Characterizing the acoustic environment of Placentia Bay: estimating the contribution of vessels to noise levels experienced by marine mammals in a coastal marine environment.

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Abstract

Rising anthropogenic noise pollution in the ocean is threatening marine environments and species. Exposure to underwater noise can elicit both behavioural and physical responses in marine species, including physiological changes, altered vocal behaviours, and reduced survival and reproductive success. These consequences, in concert with the effects of other anthropogenic stressors, have the potential to affect the health, distribution and abundance of species. As they rely on acoustic signals for foraging, socialization, and reproduction, marine mammals are among the species that can be most severely impacted by underwater anthropogenic noise. Vessels are the main and most widespread source of anthropogenic noise in the ocean, and routes collecting large volumes of traffic often overlap with the key habitats of several protected marine mammal species. In order to protect such species from further decline, there is a growing need for studies investigating how the presence of vessel noise alters underwater acoustic environments in areas important to marine mammals. This need is paired with the challenge of developing approaches for analyzing large passive acoustic monitoring (PAM) datasets with the goal of establishing links between audio recordings and environmental processes. In this dissertation, I focus on characterizing the underwater acoustic environment of a coastal marine area, Placentia Bay (Newfoundland, Canada), with the overarching goal of assessing if anthropogenic noise from vessels in the region is reaching levels that could have negative impacts on marine mammal species. First, I address the analytical challenge of establishing a relationship between audio recordings and environmental processes by applying unsupervised machine learning techniques to the analysis of underwater PAM datasets. Second, I investigate changes in underwater

ambient noise levels at two PAM stations in Placentia Bay over five months (June-October, 2019), and assess the contribution of vessels and wind to ambient noise levels that might be experienced by fin whales in the area. Finally, I provide a spatial and temporal assessment of vessel traffic, showing how the distribution of vessel noise sources in Placentia Bay has changed over a five-year period (2019-2023), with a focus on areas important to baleen and toothed whales based on previous systematic surveys and opportunistic sightings data. Together, the three studies demonstrate how unsupervised machine learning can support the analysis and interpretation of large marine PAM datasets, and provide an initial evaluation of how the presence of vessel noise in Placentia Bay exposes marine mammals to increased noise levels, sometimes exceeding the theoretical threshold for the onset of behavioural disturbance. Furthermore, growing vessel traffic accompanied by changes in the distribution of noise sources indicate that both baleen and toothed whales have experienced increasing exposure to vessel noise in Placentia Bay between 2019 and 2023. These results support the conservation of protected cetacean species by indicating a need for the introduction of noise management measures in Placentia Bay, and by informing the development of a national strategy addressing the impacts of underwater anthropogenic noise. Future research is required to better understand how noise interacts with other marine anthropogenic stressors and how these combined effects translate into impacts on marine species and communities.

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Chapter 1: Introduction and thesis overview

1. 1. Introduction

Biodiversity across the globe is under threat due to the growing intrusion of anthropogenic activities in natural environments (Brodie et al., 2021; Isbell et al., 2023). Experts in biodiversity estimate that from the year 1500, approximately 30% of all species have gone extinct or are currently under the threat of extinction (Isbell et al., 2023). Changes in land and sea use leading to habitat loss, the direct exploitation of species, climate change, pollution, and the introduction of invasive species are recognized as the drivers of biodiversity loss worldwide (Díaz & Malhi, 2022). Noise pollution is one of the most common by-products of human activity, with noise produced by vehicular (e.g., cars, aircrafts, vessels), industrial (construction sites, mining operations), commercial (e.g., pubs and bars, concerts), and recreational activities (e.g., all-terrain vehicles, jet skis) contributing to large-scale changes to the acoustic environments experienced by many terrestrial and marine species (Montes González et al., 2024). Noise pollution is a widespread health concern in urban populations, and the World Health Organization recognizes it as the second most important environmental factor affecting human health, with atmospheric pollution being the first (Fritschi et al., 2011). The effects of anthropogenic noise pollution are widespread not only in human, but also in many marine and terrestrial wildlife populations (Erbe et al., 2019; Kok et al., 2023; Kunc & Schmidt, 2019; Sordello et al., 2020).

The effects of noise pollution in animals have been documented in almost all known organizational levels of life, starting from the cellular level and extending to entire communities (Kight & Swaddle, 2011). However, not all of the impacts of noise on wildlife have been investigated equally. Except for a few studies conducted on wild populations (e.g., Injaian et al., 2019), effects at the cellular level have mostly been observed in laboratory experiments focusing on human health (Havlioglu et al., 2022). Current studies largely focus on identifying and quantifying effects occurring at the population and individual level, and mostly consider impacts on behaviour, physiology, or communication. Yet, a number of studies indicate that noise-induced changes occurring at the population level can also trigger profound changes in the composition of communities (Kok et al., 2023), for example, by altering predator-prey interactions (Senzaki et al., 2020).

The negative impacts of noise pollution are best documented in humans, with the effects of continuous exposure to noise pollution on individuals including hearing loss, cardiovascular issues, sleep disturbances, impaired cognitive function, decline in mental health, and the disruption of social interactions, including learning activities (Singh, 2024). The impacts of noise in urban areas can result in significant loss of health for large portions of the population (Fritschi et al., 2011). Outside the realm of human health, mammals are one of the taxonomic groups for which the negative effects of noise pollution have been studied more extensively, followed by birds, and fish (Sordello et al., 2020).
Among all mammals, cetaceans can be considered acoustic specialists, as all cetacean species rely strongly on sound to communicate, feed, and navigate in their environments (Burnham, 2017). Cetaceans produce sounds that range from the very low frequencies

of blue whale (*Balaenoptera musculus*) calls (i.e., between 10 and 40 Hz) to the high-frequency clicks of harbor porpoises (*Phocoena phocoena*) (i.e., above 100 kHz) (Erbe et al., 2018). Underwater noise can interfere with important life functions of cetacean species, causing a variety of effects that can have both direct (e.g., loss of hearing, tissue damage) and indirect (e.g., masking, stress) impacts on the health of individuals (Erbe et al., 2018, 2019).

Noise pollution has been increasing in natural areas (Buxton et al., 2017), reaching some of the most remote places (Anzibar Fialho et al, 2024). Among the environments being most affected are the oceans, which have experienced a steady increase in ambient noise levels of 3.3 dB per decade between 1950 and 2007 (Frisk, 2012). This trend remains unchanged in many parts of the world (Jalkanen et al., 2022), although not all areas are experiencing equal rates of increase in noise levels (Chapman and Pice, 2011). Sounds travel much further in water than in air (i.e., approximately 4.3 times faster), making anthropogenic noise in the ocean a far-reaching pollutant. For example, the noise propagating from a large vessel (e.g., tankers, containers, bulk carriers) can be detected at ranges exceeding 100 km. The distance at which vessel noise propagates, however, depends on environmental factors (i.e., depth, salinity, temperature, currents, wind, and precipitations), on the type of propeller mounted on the vessel, and on its speed and behaviour while navigating. Underwater radiated noise from vessels can originate from three distinct sources: propeller cavitation, engine and flow noise, and machinery noise (Smith & Rigby, 2022). Of these three sources, propeller cavitation is considered to be the main source of noise when vessels are traveling at high speeds, while when vessels are traveling at lower speeds, engine and machinery noise are the main noise sources (Smith & Rigby, 2022).

Vessels are the most widespread source of underwater noise pollution, and marine transportation is the main driver of the progressive increase of low-frequency noise observed in many regions of the ocean (Erbe et al., 2019b; Jalkanen et al., 2022). Intense anthropogenic activity often overlaps with marine mammal core habitats (Avila et al., 2018) and, alongside pollution and vessel strike, noise pollution is recognized as one of the threats to the recovery of several protected cetacean species in North America. Both the Canadian and US governments recognized the negative effects of vessel noise on the recovery of the endangered southern resident killer whale (DFO, 2018; NOAA, 2008), and, starting in 2018, a range of vessel noise mitigation measures have been established in both jurisdictions. In eastern Canada, Atlantic blue whales are protected under the Species at Risk Act (SARA) and their population is considered to be endangered (Beauchamp et al., 2009). The recovery strategy for the Atlantic blue whale population identifies noise pollution along important shipping routes such as the Gulf of St. Lawrence and the St. Lawrence River Estuary as a high-risk anthropogenic threat to the population (DFO, 2022). Similarly, the recovery strategy for the St. Lawrence Estuary beluga whale population (*Delphinapterus leucas*) (SARA status: endangered) recognizes that noise from marine navigation and whale watching activities is a principal threat to the health of the population (DFO, 2012), and both voluntary and mandatory measures are currently in place to reduce the impacts of vessel noise in the region (DFO, 2022b). The management plan for the north Atlantic fin whale (*Balaenoptera physa*lus) population

(SARA status: special concern) recognizes anthropogenic noise as one of the most concerning factors threatening the population (DFO, 2017).

Increasing scientific evidence documenting the negative impacts of noise on cetaceans, alongside the increasing recognition of the role of acoustic environments in the maintenance of healthy marine ecosystems, have led multiple international and national regulatory bodies to establish programs, guidelines, and thresholds for monitoring and mitigating anthropogenic noise in the ocean (Chou et al., 2021; Merchant et al., 2022). Most regulators and managers agree that efforts to mitigate and reduce noise and its potential negative impacts on marine life should follow the precautionary principle (Chou et al., 2021). Other common denominators are the recognition that anthropogenic noise can affect multiple marine taxa, including fish and invertebrates, and that noise pollution should be considered as a potentially far-reaching and transboundary pollutant (Chou et al., 2021). Despite such increased recognition, currently there are no broad international agreements delineating specific targets for the reduction of anthropogenic noise in the ocean, and so far, only the European Union has adopted mandatory rules and thresholds for the emission of noise from human activities at sea (O.J. E.U. C/24/2078, 2024).

In the remaining sections of the introduction, I provide context for my doctoral research by describing the current knowledge of the ecological role of sounds, the impacts of anthropogenic noise in terrestrial and marine species, and provide a review of current challenges in the monitoring and mitigation of anthropogenic noise. The final sections of the chapter are dedicated to the objectives of this dissertation and to the description of the study area.

1.1.1. The ecological role of sound

In physics, soundwaves are a form of energy transfer acting through the temporary displacement of the particles in a media (e.g., air, water, solids). This temporary displacement, or vibration, results in localized compressions and expansions of the media (Robinson et al., 2014). A sound wave can be described by five fundamental properties: wavelength, amplitude, time-period, frequency, and velocity or speed (Young et al., 2014). The wavelength represents the minimum distance at which a soundwave repeats itself: the combined length of a compression and adjacent rarefaction of particles are equal to the wavelength, as it is the distance between the center points of two compression (or rarefaction) phases. When a wave transits through a media, particles are temporarily displaced from their original position. Amplitude is a measure of the maximum distance that particles can reach when displaced by a soundwave. The time-period (T), indicates the amount of time required by a wave to complete a full compression-decompression cycle. The number of complete cycles per second is called the frequency (f) of the wave, and it corresponds to the inverse of the time-period, $f=1/T$. Lastly, the velocity (or speed) of a wave represents the distance traveled by a wave in one second (e.g., approximately 343 m/s in air and 1522 m/s in salt water at 20 °C).

