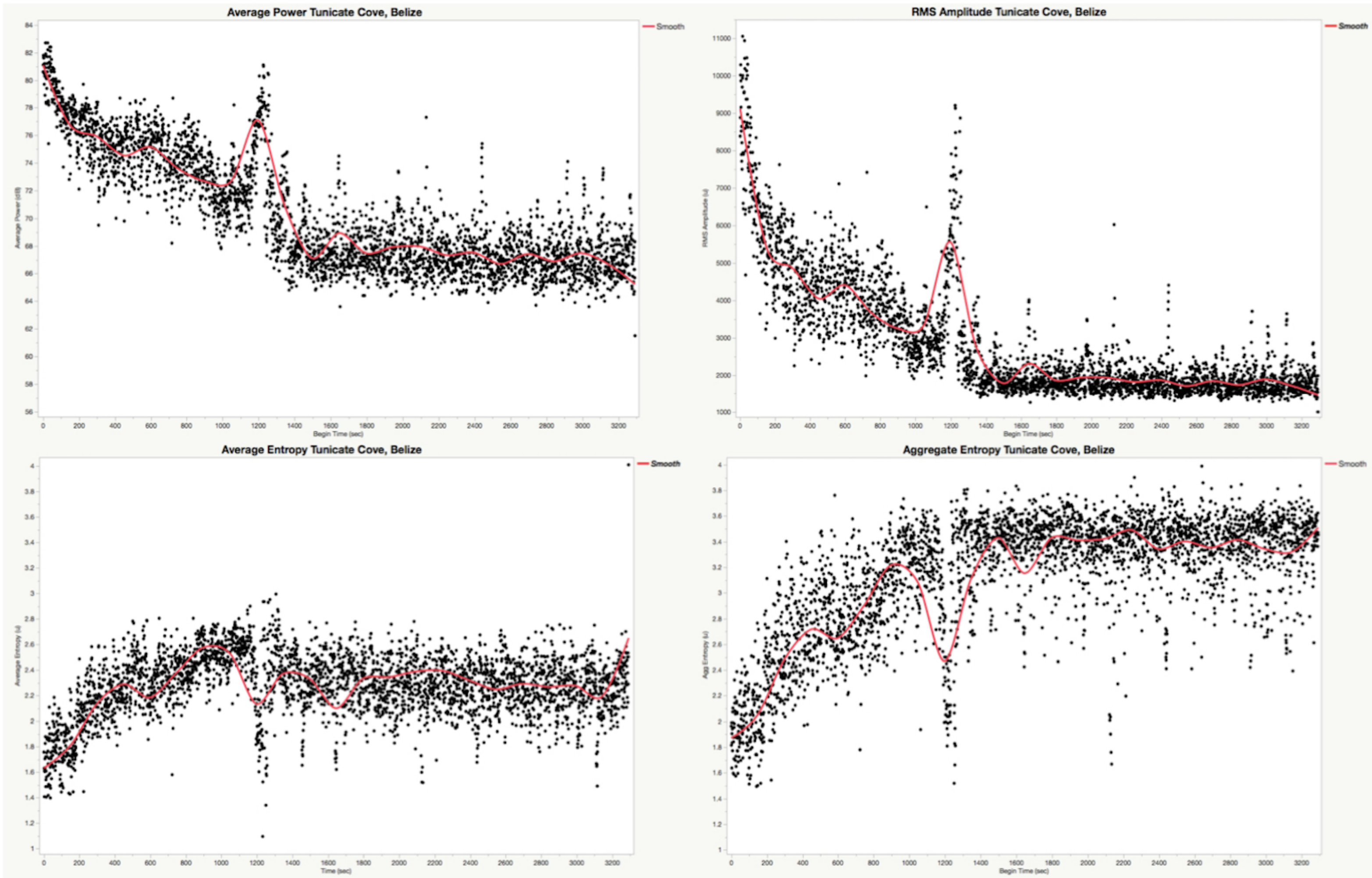

Figure 2.3: Scatterplots showing general acoustic trends between 11:00 hh:mm and 11:56 hh:mm on a coral reef at Tunicate Cove, Belize, 1996. (A) Average Power (dB); (B) Root-Mean-Square (RMS) amplitude; (C) Average Entropy; and (D) Aggregate Entropy. Note the difference in y-axes.

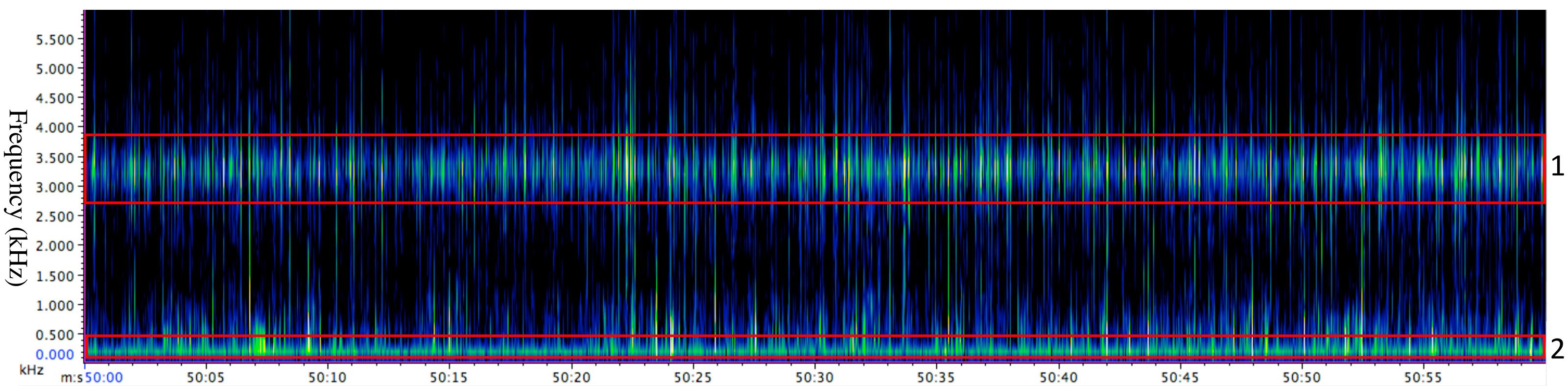

Figure 2.4: Two main frequency bands seen throughout recording taken at Tunicate Cove, Belize, 1996. **(1)** High-frequency Band: 3 – 4 kHz; **(2)** Low-frequency Band: 0.1 – 0.5 kHz.

Statistical Analyses of Time Bins/Recording Schedules

When exploring the how average power compares when averaged over different size time bins, the means of each of the 12 randomly selected minutes was within 1dB between the three different time bins (Fig. 2.5). However, the standard deviations for the 30-second (n=2 selections) ranged from 0 to 2.05 and the standard deviations for the 10-second (n=6 selections) ranged from 0.36 to 2.41 (Table 2.3).

The Spearman's and Kendall's correlation tests showed variation in statistical significance between each parameter. Only two recording schedules showed statistical significance across all three parameters tested. Recording 30 seconds every 4 minutes was significantly correlated with the continuous recording for average power (Spearman's = 0.9209, $p < 0.0001$; Kendall's = 0.8022, $p < 0.0001$), average entropy (Spearman's = 0.556, $p < 0.05$; Kendall's = 0.4066, $p < 0.05$), and aggregate entropy (Spearman's = 0.8066, $p < 0.001$). Recording 2 minutes every 10 minutes was also significantly correlated with the continuous recording for average power (Spearman's = 0.9429, $p < 0.01$; Kendall's = 0.8667, $p < 0.05$), average entropy (Spearman's = 0.9429, $p < 0.01$; Kendall's = 0.8667, $p < 0.05$), and aggregate entropy (Spearman's = 0.8286, $p < 0.05$; Kendall's = 0.7333, $p < 0.05$) (Table 2.4). Two recording schedules, 10 seconds every 10 minutes and 1 minute every 10 minutes, showed no statistically significant correlation between the continuous and simulated recordings in any of the three parameters. The remaining three simulated recording schedules tested all showed statistically significant correlation between the continuous and simulated recording schemes only for average power and aggregate entropy (Table 2.4) but not for average entropy. The Kendall's tau analyses revealed a 67% - 93%

positive correlation between all data points for each parameter and recording schedule tested.