Yet, the properties of sound go beyond the five quantities described above, as sound is a fundamental component of every ecosystem, allowing species to transmit and receive information over long distances, and playing a role in key life events for many species.

Acoustic environments have shaped species' evolution, contributed to the biodiversity we observe today, and play an active role in natural selection (Farina, 2014; Robert et al., 2019; Seddon, 2005). Two characteristics of soundwaves make this form of energy transmission an ideal vehicle for the delivery and reception of biological information:

First, soundwaves are source-specific, allowing organisms to evolve mechanisms and strategies to detect and interpret environmental sounds to their advantage. For example, the flowers of the beach evening primrose (*Oenothera drummondii*) vibrate mechanically when exposed to the sound of flying pollinators and the plant responds by increasing the sugar content of nearby flowers (Veits et al., 2019). In the marine realm, the acoustic energy of a coral reef plays a role in the settlement of fish larval stages (Gordon et al., 2018, 2019) . Settling fish larvae find active and "noisy" reefs, sprawling with diversity, to be more attractive than more "quiet" and degraded reefs characterized by lower diversity and abundance of reef species (Gordon et al., 2018).

Second, soundwaves can be finely modulated by altering their characteristics (e.g., frequency, amplitude, repetition rate), allowing organisms to adapt to different acoustic environments, thus maximizing their performance in receiving and delivering information. Many species of baleen whales have evolved communication strategies that ensure the transmission of information over very long-ranges. For example, blue whales singing in the depths of the ocean can reach conspecifics located hundreds of kilometers away (Širović et al., 2007). Another example can be found in bottlenose dolphins (*Tursiops truncates*), which live in complex and dynamic societies (i.e., fission-fusion societies) where individual recognition plays a more important role then group recognition (Janik & Sayigh, 2013). Bottlenose dolphins learn to produce signature whistles that are unique to the individual and that are used to communicate the presence and location of a specific dolphin within a group (Janik & Sayigh, 2013; Luís et al., 2016).

Acoustic environments are emerging as a central aspect of the ecology of many different species belonging to a wide variety of taxa, including vertebrates (mammals, birds, fish, turtles) (Ladich & Winkler, 2017), invertebrates (crustaceans, molluscs, insects) (Morley et al., 2014), and plants (Del Stabile et al., 2022). Acoustic environments play a role in the reproduction, survival, and communication of many species by shaping behaviours, enabling complex social interactions, defining settlement preferences, and by influencing species interactions, among others, highlighting the potential for anthropogenic noise to disrupt a number of key ecological functions in both marine and terrestrial environments.

1.1.2. The ecological role of noise

In many fields, noise represents a complex phenomenon generally associated with the loss of information. In electronics, for example, noise represents an electromagnetic disturbance that can limit or degrade the performance of electrical equipment (Shahparnia et al., 2004). In photography, noise can indicate the visible consequences of errors or interferences that occurred when an image was captured (Rabie, 2004). In the field of ecoacoustics, which encompasses both bioacoustics and soundscape ecology, noise is largely defined as uninformative sound, sound without a function, or sound that interferes with an acoustic signal of interest (Farina, 2017; McKenna et al., 2016; Risch & van Geel, 2019).

However, noise should not be considered as an alien presence in the natural environment. Rather than being simply framed as uninformative sound, noise can be a source of vital information (Farina, 2017), thus influencing animals' decision-making processes (Geipel et al., 2019). Ambient noise (i.e., natural background noise) originates from both biotic and abiotic entities. Landscape features such as rivers and waterfalls, as well as meteorological events, such as rainfalls and wind-driven waves, are all sources of noise that naturally occur in different habitats (Farina, 2017).

These sources of natural noise, in some cases, can inhibit animals from producing vocalizations. For example, most animal communication is disrupted in proximity of waterfalls, and birds are usually silent when strong winds are blowing (Farina, 2017). Nonetheless, species can receive relevant biological information from natural background noise. The noise of heavy rainfall alters bats decision-making, as rain reduces the efficiency of bats echolocation signals and increases energy consumption by reducing their flight efficiency (Geipel et al., 2019). Bats exposed to playbacks of rain sounds from a single speaker tend, in the absence of other sensory cues (e.g., drop in humidity and temperature), to leave their shelter significantly later than bats exposed to control conditions (i.e., ambient noise in the absence of rain noise) (Geipel et al., 2019). While disruptive for some species, natural sounds can be informative for others. For example, the sound produced by snapping shrimps while feeding, which can dominate the acoustic environment in warm shallow waters at medium to high frequencies (> 2 kHz), represents a challenge for the acquisition of signals using digital recorders (Mahmood & Vishnu, 2017), assuming the connotation of noise in this context. At the same time, snapping shrimps are thought to provide important cues on habitat conditions for other species (Lillis & Mooney, 2018; Rossi et al., 2016). In this sense, the sounds produced by snapping shrimps carry relevant biological information, thus do not fit the definition of "noise" for animals that monitor this source of acoustic energy.

As a new and emerging field, Ecoacoustics (Farina & Gage, 2017) provides a framework of theories and methods to describe the complexity of species' acoustic behaviours and the effects of anthropogenic noise on such complexity. Central to the field of Ecoacoustics is the concept of soundscape, which can be defined as the total acoustic energy contained within an environment (Farina & Li, 2021). A soundscape delineates an acoustic space that can be studied to answer ecological questions, and has four main components: Geophonies, which include all sounds produced by natural abiotic sources; Biophonies, which include all sounds produced by biotic sources, either voluntarily or involuntarily; and anthropophonies, which include all sounds produced by humans and their activities (Grinfeder et al., 2022).

The term anthropogenic noise, sometimes referred to as technophonies, is an umbrella term referring to all emission of sounds that are linked to human activities involving the use of either static (e.g. industries) or moving (e.g., cars, planes, boats) machinery (Farina & Li, 2021). These include two main groups of acoustic emissions: active noise, in which the sounds produced are important to the success of an activity (e.g., sonar, seismic exploration for resources), and by-product noise, in which the emission of acoustic energy is an unintended consequence of an activity (e.g., subsea explosions, vessel traffic, construction of infrastructure). Active anthropogenic noise sources are among the loudest sources of noise found in natural environments; however, their temporal and spatial distribution is often contained. Noise as a by-product of human activities, such as the sounds produced by engines (e.g., vessels and aircraft overflights), is one of the most widespread pollutants found in the ocean.

So far the effects of anthropogenic noise, have been documented in mammals, birds, reptiles, amphibians, fishes, and different groups of invertebrates, including both macro invertebrates (e.g., large molluscs and crustaceans) and plankton (Kight & Swaddle, 2011; Kunc & Schmidt, 2019; Morley et al., 2014; Rojas et al., 2023; Shannon et al., 2016). The impacts of anthropogenic noise can be grouped into two broad categories: direct and indirect. Direct impacts include death, permanent damage to animals' auditory and non-auditory tissues, temporary shifts in animals' hearing abilities, avoidance reactions, changes in behaviour, masking of sounds leading to reduced ability to perceive and interpret acoustic information, and induced changes in hormone levels as stress responses (Kunc et al., 2016). The indirect impacts of noise include all consequences extending beyond individuals and populations, and resulting in the modification of species' interactions within ecological communities (Kok et al., 2023; Senzaki et al., 2020). Variations in species' local abundance resulting from avoidance, reduced survival rates, and decreased population growth due to noise pollution can drive changes in competitor, predator-prey, and parasites-host interactions (Kok et al., 2023). Therefore, the indirect effects of noise pollution have the potential of affecting non-auditory species (i.e., species that do not rely heavily on acoustic signals for survival, feeding, reproduction, and socialization) (Senzaki et al., 2020). All of the impacts mentioned above have been observed in marine mammal species. Permanent and temporary shifts in hearing thresholds were first described and measured in marine mammals. Acoustic masking of both social signals and echolocation signals is considered one of the most widespread impacts of anthropogenic noise on marine mammals (Chahouri et al., 2022). For example, vessel noise can reduce the efficiency of foraging resident killer whales, which rely on echolocation to find and hunt salmons (Trounce et al., 2019). The behavioral responses observed in marine mammals include the avoidance of areas affected by noise-generating activities, the interruption of feeding, and the interruption of vocal behaviors, among others (Erbe et al., 2018). Stress responses to the presence of vessel noise have been documented and measured in at least two species of baleen whales: right whales (Rolland et al., 2012); and gray whales (Lemos et al., 2022).

1.1.3. Challenges in monitoring and mitigating ocean noise pollution

Despite growing evidence of the importance of unaltered acoustic environments and on the impacts that noise pollution can have on wildlife populations, there are still several challenges that need to be overcome to address this pressing environmental problem. Such challenges range from finding efficient approaches to analyzing and interpreting passive acoustic dataset, to the design, implementation, and assessment of effective noise mitigation measures.

Monitoring Acoustic Environments

Passive Acoustic Monitoring (PAM), the systematic collection of environmental audio recordings for environmental monitoring, is being used to answer a range of ecological and conservation management questions pertaining to species, populations, and communities across the globe (Gibb et al., 2019; Ross et al., 2023). In conservation applications in particular, environmental sounds can be used as indicators to monitor ecological processes (e.g., species' migrations and seasonal habitat use) and for assessing anthropogenic disturbances (e.g., measuring noise pollution levels).

This breadth of PAM applications has been made possible by recent developments in the technology used for acquiring, storing, and processing audio datasets (Farina et al., 2024). Current PAM technology allows the collection and storage of acoustic data for long periods (sometimes years), can be deployed in remote areas that would otherwise be difficult to access by other means (e.g., vessel-based visual surveys), and is less invasive than other environmental monitoring techniques (e.g., satellite tags). These advantages have led to the widespread use of PAM as a tool for monitoring anthropogenic noise sources in the ocean (Halliday et al., 2021; Haver et al., 2018; Jalkanen et al., 2022). However, the development of PAM technology also resulted in a rapid and voluminous growth in the size of PAM datasets, which was not matched with an increase in our capacity to process and interpret the ecological information contained in acoustic datasets (Napier et al., 2024). With an increasing number of managers and decision makers being tasked with monitoring the health of marine environments, finding effective approaches that routinely extract ecological information from PAM datasets remains an open challenge and a main goal for bioacoustics and ecoacoustics researchers across the globe (Desjonquères et al., 2020; Gibb et al., 2019).