Discussion

Soundscape Characterization

The higher frequency band (3 – 4 kHz) may correspond mainly to abiotic sounds, while the lower frequency band (0.1 – 0.5 kHz) generally corresponds to biological sounds (Wenz, 1962). The audio recording had relatively constant noise from snapping shrimp, which have been found to be one of the main contributors to ambient sound on coral reefs (Au et al., 2012). While the acoustic signatures of most fish species remain undocumented, the distinctive "boatwhistle" of toadfishes (*Batrachoides gilberti*) can be heard throughout the entire recording and seen in the spectrogram and waveform (Fig 2.6). Several other distinctive acoustic events were noted in the recording and spectrogram; however, the sources of these events were unable to be identified (Fig 2.7). One of these events sounded to be of biological origin; however, no definitive source could be identified.

There were a couple of events in which schools of fish swam quickly by the hydrophone, leading to peculiar increases in both amplitude and frequency. The coupling of audio and video allowed for these events to be linked to these schools of fish swimming near the hydrophone (Fig 2.8). The identification of these acoustic events demonstrates the importance of using both audio and video recording during acoustic monitoring, especially as the field continues to rapidly grow.

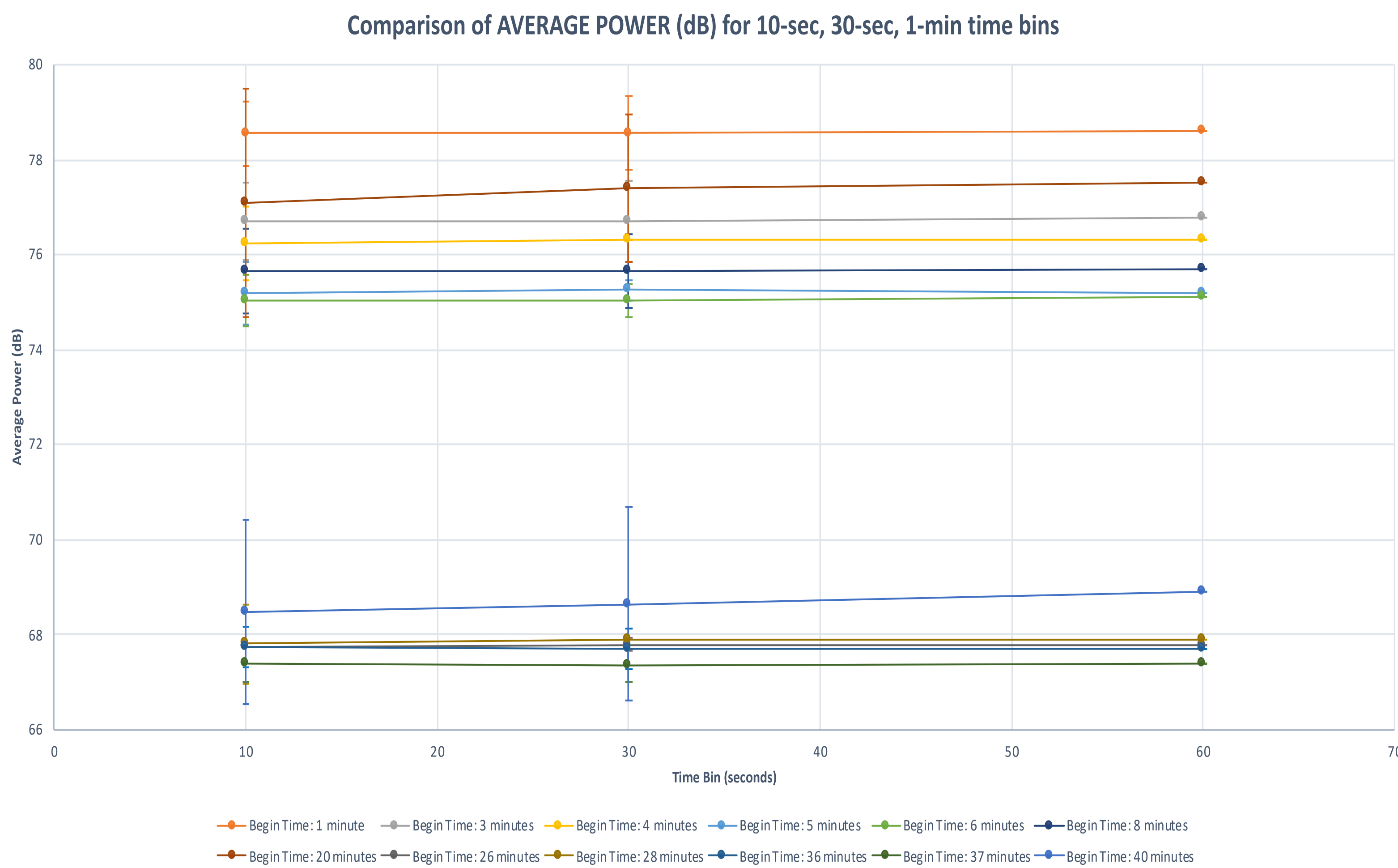

Fig. 2.5: Average Power (dB) of 10-second (n=6), 30-second (n=2), and 60-second time bins and respective standard deviations for 12 randomly selected minutes from a 56-minute continuous recording. The original recording was made on a coral reef in Tunicate Cove, Belize in 1996 by Dr. Phillip Lobel. This figure represents the variability of average power across individual minutes of a continuous acoustic recording.

Begin Time (minute)	Average power (dB) of 60 second time bin (n=1)	Average power (dB) of 30 second time bins (n=2)	Average power (dB) of 10 second time bins (n=6)	Standard Deviation 60 second	Standard Deviation 30 second	Standard Deviation 10 second