An additional challenge arises from one of the greatest advantages of PAM: enabling continuous environmental monitoring. As all acoustic data are time series in which repeated measures are collected from the same location at different times, caution should be taken when conducting statistical analyses with the goal of linking time-varying sound with ecological processes (Desjonquères et al., 2020). Averaging acoustic samples over regular time intervals and including variables that take into account temporal changes when applying statistical models are two possible solutions to the issue of non-independence of data points in PAM analysis (Desjonquères et al., 2020). Furthermore, PAM systems are not selective, recording all sounds occurring in the environment falling within the frequency range of the instrument being used. This issue is particularly relevant for underwater applications, where the recorders are moored using multiple structures (e.g., frames, weights, ropes) that, due to mooring design, seafloor characteristics, and the action of waves and currents, can generate spurious self-noise (Lammers et al., 2013; Risch & van Geel, 2019; van Geel et al., 2022). If not accounted for, instrument self-noise can reduce the accuracy of ambient noise measurement and affect the results of statistical analyses, leading, for example, to the overestimation of ambient Sound Pressure Level (SPL) (van Geel et al., 2022).

Managing and mitigating underwater noise from vessel

Underwater noise pollution is internationally recognized as a threat to the preservation of biodiversity (Boyd et al., 2011; Harding & Cousins, 2022; IMO, 2014, 2023), with particularly severe impacts on the health and recovery potential of threatened and endangered cetacean populations (Erbe et al., 2019; Maruf & Gullett, 2022). In response to these threats, a range of mitigation measures and policies are being developed and tested in marine areas where vessels and other anthropogenic noise sources overlap with important cetacean habitats (Burnham et al., 2021; Chion et al., 2017; ZoBell et al., 2021). In Canada, ocean noise is addressed under the Ocean Protection Plan, which has the objective of protecting Canadian oceans and coastlines from the potential impacts of marine shipping (Government of Canada, 2020). One of the main goals of the Ocean Protection Plan is addressing the impacts of underwater noise pollution. On August 23, 2024, the Government of Canada released the first draft of its Ocean Noise Strategy (ONS) for public consultation (DFO, 2024). The ONS will inform the development of a pan-government approach for addressing underwater noise pollution in Canada, including the creation of measures for the mitigation of underwater anthropogenic noise and the identification of appropriate thresholds and measurement standards. Furthermore, the ONS recognizes the transboundary nature of noise, and the current draft aligns with strategies adopted in the United States (NOAA's Ocean Noise Strategy) (Gedamke et al., 2016) and in Europe (i.e., MSFD 2008/56/EC).

In addition to NOAA's Ocean Noise Strategy, marine mammals in the US are protected from exposure to excessive levels of anthropogenic noise through the Marine Mammal

Protection Act (MMPA) and the Endangered Species Act (ESA). These two regulations address impacts at the individual level and requires proposed projects to minimize the number of animals that will be affected by anthropogenic noise. In particular, NOAA established a set of noise exposure thresholds for the onset of physical (permanent and temporary auditory threshold shifts) and behavioural impacts (e.g., avoidance reactions, interruption of feeding) on marine mammals. In the European Union, the impacts of underwater noise are managed and regulated through the Marine Strategy Framework Directive (MSFD) (Directive 2014/89/EU). Specifically, Descriptor 11 of the MSFD indicates that in order to maintain healthy marine environments, the noise emitted by anthropogenic sources within EU waters should be below levels that can adversely affect species and habitats. In 2022, the MSFD introduced the first specific national targets for the mitigation of underwater noise from vessels. Instead of focusing on direct damage to the health and behaviour of individual animals, the EU targets focus on the area of marine habitat being affected by anthropogenic noise. The recommendations requires that continuous underwater noise, largely produced by marine transportation – must not be present in more the 20% of a given marine area over the course of a year.

Canada’s ONS recognizes Marine spatial planning (MSP) as a tool for optimizing the spatial and temporal distribution of ships and reduce their impacts on marine environments. MSP for vessel traffic management involves designing, implementing, and monitoring the success of targeted mitigation measures (Burnham et al., 2021; Chion et al., 2018; Ménard et al., 2022). MSP is at the core of multiple Canadian initiatives aimed at reducing the impact of vessels on marine mammals (e.g., the Enhancing Cetacean and

Habitat Observation program by the Port of Vancouver). Such initiatives employ a range of permanent and seasonal measures, often adapting the measures to target noise emissions from specific vessel classes (e.g., speed limits, permanent and temporary no-go areas, incentives for noise reduction), and rely on regular monitoring to evaluate their outcomes. Under the objectives of the ONS, Canada's federal agencies are now tasked with establishing ocean noise monitoring standards and with defining thresholds for its emission in the marine environment. Assessing underwater noise pollution levels using criteria that have already been established in other jurisdictions can provide guidance for the definition of Canadian standards and thresholds for underwater noise pollution, but should not be considered proscriptive.

So far, only a small fraction of coastal and open ocean areas has been investigated using PAM. Darras et al. (2024) provides an overview of more than 400 PAM projects and 12,000 study sites conducted in terrestrial, marine, and subterranean environments. Marine environments, including open ocean and coastal sites, have a coverage of 0.3 sites per million square kilometers (Mkm^2), while terrestrial environments reach 45 sites/Mkm^2 (Darras et al., 2024). Of the marine sites, only a few areas in Canada have been studied using PAM, with the majority of coastal habitats still in need of assessment (Darras et al., 2024). Canada has the longest coastline of any country in the world, spanning more than 240,000 km, making the implementation of large-scale PAM monitoring programs and the introduction of ad hoc noise mitigation solutions focused on specific regions of the ocean challenging. The spatio-temporal and habitat-based approach adopted by the EU could be a possible solution to reduce the impacts of vessel noise along Canada’s coastlines. At the same time, as the recovery of many protected cetacean species in Canada is threatened by growing anthropogenic noise levels, introducing species-specific acoustic thresholds for marine species at risk could be a way to tackle the most pressing impacts of ocean noise pollution by setting unambiguous noise exposure limits.

1. 2. Objectives

As part of the ongoing effort in developing and implementing Canada’s ONS, Placentia Bay was selected as one of the regional study sites for DFO’s Marine Environmental Quality Program (MEQ). The MEQ initiative in Placentia Bay has two goals: i) better understanding marine mammal’s habitat use, and ii) estimating underwater noise exposure for marine mammals and other marine species within the bay.

The overall objective of this dissertation is to explore how the natural (i.e., biotic and abiotic) and anthropogenic sound sources found in Placentia Bay interact and contribute to shaping its underwater acoustic environments.

This was done with the goal of answering a pressing, overarching management and research question:

- Is vessel noise in Placentia Bay reaching levels that could have negative impacts on marine mammals and other marine species?

Besides aligning with the ONS and the MEQ program, the research chapters presented in my dissertation contribute to broadening our understanding of the distribution and prevalence of vessel noise as a pollutant in coastal marine areas. Specifically, my research contributes by:

(i) advancing the integration of unsupervised machine learning approaches in PAM analysis as a way to overcome the challenges of analyzing large datasets spanning multiple months and collected at multiple stations (**Chapters Two** and **Three**);

(ii) providing baseline acoustic measures that can be used as a reference to assess likely changes in the levels of anthropogenic noise in Placentia Bay (**Chapter Three**);

(iii) advancing current knowledge on the exposure of protected marine mammals and their habitat to anthropogenic noise (**Chapters** Three and **Four**);

(iv) documenting how changes in economic activities occurring within a coastal area can result in significant changes in the distribution of noise sources and in increased exposure of protected cetacean species to noise pollution (**Chapters Three** and **Four**); and

(v) providing an assessment of how the current configuration of vessel traffic in Placentia Bay results in noise pollution levels that are exceeding thresholds adopted in the EU and US (**Chapter Four**).

Specifically, the three research chapters have the following objectives:

Chapter Two*.* The objective of this methodological study was to test how Machine-Learned acoustic features generated by a pre-trained audio classification Convolutional Neural Network model (VGGish) could provide a tool to link marine PAM audio recordings to environmental features occurring at different temporal scales. These included applications to discriminate between the vocalizations produced by twelve different species of marine mammals, as well as applications to explore the relationship between PAM recordings and local environmental conditions.

Chapter Three*.* Here, the objectives were to: i) assess the underwater acoustic environment at two Passive Acoustic Monitoring (PAM) stations in Placentia Bay; ii) investigate the effects of environmental conditions and the presence of vessels on the recorded noise levels at the hydrophone locations; and iii) provide a first assessment of the exposure of threatened north Atlantic fin whales to vessel noise in the region.

Chapter Four*.* The objectives of this chapter were to: i) document how vessel traffic changed in Placentia Bay over the period 2019-2023; and ii) assess how those changes affected the spatial and temporal distribution of vessel noise sources in the region, including within areas that are important to cetacean species.

The conclusive chapter (**Chapter Five**) summarizes the main findings of the three research chapters and their management implications, as well as their limitations and methodological challenges, and highlights future research directions to address the impacts of noise pollution from vessels on cetaceans in Canada.

1. 3. Study Area

Placentia Bay (PB) is a large bay, approximately 130 km long and with a width of 100 km at its mouth, located on the southeast coast of the Island of Newfoundland, in the province of Newfoundland and Labrador, Canada. The average depth of Placentia Bay is 125 m, with three deep channels with depths reaching more than 400 m found in the inner portion of the bay. The geomorphology of Placentia Bay's seafloor varies going from the opening of the bay having predominantly mud sand and gravel substrates, to the deeper channels in the inner bay, where bedrock formations are common (Shaw et al., 2011).

Placentia Bay is an important and expanding economic hub for the province of Newfoundland and Labrador. Since 1973, an oil refinery has been operating in the region, and the production plant was recently repurposed for the production and export of biodiesels. The port of Argentia includes both commercial docks and ferry terminals, and is projected to undergo a significant expansion in activity due to several proposed hydrogen production and export projects (https://portofargentia.ca/). Since 2019, Placentia Bay has also been hosting a growing aquaculture industry, and a number of new licenses for the installation of salmon sea pens within the inner portion of the bay have between issued between 2019 and 2024. Furthermore, Placentia Bay hosts different commercial and traditional fisheries, as well as recreational and tourism activities.

Placentia Bay is a site of ecological relevance for Newfoundland and Labrador and eastern Canada. The area hosts aggregations and spawning sites of commercially and ecologically important marine species, as well as several seabird colonies and important foraging habitats for endangered Atlantic leatherback sea turtles (*Dermochelys coriacea*). Placentia Bay is a hotspot of marine mammal diversity, with fourteen species found there. These include three baleen whale species protected under SARA: blue whales, fin whales, and right whales (*Eubalaena glacialis*).

Due to its ecological and economical relevance, the area was designated as an Ecologically or Biologically Significant Marine Area (EBSA) in 2007. Furthermore, in 2016, Placentia Bay was selected as one of the Atlantic study-sites for DFO's MEQ initiative, with the objective of establishing environmental baseline measurements to track the health of marine coastal environments. The area is also an important study site for the development of Canada's ONS, and the underwater noise studies conducted in the area, including the research I present in this dissertation, contribute to the creation of a national underwater noise management plan for Canada's oceans.

1. 4. Co-authorship Statement

Chapter 2 titled "*Acoustic Features as a Tool to Visualize and Explore Marine Soundscapes: Applications Illustrated using Marine Mammal Passive Acoustic Monitoring Datasets"* was published in the Journal of Ecology and Evolution in 2024, volume 14, issue 2. This chapter was a collaborative effort with Dr. Nicolo' Bellin (University of Parma, Italy), Dr. Carissa D. Brown (Memorial University of Newfoundland and Labrador), Dr.

Valeria Rossi (University of Parma, Italy), and Dr. Jack Lawson (Department of Fisheries and Oceans). In this chapter, I was the principal contributor in conceptualizing the study, seeking collaborators, developing the methodology, analyzing the datasets, and preparing, submitting, and revising the final published manuscript. Dr. Nicolo' Bellin contributed to the development of the methodology described in the chapter and provided expert knowledge in Machine Learning and its application to ecological problems. Dr. Carissa Brown, Dr. Valeria Rossi, and Dr. Jack Lawson provided feedback and reviewed the manuscript, and provided space and equipment for conducting the research. Dr. Jack Lawson provided access to DFO's PAM databases, provided input during the development of the methodology, and reviewed the analysis results.

The publication is open-source and can be accessed at the following link:

https://doi.org/10.1002/ece3.10951

Scripts to reproduce the images and analysis results reported in this Chapter 2, and tables containing the VGGish acoustic features and labels for the two datasets can be found at the following links:

Dryad (data tables): https://doi.org/10.5061/dryad.3bk3j9kn8

Zenodo (python scripts): https://doi.org/10.5281/zenodo.10019845

Chapter 3 titled "*Characterizing the Acoustic Environment of Placentia Bay: Unsupervised Clustering of Loud Events and QGAM Models Applied to PAM Data from Two Monitoring Stations During Fall and Summer 2019"* is co-authored by Carissa D. Brown, Dr. Jack Lawson, and Dr. Leonard Zedel. I was the principal contributor to the conceptualization of the study, the design of the methodology, data acquisition and analysis, and the preparation and review of the manuscript. Dr. Carissa Brown contributed to the study design and provided input to refine the manuscript's objectives and methodology. Dr. Jack Lawson reviewed the manuscript, contributed to defining the study objectives, and provided expert knowledge relative to the study area as well as access to the data presented in the manuscript (PAM recordings, marine mammal acoustic detections). Dr. Len Zedel reviewed the manuscript and contributed expert knowledge in ocean acoustics.

Chapter 4 titled "Spatial and temporal assessment of vessel noise and intensity within an ecologically and biologically significant North Atlantic marine mammal habitat" is co-authored by Carissa D. Brown, Dr. Jack Lawson, and Dr. Leonard Zedel. I was the principal contributor to the conceptualization of the study, the design of the methodology, data acquisition and analysis, and the preparation and review of the manuscript. All co-authors contributed to refining the methodological approach and scope of the manuscript, and reviewed and provided feedback throughout its preparation. Dr. Jack Lawson and his team provided marine mammal line transect survey data for the study area.

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Chapter 2: Acoustic Features as a Tool to Visualize & Explore Marine Soundscapes: Applications Illustrated using Marine Mammal Passive Acoustic Monitoring Datasets

2. 1. Introduction

Abrupt changes in the ocean environment are increasing in frequency as climate change accelerates (Ainsworth et al., 2020), resulting in loss of key ecosystems (Sully et al., 2019), and shifts in endangered species' distributions (Plourde et al., 2019). Detecting such changes requires both historical and real-time (or near-real time) data made readily available to managers and decision-makers. Scientists and practitioners are being tasked with finding efficient solutions for monitoring environmental health and detecting incipient change (Gibb et al., 2019; Kowarski & Moors-Murphy, 2021). This challenge includes monitoring for changes in species' presence, abundance, distribution, and behaviour (Durette-Morin et al., 2019; Fleming et al., 2018; Root-Gutteridge et al., 2018), monitoring anthropogenic activity and disturbance levels (Gómez et al., 2018), monitoring changes in the environment (Almeira & Guecha, 2019), and detecting harmful events (Rycyk et al., 2020), among others.

Environmental sounds provide a proxy to investigate ecological processes (Gibb et al., 2019; Rycyk et al., 2020), including exploring complex interactions between anthropogenic activity and biota (Erbe et al., 2019; Kunc et al., 2016). Sound provides useful information on environmental conditions and ecosystem health, allowing, for example, the rapid identification of disturbed coral reefs (Elise et al., 2019). In concert, numerous species (i.e., birds, mammals, fish, and invertebrates) rely on acoustic communication for foraging, mating and reproduction, habitat use and other ecological functions (Eftestøl et al., 2019; Kunc & Schmidt, 2019; Luo et al., 2015; Schmidt et al., 2014). Noise produced by anthropogenic activities (e.g., vehicles, stationary machinery, explosions) can interfere with such processes, affecting the health and reproductive success of multiple marine taxa (Kunc & Schmidt, 2019). In response to concerns about noise pollution, increasing effort is being invested in developing, testing, and implementing noise management measures in both terrestrial and marine environments. Consequently, Passive Acoustic Monitoring (PAM) has become a mainstream tool in biological monitoring (Gibb et al., 2019). PAM represents a set of techniques that are used for the systematic collection of acoustic recordings for environmental monitoring. It allows collecting large amounts of acoustic recordings that can then be used to understand changes happening in the environment at multiple spatial and temporal scales.

One of PAM's most common applications is in marine mammal monitoring and conservation. Marine mammals produce complex vocalizations that are species-specific (if not individually unique), and such vocalizations can be used when estimating species' distributions and habitat use (Durette-Morin et al., 2019; Kowarski & Moors-Murphy, 2021). PAM applications in marine mammal research span from the study of their vocalizations and behaviours (Madhusudhana et al., 2019; Vester et al., 2017) to assessing anthropogenic disturbance (Nguyen Hong Duc et al., 2021). PAM datasets can reach considerable sizes, particularly when recorded at high sampling rates, and projects often rely on experts to manually inspect the acoustic recordings for the identification of sounds of interest (Nguyen Hong Duc et al., 2021). For projects involving recordings collected over multiple months at different locations, conducting a manual analysis of the entire dataset can be prohibitive, and often only a relatively small portion of the acoustic recordings is subsampled for analysis.

At its core, studying acoustic environments is a signal detection and classification problem in which a large number of spatially and temporally overlapping acoustic energy sources need to be differentiated to better understand their relative contributions to the soundscape. Such an analytical process, termed acoustic scene classification (Geiger et al., 2013), is a key step in analysing environmental information collected by PAM recorders. Acoustic scenes can contain multiple overlapping sound sources, which generate complex combinations of acoustic events (Geiger et al., 2013). This definition overlaps with the ecoacoustics definition of soundscape (Farina & Gage, 2017), providing a bridge between the two fields, where a soundscape represents the total acoustic energy contained within an environment and consists of three intersecting sound sources: geological (i.e., geophony), biological (i.e., biophony), and anthropogenic (i.e., anthrophony). A goal of ecoacoustics is to understand how these sources interact and influence each other, with a particular focus on biological-anthropogenic acoustic interactions. The concept of soundscape has recently been reframed and expanded to encompass three distinct categories: the distal soundscape, the proximal soundscape, and the perceptual soundscape (Grinfeder et al., 2022). The distal soundscape describes the spatial and temporal variation of acoustic signals within a defined area or environment. The proximal soundscape represents acoustic signals that occur at a specific location within a defined area – a distal soundscape can be interpreted as a collection of proximal soundscapes and include all potential receiver positions. The perceptual soundscape is the subjective interpretation of a specific proximal soundscape and involves sensory and cognitive processes of the individual. In this study, we focus on the analysis of distal soundscapes, which allow investigating how biotic and abiotic factors relate to acoustic recordings.

Automated acoustic analysis can overcome some of the limitations encountered in manual PAM analysis, allowing ecoacoustics researchers to explore full datasets (Houegnigan et al., 2017). Deep learning represents a novel set of computer-based artificial intelligence approaches which has profoundly changed biology and ecology research (Christin et al., 2019). Among the deep learning approaches, Convolutional Neural Networks (CNNs) have demonstrated high accuracy in performing image classification tasks, including the classification of spectrograms (i.e., visual representations of sounds according to time, frequency, and acoustic amplitude)) (Hershey et al., 2017; LeBien et al., 2020; Stowell, 2022).

CNNs have been applied successfully to several ecological problems, such as processing camera trap images to identify species, age classes, numbers of animals, or for classifying behavioural patterns (Lumini et al., 2019; Norouzzadeh et al., 2018; Tabak et al., 2019), and their use in ecology has been growing (Christin et al., 2019). CNN's algorithms perform well for acoustic classification (Hershey et al., 2017), including the identification of a growing number of species vocalizations such as crickets and cicadas (Dong et al., 2018), birds and frogs (LeBien et al., 2020), fish (Mishachandar & Vairamuthu, 2021), and lately marine mammals (Usman et al., 2020). Recent applications of deep learning to the study of marine soundscapes include automated detectors for killer whales (Bergler et al., 2019) and humpback whales (Allen et al., 2021), the detection of North Atlantic right whales under changing environmental conditions (Vickers et al., 2021), and the detection of echolocation click trains produced by toothed whales (Roch et al., 2021).

Most CNN applications focus on species detection rather than a broader characterization of the acoustic environment. Furthermore, automated acoustic analysis algorithms often rely on supervised classification based on large datasets of known sounds (i.e., training datasets) used to train acoustic classifiers; creating training datasets is time-consuming and requires expert-driven manual classification of the acoustic data (Bittle & Duncan, 2013).

Recent developments in acoustic scene analysis demonstrate how the implementation of acoustic feature sets derived from CNNs, along with the use of dimensionality reduction (UMAP), can improve our ability to understand ecoacoustics datasets while providing a common ground for analysing recordings collected across multiple environments and temporal scales (Clink & Klinck, 2021; Mishachandar & Vairamuthu, 2021; Sethi et al., 2020).

In this study, we applied multiple machine learning techniques to the analysis of two PAM datasets (the Watkins Marine Mammal Sounds Database [1], and two months of continuous PAM recordings collected by Fisheries and Oceans Canada in Placentia Bay Newfoundland, Canada during July and August 2019). We combined pre-trained acoustic classification models (VGGish, NOAA and Google Humpback Whale Detector), dimensionality reduction (UMAP), and balanced random forest algorithms to demonstrate how machine-learned acoustic features capture different aspects of the marine acoustic environment.

- We used the pre-trained VGGish algorithm to extract sets of acoustic features at different temporal resolutions for both datasets.
- Using UMAP, we reduced the acoustic features from the WMD to visualize the dataset structure and explore the relationship between audio recordings and labels describing species taxonomy and geographic locations.
- For the PBD dataset, UMAP visualizations were paired with the use of balanced random forest classifiers fitted on the VGGish acoustic features. With this, we tested how learned acoustic features can be used to identify the biophonic (humpback whale vocalizations) and geophonic (wind speed, surface temperature, and current speed) components of the distal soundscape of Placentia Bay.