1	78.6	78.55	78.55	0	0.7778	0.6834
3	76.8	76.7	76.7	0	0.8485	0.8222
4	76.3	76.3	76.2333	0	0	0.7711
5	75.2	75.25	75.1833	0	0.2121	0.6676
6	75.1	75.05	75.05	0	0.3535	0.5468
8	75.7	75.65	75.65	0	0.7778	0.8961
20	77.5	77.4	77.1	0	1.5556	2.4100
26	67.8	67.8	67.75	0	0.1414	0.7287
28	67.9	67.9	67.8167	0	0	0.8353
36	67.7	67.7	67.7333	0	0.4243	0.4179
37	67.4	67.35	67.3833	0	0.3535	0.3601
40	68.9	68.65	68.4833	0	2.0506	1.9343

Table 2.3: Average power (dB) and standard deviation of 10-second (n=6), 30-second (n=2), and 60-second (n=1) time bins for 12 randomly selected minutes from a 56-minute continuous recording taken at Tunicate Cove, Belize, 1996.

Recording Rate	Metric	Spearman's rho	p-value	Kendall's tau	p-value
30 sec every 4 min	Average Power	0.9209	**< 0.0001**	0.8022	**< 0.0001**
30 sec every 4 min	Average Entropy	0.556	*0.0389*	0.4066	*0.0428*
30 sec every 4 min	Aggregate Entropy	0.8066	**0.0005**	0.6264	**0.0018**
12 sec every 5 min	Average Power	0.7091	*0.0146*	0.4909	*0.0356*
12 sec every 5 min	Average Entropy	0.4618	0.1334	0.3818	0.1021
12 sec every 5 min	Aggregate Entropy	0.9	**0.0002**	0.7455	**0.0014**
20 sec every 5 min	Average Power	0.7273	*0.0112*	0.4909	*0.0356*
20 sec every 5 min	Average Entropy	0.5	0.1173	0.3818	0.1021
20 sec every 5 min	Aggregate Entropy	0.8909	**0.0002**	0.7455	**0.0014**
30 sec every 5 min	Average Power	0.7545	**0.0073**	0.5273	*0.024*
30 sec every 5 min	Average Entropy	0.5091	0.1097	0.3818	0.1021
30 sec every 5 min	Aggregate Entropy	0.9545	**< 0.0001**	0.8545	**0.0003**
10 sec every 10 min	Average Power	0.7714	0.0724	0.6	0.0909
10 sec every 10 min	Average Entropy	0.3714	0.4685	0.3333	0.3476
10 sec every 10 min	Aggregate Entropy	0.7714	0.0724	0.6	0.0909
1 min every 10 min	Average Power	0.7714	0.0724	0.6	0.0909
1 min every 10 min	Average Entropy	0.5429	0.2657	0.4667	0.1885
1 min every 10 min	Aggregate Entropy	0.743	0.1108	0.4667	0.1885
2 min very 10 min	Average Power	0.9429	**0.0048**	0.8667	*0.0146*
2 min very 10 min	Average Entropy	0.9429	**0.0048**	0.8667	*0.0146*
2 min very 10 min	Aggregate Entropy	0.8286	*0.0416*	0.7333	*0.0388*

Table 2.4: Summary of the results of the Spearman's rho and Kendall's tau correlation analyses for the average power, average entropy, and aggregate entropy of the seven recording schedules. It is important to note the small sample sizes (n=6) for the final three recording schedules; p-values for these three recording schedules are suspect.

There were a couple of events in which schools of fish swam quickly by the hydrophone, leading to peculiar increases in both amplitude and frequency. The coupling of audio and video allowed for these events to be linked to these schools of fish swimming near the hydrophone (Fig 2.8). The identification of these acoustic events demonstrates the importance of using both audio and video recording during acoustic monitoring, especially as the field continues to rapidly grow.

This study focused on recording schemes for ambient sound, which may not directly translate to studies choosing to capture biological sounds and/or patterns. The biophony, especially sounds produced by spawning coral reef fishes, tend to occur around sunset with some species being more acoustically active at sunrise. Therefore, studies aiming to perform acoustic biodiversity counts need a-priori knowledge of the biological life in that area, including where and when different species spawn. Focusing on capturing biological sounds may benefit from more intensive recording around the most acoustically active times of day as opposed to recording intermittently throughout the entire day. Determining recording schemes for bioacoustics presents a different sampling question from ambient sound.

Recording Schedules

The initial Spearman's rho and Kendall's tau analyses indicate that more intensive recording schedules provide the most accurate acoustic data. These initial results may suggest that long-term, underwater PAM studies may want to choose more intensive recording schedules and shorter total recording time in order to collect the most accurate acoustic data. The increase of the duration and/or number of "off" periods during recording increases the likelihood of missing important acoustic events, especially while the acoustic signatures of the vast majority of fish species remain undocumented. While researchers aim to characterize the soundscapes of important habitats throughout the world's oceans as well as to understand the acoustics of 'healthy' vs 'degraded' marine ecosystems, it is imperative that we gain full temporal understandings of these ecosystems. Soundscapes are unpredictable; therefore, continuous recordings taken over shorter timeframes are important in building a complete understanding of unique soundscapes.

However, these results also indicate that the accuracy of each recording schedule may depend on which acoustic indices are being analyzed. This supports the recommendation by several studies to use multiple acoustic indices when analyzing recordings and characterizing soundscapes.

Future Recommendations

This study should be repeated with longer continuous recordings, which investigate the number of days of recording per month, season, or year. This study should also be repeated with recordings collected in different marine ecosystems, such as sand flats, seagrass beds, rocky reefs, etc., in order to investigate the most accurate recording schedules for different ecosystems. Each of these ecosystems have unique soundscapes and may exhibit different acoustic complexity and temporal patterns, which could allow for less intensive recording schedules. Therefore, studies to determine the recording schedule for each unique ecosystem are an important next step in the standardization of soundscape ecology methods.