[1] https://cis.whoi.edu/science/B/whalesounds/index.cfm

This approach is not tied to a specific environment or group of species and can be used to simultaneously investigate the macro and micro characteristics of marine soundscapes.

2. 2. Materials & Methods

2.2.1. Data Acquisition & Preparation

We collected all records available in the Watkins Marine Mammal Database (WMD) website listed under the “all cuts" page. For each audio file in the WMD the associated metadata included a label for the sound sources present in the recording (biological, anthropogenic, and environmental), as well as information related to the location and date of recording. To minimize the presence of unwanted sounds in the samples, we only retained audio files with a single source listed in the metadata. We then labelled the selected audio clips according to taxonomic group (*Odontocetae, Mysticetae*), and species.

We limited the analysis to 12 marine mammal species by discarding data when a species: had less than 60 s of audio available, had a vocal repertoire extending beyond the 8 kHz maximum frequency accepted by the acoustic classification model (VGGish), or was recorded in a single country. To determine if a species was suited for analysis using VGGish, we inspected the Mel-spectrograms of 3-s audio samples and only retained species with vocalizations that could be captured in the Mel-spectrogram (Appendix A). Mel-spectrograms use the Mel scale rather than hertz to plot frequency. The Mel scale is a perceptual scale mimicking how human listeners hear sounds. The vocalizations of species that produce very low frequency, or very high frequency were not captured by the Mel-spectrogram, thus we removed them from the analysis. To ensure that records included the vocalizations of multiple individuals for each species, we only considered species with records from two or more different countries. Lastly, to avoid overrepresentation of sperm whale vocalizations, we excluded 30,000 sperm whale recordings collected in the Dominican Republic. The resulting dataset consisted of 19,682 audio clips with a duration of 960 milliseconds each (0.96 s) (Table 1).

The Placentia Bay Database (PBD) includes recordings collected by Fisheries and Oceans Canada in Placentia Bay (Newfoundland and Labrador, Canada), in 2019. The dataset consisted of two months of continuous recordings (1230 hours), starting on July 1st, 2019, and ending on August 31st, 2019. The data were collected using an AMAR G4 hydrophone (sensitivity: -165.02 dB re 1V/µPa at 250 Hz) deployed at 64 m of depth. The hydrophone was set to operate following 15 min cycles, with the first 60 s sampled at 512 kHz, and the remaining 14 min sampled at 64 kHz. For the purpose of this study, we limited the analysis to the 64 kHz recordings.

Table 1 List of species selected from the WMD and corresponding sample sizes.

Species	Location (Year)	N	Total
Bowhead whale	Canada (1988)	705	772
	United States (1972, 1980)	67	
Beluga	Canada (1949,1962,1965)	153	224
	United States (1963,1965,1968)	71	
Southern right whale	Argentina (1979)	99	109
	Australia (1983)	10	
North Atlantic right whale	Canada (1981)	205	376
	United States (1956,1959,1970,1974)	171	
Short finned pilot whale	Bahamas (1957,1961)	576	696
	Canada (1958,1965,1966,1967)	83	
	St. Vincents and the Grenadines (1981)	37	
Long finned pilot whale	Canada (1954,1975)	1154	2029
	Italy (1994)	26	
	North Atlantic Ocean (1975)	166	
	United States (1977)	426	
	Unknown (1975)	257	
Humpback whale	Bahamas (1952,1955,1958,1963)	4819	5601
	Puerto Rico (1954)	6	
	British Virgin Islands (1992)	254	
	United States (1975,1979,1980)	269	
	Unknown (1954,1961)	253	
Orca	Canada (1961,1964,1966,1979)	492	4416
	Norway (1989,1992)	1696	
	United States (1960,1997)	2228	
Sperm whale	Bahamas (1952)	4	4368
	Italy (1985,1988,1994)	1143	
	Madeira (1966)	1	
	Malta (1985)	220	
	Canada (1975)	966	
	Canary Islands (1987)	7	
	St. Vincents and the Grenadines (1983)	18	
	United States (1972)	1954	
	Unknown (1961,1962,1963,1975)	55	
Rough-thooted dolphin	Italy (1985)	67	75
	Malta (1985)	8	
Clymene dolphin	Santa Lucia (1983)	286	907
	St. Vincents and the Grenadines (1983)	621	
Bottlenose Dolphin	Croatia (1994)	58	109
	United States (1951,1984,1989)	38	
	Unknown (1956)	13	

2.2.2. Acoustic Feature Extraction

The audio files from the WMD and PBD databases were used as input for VGGish (Abu-El-Haija et al., 2016; Chung et al., 2018), a CNN developed and trained to perform general acoustic classification. VGGish was trained on the Youtube8M dataset, containing more than two million user-labelled audio-video files. Rather than focusing on the final output of the model (i.e., the assigned labels), here the model was used as a feature extractor (Sethi et al., 2020). VGGish converts audio input into a semantically meaningful vector consisting of 128 features. The model returns features at multiple resolutions: ~1 s (960 ms); ~5 s (4800 ms); ~1 min (59'520 ms); ~5 min (299'520 ms). All of the visualizations and results pertaining to the WMD were prepared using the finest feature resolution of ~1 s. The visualizations and results pertaining to the PBD were prepared using the ~5 s features for the humpback whale detection example, and were then averaged to an interval of 30 min in order to match the temporal resolution of the environmental measures available for the area.

2.2.3. UMAP Ordination & Visualization

UMAP is a non-linear dimensionality reduction algorithm based on the concept of topological data analysis which, unlike other dimensionality reduction techniques (e.g., the t-distributed stochastic neighbor embedding, tSNE), preserves both the local and global structure of multivariate datasets (McInnes et al., 2018). To allow for data visualization and to reduce the 128 features to two dimensions for further analysis, we applied Uniform Manifold Approximation and Projection (UMAP) to both datasets and inspected the resulting plots.

The UMAP algorithm generates a low-dimensional representation of a multivariate dataset while maintaining the relationships between points in the global dataset structure (i.e., the 128 features extracted from VGGish). Each point in a UMAP plot in this paper represents an audio sample with duration of ~ 1 second (WMD dataset), ~ 5 seconds (PBD, humpback whale detections), or 30 minutes (PBD, environmental variables). Each point in the two-dimensional UMAP space also represents a vector of 128 VGGish features. The nearer two points are in the plot space, the nearer the two points are in the 128-dimensional space, and thus the distance between two points in UMAP reflects the degree of similarity between two audio samples in our datasets. Areas with a high density of samples in UMAP space should, therefore, contain sounds with similar characteristics, and such similarity should decrease with increasing point distance. Previous studies illustrated how VGGish and UMAP can be applied to the analysis of terrestrial acoustic datasets (Heath et al., 2021; Sethi et al., 2020). The visualizations and classification trials presented here illustrate how the two techniques (VGGish and UMAP) can be used together for marine ecoacoustics analysis. UMAP visualizations were prepared using the umap-learn package for python programming language (version 3.10). All UMAP visualizations presented in this study were generated using the algorithm's default parameters.

2.2.4. Labelling Sound Sources

The labels for the WMD records (i.e., taxonomic group, species, and location) were obtained from the database metadata.

For the PBD recordings, we obtained measures of wind speed, surface temperature, and surface current speed (Fig 1) from an oceanographic buoy located in proximity of the recorder[2]. We chose these three variables for their different contributions to background noise in marine environments. Wind speed contributes to underwater background noise at multiple frequencies, ranging from 500 Hz to 20 kHz (Hildebrand et al., 2021). Sea surface temperature contributes to background noise at frequencies between 63 Hz and 125 Hz (Ainslie et al., 2021), while ocean currents contribute to ambient noise at frequencies below 50 Hz (Han et al., 2021). Prior to analysis, we categorized the environmental variables and assigned the categories as labels to the acoustic features (Table 2).

[2] https://www.smartatlantic.ca/station_alt.html?id=placentiabay_redisland

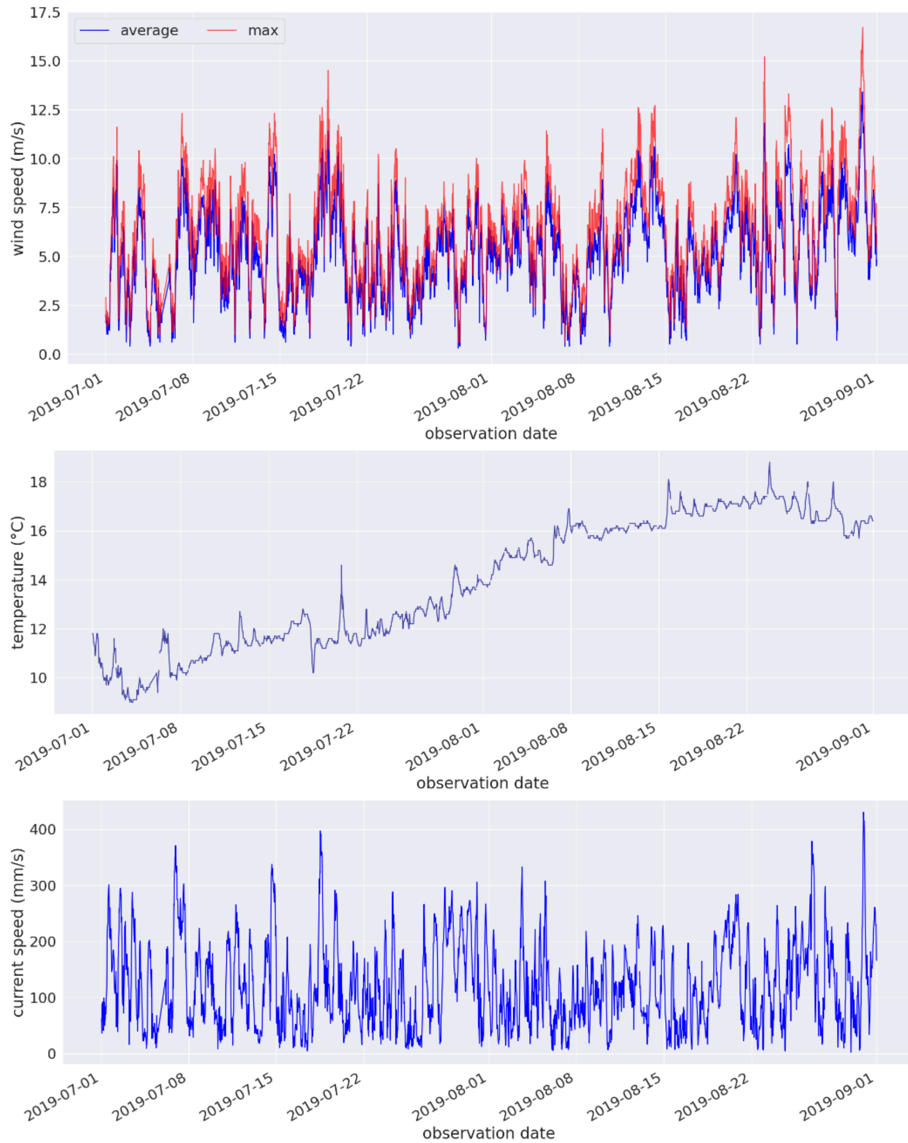

Figure 1 Time series (30 min. intervals) of the environmental variables for the months of July and August 2019. Wind speed (top), ocean surface temperature (middle), and current speed (bottom). All data were obtained from the Red Island SmartAtlantic oceanographic buoy.