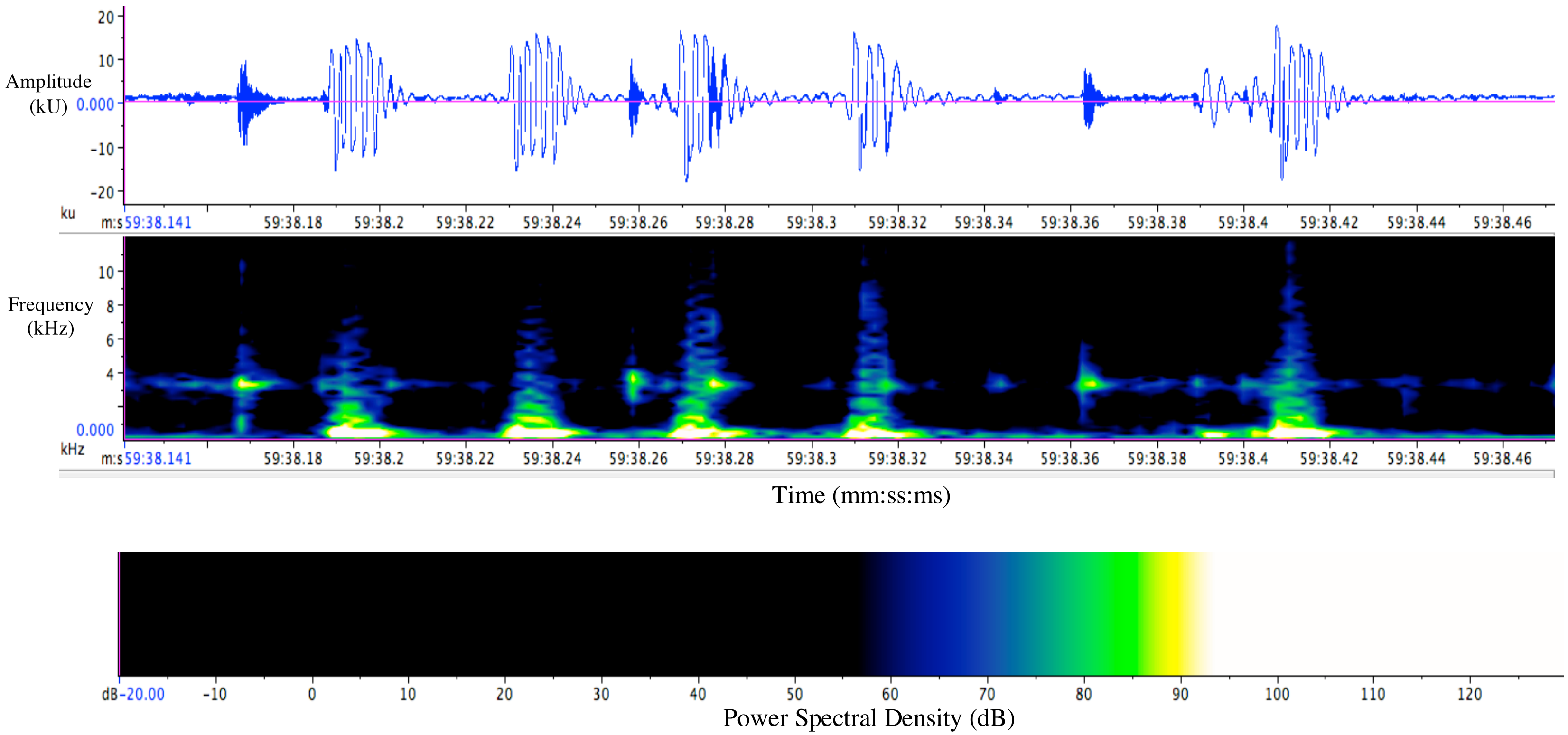

Figure 2.6: Waveform (top) and spectrogram (middle) showing the distinctive "boatwhistle" call of a Toadfish species (*Batrachoides gilberti*) in Tunicate Cove, Belize. The bottom row is the color bar representing different power spectral density (dB) values in the spectrogram.