Humpback whale vocalizations in the PBD recordings were processed using the humpback whale acoustic detector created by NOAA and Google (Allen et al., 2021), providing a model score for every ~5 s sample. This model was trained on a large dataset (14 years and 13 locations) using humpback whale recordings annotated by experts

(Allen et al., 2021). The model returns scores ranging from 0 to 1 indicating the confidence in the predicted humpback whale presence. We used the results of this detection model to label the PBD samples according to presence of humpback whale vocalizations. To verify the model results, we inspected all audio files that contained a 5 s sample with a model score higher than 0.9 for the month of July. If the presence of a humpback whale was confirmed, we labelled the segment as a model detection. We labelled any additional humpback whale vocalization present in the inspected audio files as a visual detection, while we labelled other sources and background noise samples as absences. In total, we labelled 4.6 hours of recordings. We reserved the recordings collected in August to test the precision of the final predictive model.

2.2.5 Label Prediction Performance

We used Balanced Random Forest models (BRF) provided in the imbalanced-learn python package (Lemaître et al., 2017) to predict humpback whale presence and environmental conditions from the acoustic features generated by VGGish. We chose BRF as the algorithm as it is suited for datasets characterized by class imbalance. The BRF algorithm performs under sampling of the majority class prior to prediction, allowing to overcome class imbalance (Lemaître et al., 2017). For each model run, the PBD dataset was split into training (80%) and testing (20%) sets.

The training datasets were used to fine-tune the models though a nested k-fold cross validation approach with ten-folds in the outer loop, and five-folds in the inner loop. We selected nested cross validation as it allows optimizing model hyperparameters and performing model evaluation in a single step. We used the default parameters of the BRF algorithm, except for the ‘n_estimators’ hyperparameter, for which we tested five different possible values: 25, 50, 100, 150, 200. We chose to optimize the model for ‘n_estimators’ as this parameter determines the number of decision trees generated by the BRF model and finding an optimal value reduces the chances of overfitting. Every iteration of the outer loop generates a new train-validation split of the test dataset, which is then used as input to a BRF.

The testing datasets were then used to evaluate model performance. We evaluated model performance using the balanced-accuracy score, computed as:

$$Balanced\ Accuracy\ (BA) = \frac{Sensitivity + Specificity}{2} \qquad (eq. 1)$$

Where: *sensitivity*, or the true positive rate, indicates the percentage of positive labels correctly identified by the model; and *specificity*, or the true negative rate, indicates the percentage of negative labels (i.e., absences) correctly identified by the model.
We chose balanced-accuracy scores as the evaluation metric for both datasets as it is suited for measuring model performance when samples are highly imbalanced (Brodersen et al., 2010).

In total, we conducted four trials on the PBD dataset. In the first three trials, we used the PBD dataset to test the ability of VGGish in predicting one of the three environmental variables: wind speed, ocean surface temperature, and current speed. In the fourth trial we tested the ability of VGGish in identifying humpback whale vocalizations. Lastly, we tested the humpback whale model on the recordings from the month of August, which were not part of model training and evaluation. We inspected all detections in August and computed model precision as:

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \qquad (eq.2)$$

All predictive models for the PBD were trained and tested on the 128 acoustic features generated by VGGish. The UMAP plots were used to visually inspect the structure of the PBD and WMD features datasets. For the WMD dataset, we used violin plots to explore the distribution of the two UMAP dimensions in relation to the clusters of data points labelled according to taxonomic group, species, and location of origin of the corresponding audio samples.

2. 3. Results

2.3.1 Watkins Marine Mammal Sounds Database

The UMAP visualizations of the WMD features showed a complex structure that reflected both taxonomic labels (group and species) and locations. At the macro scale, UMAP separated samples according to the taxonomic group label. Samples belonging to the mysticete and odontocete species occupied two distinct regions of the plot, with little overlap (Fig. 2). When looking at the distribution of the two UMAP dimension, this separation was more evident along the second UMAP dimensions, while samples had a higher degree of overlapping values along the first dimension (Appendix B, Fig. B.1).

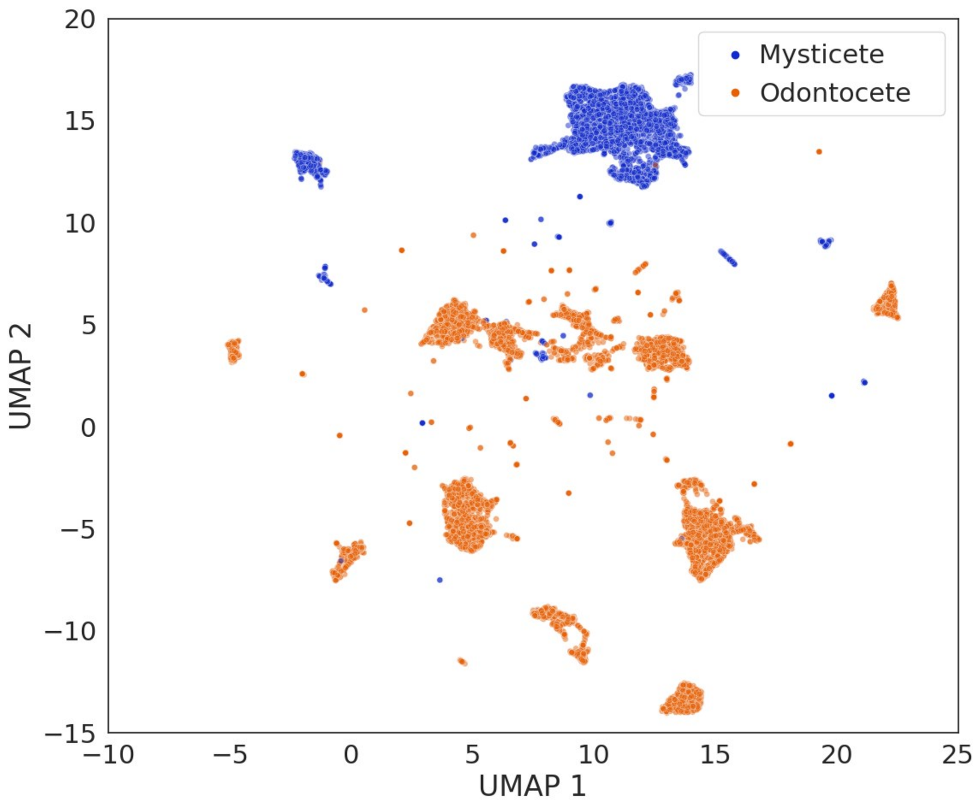

Figure 2 UMAP ordination of the WMD dataset with samples coloured according to two marine mammals' taxonomic groups: Mysticete and Odontocete.

Of the 12 species considered, eight species formed clear and large clusters: humpback whales, bowhead whales, sperm whales, orcas, long and short finned pilot whales, Clymene dolphins and North Atlantic right whales (Fig 3). Samples belonging to bottlenose dolphins, beluga whales, rough-toothed dolphins, and southern right whales, on the other hand, did not form distinct clusters. The distribution of the two UMAP dimensions showed that species were better separated along the second UMAP dimension, while species had overlapping distribution along the first UMAP dimension (Appendix B, Fig B.2).

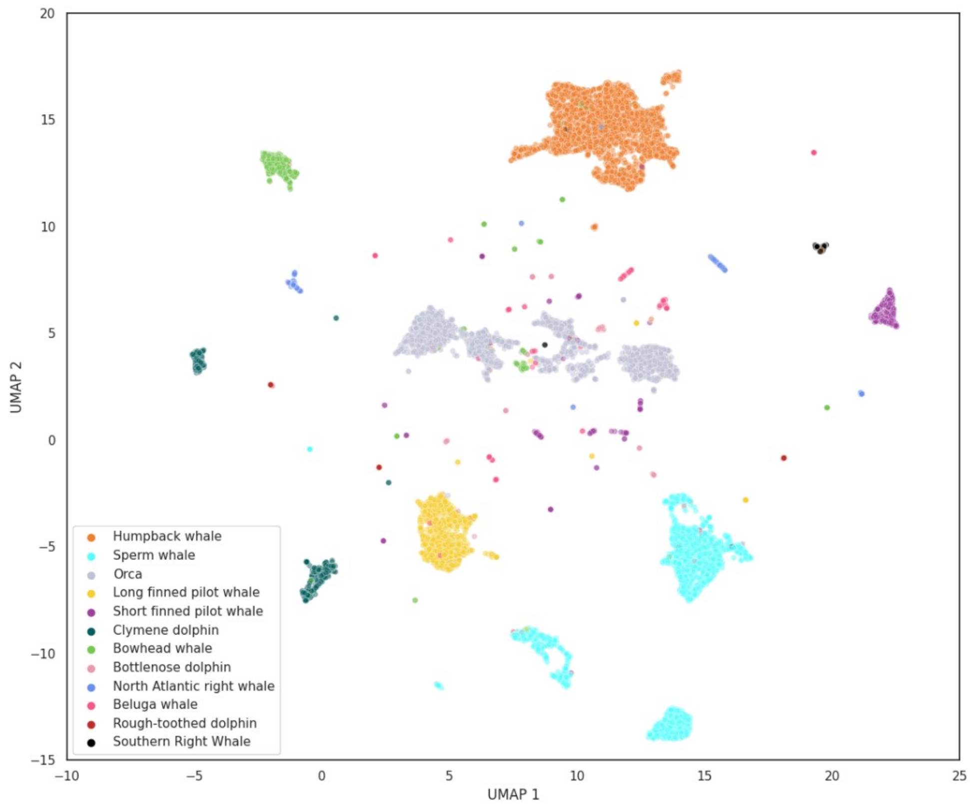

Figure 3 UMAP ordination of the WMD dataset with samples coloured according to 12 species of marine mammals.

Samples collected in different locations but belonging to the same species formed close clusters in the UMAP plots. For example, samples of humpback whale vocalizations collected in the Bahamas, the British Virgin Islands, Puerto Rico, and the United States formed a large cluster (Fig 4) with overlapping distributions of the two UMAP dimensions (Appendix A, Fig B.3). Similarly, the killer whale samples, collected in the United States, Canada, and Norway, all occupied the same region of the UMAP plot (Fig 5).

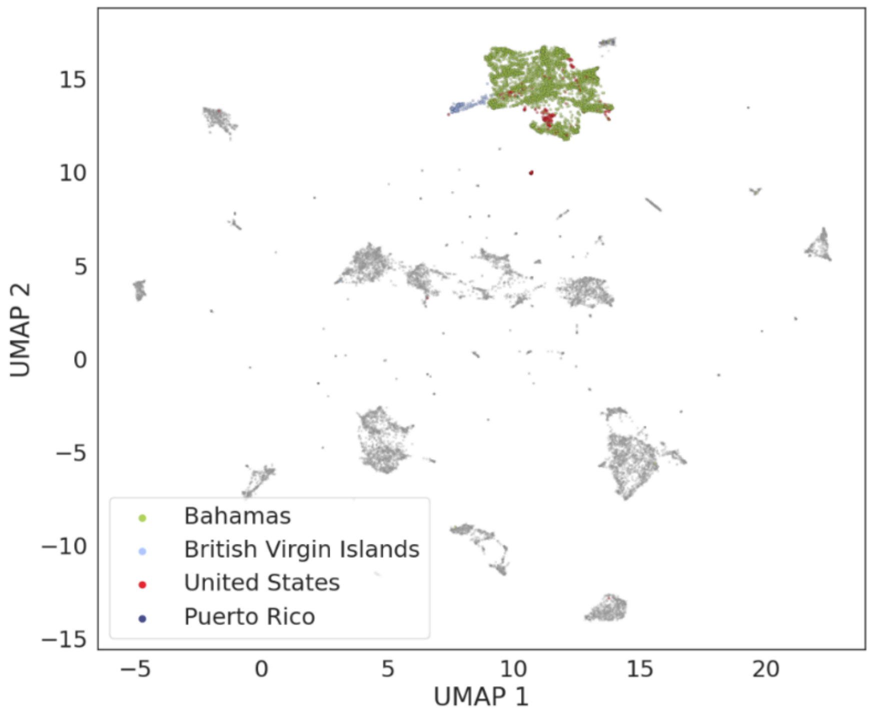

Figure 4 UMAP visualization of the WMD dataset showing humpback whale samples coloured according to location.

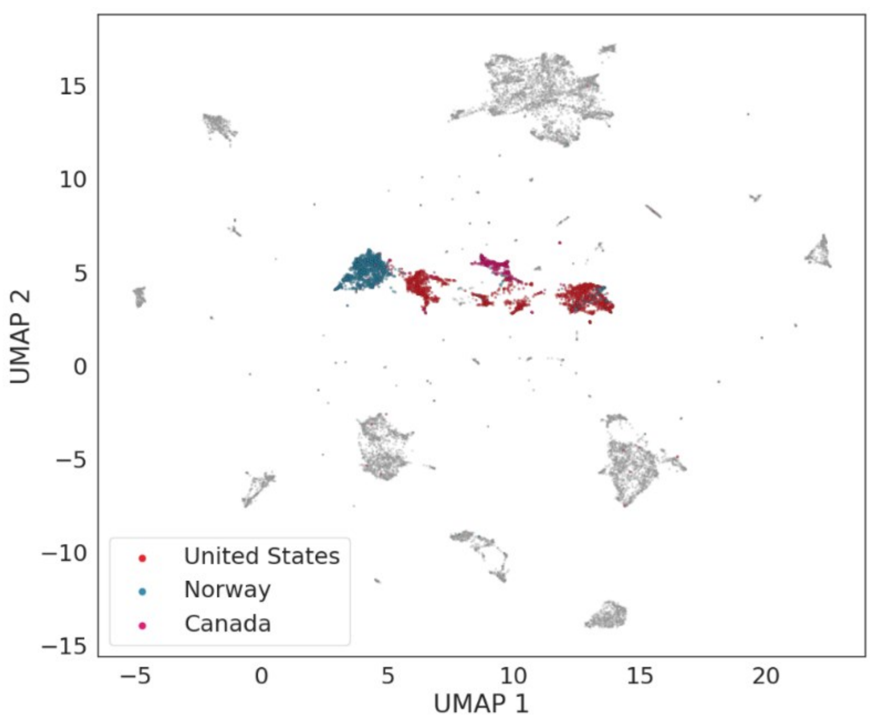

Figure 5 UMAP visualization of the WMD dataset showing orca samples coloured according to location.

2.3.2 Placentia Bay Dataset

Results of model parameter selection for the four BRF algorithms fitted on the PBD labels are shown in Table 2.

Table 2 Summary of the BRF models. Variables, labels, number of samples, the n_estimators value selected during cross-validation, and balanced accuracy scores (Eq. 1) are reported for the four BRF models.

Variable	Labels	Number of samples	n estimators	Balanced accuracy
wind speed	0 to 4 m/s	986	150	0.72
	4 to 6 m/s	906		
	6 to 8 m/s	746		
	8 to 16 m/s	304		
surface temperature	8 to 10 °C	148	200	0.41
	10 to 12 °C	806		
	12 to 14 °C	478		
	14 to 16 °C	445		
	16 to 18 °C	980		
current speed	0 to 20 mm/s	148	200	0.35
	20 to 60 mm/s	590		
	60 to 110 mm/s	735		
	110 to 170 mm/s	733		
	170 to 260 mm/s	587		
	260 to 400 mm/s	148		
humpback whale vocalizations	Absent (0)	3279	200	0.84
	Present (1)	181		

Oceanographic Variables

Of the three BRF fitted on environmental variables, only the model fitted to the wind speed labels provided overall accurate predictions. This is reflected by the model's balanced accuracy score (0.72) (Table 2). The model accurately discriminated between low (0 to 4 m/s) and medium (4 to 6 m/s) wind speeds, while the model ability to correctly classify the higher wind speeds (6 to 8 m/s and 8 to 16 m/s) was lower (Appendix B, Fig B.4). The BRF models fitted on surface temperature and current speed performed poorly, achieving balanced accuracy scores of 0.41 and 0.35 respectively (Table 2). In the case of temperature, the lowest (8 to 10 °C), the medium (12 to 14 °C), and highest (16 to 18 °C) values were correctly classified for approximately 50% of the testing datasets (Appendix B, Fig B.5). In the case of current speed, only the lowest (0 to 20 mm/s) and highest (260 to 400 mm/s) were correctly classified for approximately 60% of the dataset (Appendix B, Fig B.6). These results are reflected in the UMAP visualizations for the oceanographic variables. Samples labelled by wind speed formed clear and separated clusters (Fig 6). Samples labelled by surface temperature and current speed did not show clear clusters separating the acoustic samples (Appendix B, Figs B.8 and B.9).

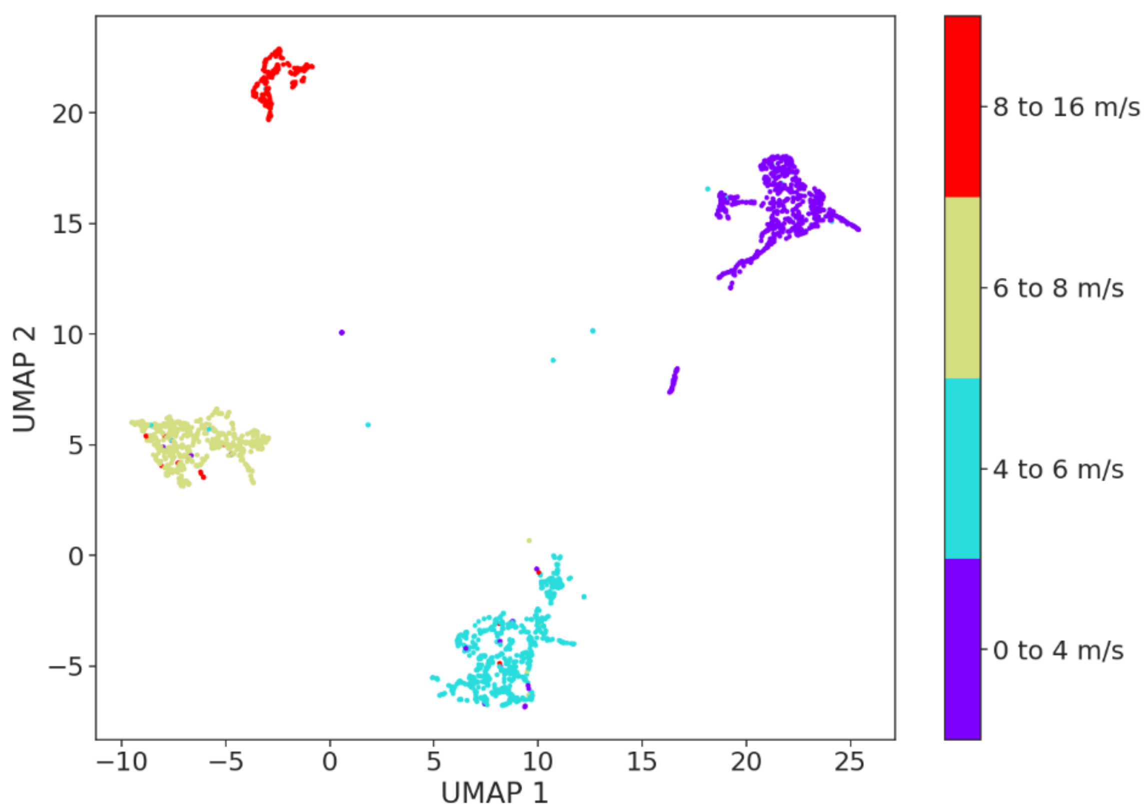

Figure 6 UMAP visualization of the wind speed labels.

Humpback Whale Detections

The BRF fitted on the humpback whale labels achieved a balanced accuracy score of 0.84 (Table 2) and showed similar performance for both the presence and absence labels (Appendix B, Fig B.7). The UMAP visualization for the humpback whale labels showed a clear cluster of presences (Fig 7). However, several presences plotted within the clusters formed by samples labelled as absences, and a few samples were located between the absences and the presences clusters.