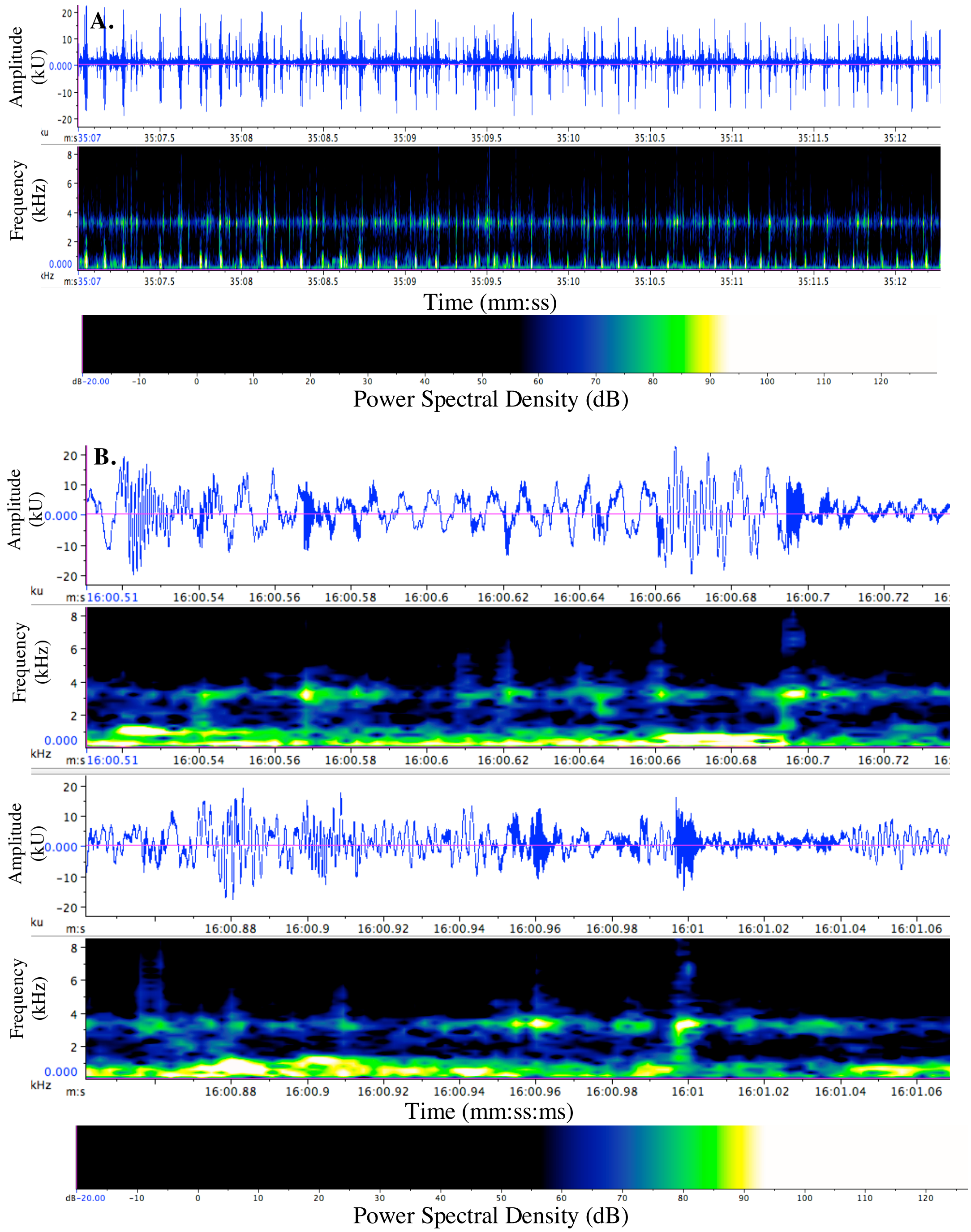

Figure 2.7: (A) One series of sounds from an unidentified source. The source sounded of biological origin in the original recording taken in Tunicate Cove, Belize, 1996. **(B)** Second series of sounds from an unidentified source, which also sounded to be of biological origin in a recording from Tunicate Cove, Belize, 1996.

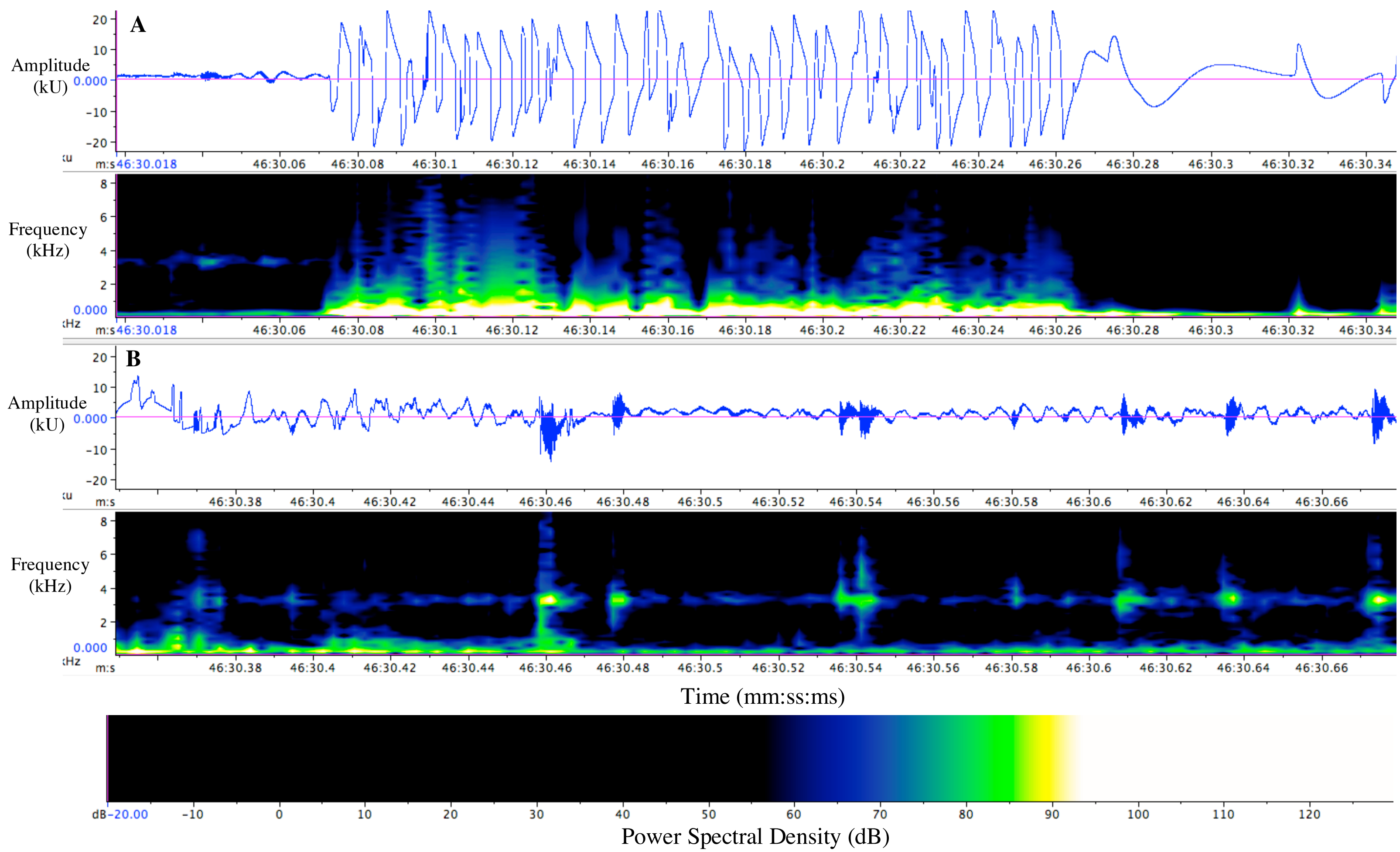

Figure 2.8: **(A)** The waveform and spectrogram of a school of jacks swimming quickly near the hydrophone. **(B)** The waveform and spectrogram of a toadfish call directly after the school of jacks. The bottom row is the color bar representing different power spectral density (dB) values in the spectrograms.

Conclusions

Acoustics can provide valuable information about biodiversity, habitat quality, and effects of human activity on vulnerable species and ecosystems. The relatively rapid advancements in technology to collect, store, and analyze acoustic data has led to quick growth in acoustic related fields. As the use of acoustics in ecological studies continues to improve, researchers must focus on several of the most important limitations.

One of the major limitations in any growing field of science is the standardization of methods. Standardizing data collection and analysis allows for better comparisons of results across studies and the ground-truthing of current methods helps to demonstrate that accurate data is being collected. As the field of soundscape ecology continues to rapidly grow, the recording schedules used in these studies must be tested for accuracy and efficiency.

The results found in this study agree with those of the terrestrial study by Pieretti et al., 2015. However, this is the first study, to our knowledge, testing the accuracy of temporal recording schedules being used in underwater soundscape studies. This study shows that, whenever possible, researchers should use more intensive recording rates. This may mean that overall recording time is shortened; however, these more intense recording rates will give researchers a more accurate overall view of the unpredictable, acoustic environment.

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