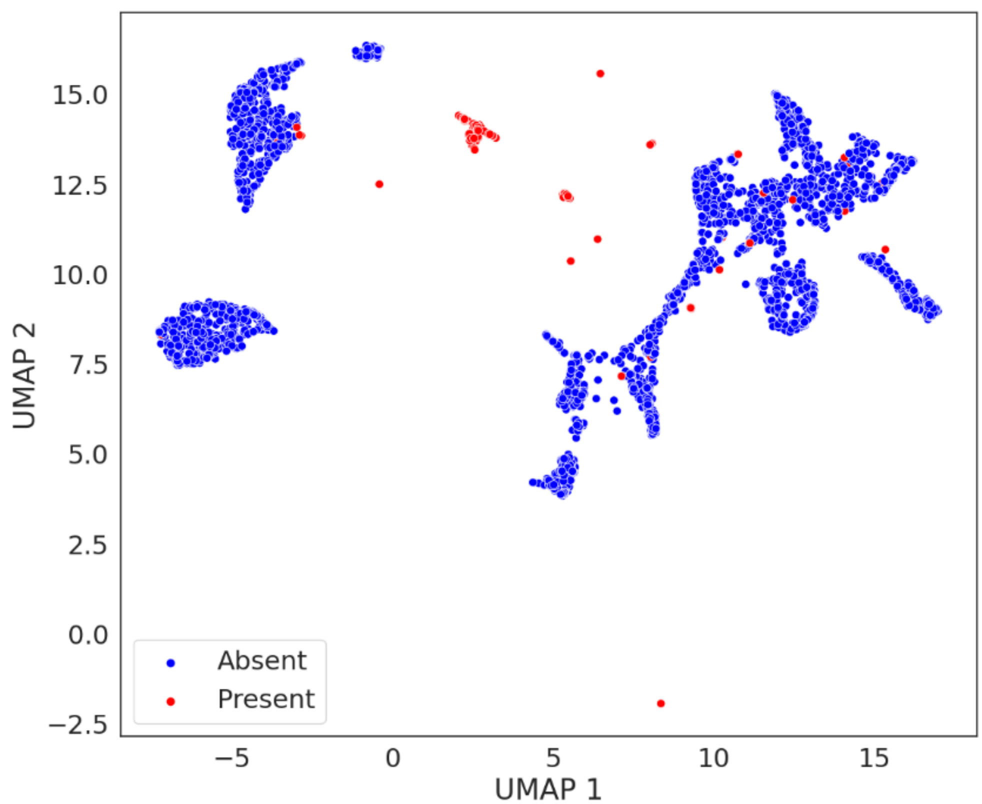

Figure 7 UMAP visualization of the humpback whale labels.

Lastly, the humpback whale BRF model, trained and tested on PBD samples collected in July, predicted 19 presences when run on the samples collected in August. Of these, 15 samples were true presences while the remaining four were false presences, resulting in a precision score of 0.79. All predicted presences were limited to the 23rd of August.

2. 4. Discussion & Conclusions

Managing the wellbeing of ecosystems requires identifying when and where human activities are impacting species' occurrence, movement, and behaviour. PAM is a useful approach for the detection of both large- and small-scale changes in urban and wild environments, as it allows for continuous and prolonged ecosystem monitoring. Challenges in employing PAM as a standard monitoring tool arise after data collection, when researchers and practitioners need to quickly extract useful information from large acoustic datasets, to understand when and where management actions are needed to preserve the well-being of ecosystems. The relatively new field of ecoacoustics provides the theoretical background for linking specific characteristics of the acoustic environment to biodiversity and ecosystem health.

The objective of our study was testing how the acoustic features generated by a pre-trained CNN (VGGish) can be used to link recorded sounds to environmental features and better understand processes happening in marine environments at multiple scales – from changes in oceanographic conditions over the span of months, to punctuate events such as the vocalizations produced by marine mammals.

Our analyses revealed several applications for inferring population- and location-specific information from acoustic datasets. The analysis conducted on the WMD dataset shows that the VGGish acoustic features are suited for discriminating between marine mammal species recorded in different environments.

Understanding the evolution of vocal diversity and the role of vocalizations in the ecology of a species is one of the key objectives of bioacoustics research (Luís et al., 2021). Full acoustic repertoires are not available for most species, as building comprehensive lists of vocalizations requires considerable research effort. Here we show how a general acoustic classification model (VGGish) used as a feature extractor allows us to detect differences and similarities among marine mammal species, without requiring prior knowledge on the species' vocal repertoires. For example, all humpback whale samples formed a compact cluster (Fig 4) and humpback whale populations share common traits in their songs, even when populations are acoustically isolated (Mercado III & Perazio, 2021). Killer whales, on the other hand formed distinct clusters (Fig 5), and different populations of orcas are characterized by differences in call repertoires and call frequencies (Filatova et al., 2015; Foote & Nystuen, 2008). Although we cannot consider our results as definitive evidence of convergence or divergence in vocal behaviour for these two species, we suggest that this aspect should be further investigated, perhaps using more recent recordings of these two species from different populations. Samples from four of the twelve marine mammal species (bottlenose dolphins, beluga whales, rough-toothed dolphins, and southern right whales), did not form clear clusters. This was most likely due to the low number of samples available for these four species (Table 1).

The analysis conducted on the PBD dataset shows how the VGGish features can be used as a tool to establish relationships between sound recordings and the environment at multiple scales. At the macro scale, the VGGish features were successful in classifying acoustic recordings according to measured wind speeds. This result is particularly useful for determining how winds contribute to underwater background noise. At the fine scale, the VGGish features could be used to identify vocalizations of humpback whales in Placentia Bay. However, presences for the month of August occurred within a single day, indicating that the BRF model may be declaring a large number of samples containing humpback whale vocalizations as absences. Furthermore, the model labelled some of the PBD samples containing only background noise and low-frequency noise from a passing ship as presences (Appendix A). The results of the BRF model trained on humpback whale detections could be improved by extending the analysis to longer time frames and to multiple locations, and by including labels for additional sound sources.

Our results highlight a limitation of using a general acoustic classification algorithm trained on recordings collected in terrestrial environments. The audio files used as input in VGGish are limited to a sampling rate of 16 kHz, resulting in a Nyquist frequency of 8 kHz. This is sufficient to capture marine mammal vocalizations that overlap with VGGish frequency limit (Appendix A), while the method is not suited for species using high frequency (e.g., harbour porpoises) or very low-frequency (e.g., blue and fin whales) vocalizations. This led to the removal of a large number of samples from the WMD dataset. This limitation also explains the poor performance of the models trained on surface temperature and current speed, as their contribution to background noise is evident at frequencies below 125 Hz. Nonetheless, the acoustic features relative to species vocalizing within the 8 kHz range provide useful information relative to the acoustic behaviour of marine mammal species. Similarly, the features provided information relative to changes in the acoustic environment of Placentia Bay due to changes in wind speeds. Other CNN approaches, such as AclNet (Huang & Leanos, 2018), allow processing audio with higher sampling rates (e.g., 44.1 kHz) at the cost of increased computing requirements.

Machine-learned acoustic features respond to multiple marine sound sources, and can be employed successfully for investigating both the biological and anthropic components of marine soundscapes (Heath et al., 2021; Sethi et al., 2020). However, their ability to detect species and changes in marine environments is limited by the algorithm's frequency range. A second limitation is that acoustic features are not a plug and play product, as establishing links between features and relevant ecological variables requires additional analyses and data sources. The objective of this study was to explore the application of the methods proposed by Sethi et al. (2020) in a new and unexplored context – the analysis of underwater soundscapes. This approach was particularly suitable for our study, as the acoustic samples are not pre-processed to remove background noises. This approach has also been demonstrated to be resilient to the use of multiple recording devices, as well as to different levels of compression and recording schedules (Heath et al., 2021; Sethi et al., 2020), making it ideal for the analysis of the WMD dataset. An alternative approach where datasets of spectrogram images are directly used as input to dimensionality reduction algorithms is provided by Sainburg and colleagues (Sainburg et al., 2020; Thomas et al., 2022). However, this approach relies on removing background noise from the recordings, which, in the case of our study, would have led to loss of information relative to the relationship between environments and acoustic recordings.

By presenting a set of examples focused on marine mammals, we have demonstrated the benefits and challenges of implementing acoustic features as descriptors of marine acoustic environments. Our future research will extend feature extraction and testing to full PAM datasets spanning several years and inclusive of multiple hydrophone deployment locations. Other aspects warranting further investigation are how acoustic features perform when the objective is discriminating vocalizations of individuals belonging to the same species or population, as well as their performance in identifying samples with multiple active sound sources.

Acoustic features are abstract representations of PAM recordings, which preserve the original structure and underlying relationships between the original samples, and, at the same time, are a broadly applicable set of metrics that can be used to answer ecoacoustics, ecology, and conservation questions. As such, they can help us understand how natural systems interact with, and respond to, anthropogenic pressures across multiple environments. Lastly, the universal nature of acoustic features analysis could help bridge the gap between terrestrial and marine soundscape research. This approach could deepen our understanding of natural systems by enabling multi-system environmental assessments, allowing researchers to investigate and monitor, for example, how stressor-induced changes in one system may manifest in another. And these benefits accrue from an approach that is more objective than manual analyses and requires far less human effort.

2. 5. Chapter 2 Bibliography

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Chapter 3: Characterizing the Acoustics Environment of Placentia Bay: Unsupervised Clustering of Loud Events & QGAM Models Applied to PAM Data from Two Monitoring Stations

3. 1. Introduction

Low-frequency noise generated by vessels may be negatively affecting the health of marine coastal environments. The negative effects of noise pollution have been documented for a multitude of marine species, including marine mammals, fish, and invertebrates (Kunc & Schmidt, 2019). The effects of noise in marine environments have been studied extensively for cetaceans (e.g., Erbe et al., 2019). The documented effects of noise on cetaceans include behavioural responses, such as displacement, auditory effect, such as masking (i.e., where by reducing the ability to detect and interpret sounds of interest), as well as stress responses, and temporary and permanent changes in hearing (i.e., permanent and temporary threshold shifts) (Erbe et al., 2019). Of all anthropogenic noise sources found in the ocean, underwater radiated noise (URN) from vessels is the most pervasive. It is estimated that, between the 1960s and the early 2000s, URN from vessels contributed to an average increase of 12 - 16 dB in low frequency noise recorded in different parts of the world (Hildebrand, 2009). This trend of growing noise pollution continued in the following decades, in concert with global URN emissions from vessels doubling between 2014 and 2020 followed by limited setbacks due to the COVID-19 pandemic (Jalkanen et al., 2022). Even the most remote areas of our planet are experiencing increases in noise pollution due to vessel traffic intensifying (Erbe et al., 2019; Halliday et al., 2021).

Growing evidence that anthropogenic noise pollution in the ocean affects marine species and environments has prompted action from numerous international and national organizations (Chou et al., 2021). Due to its nature as a transboundary pollutant and the ongoing challenges in measuring and linking underwater noise pollution to specific and quantifiable effects on marine species, most regulators and manager agree that efforts to mitigate and reduce noise and its potential negative impacts on marine life should follow the precautionary principle (Chou et al., 2021). In Canada, the Department of Fisheries and Oceans (DFO) has recently released the Ocean Noise Strategy (ONS) (DFO, 2024), a framework to regulate the emission of anthropogenic noise in marine environments. In support of the objective of ONS, DFO's Marine Environmental Quality (MEQ) program established monitoring programs to identify coastal areas where marine mammals and other marine species may be impacted by anthropogenic noise. Placentia Bay is a large bay located in the southeast region of the island of Newfoundland (Newfoundland and Labrador, Canada) and one of the Atlantic study sites for the MEQ program.

Our study assesses the underwater acoustic environment at two Passive Acoustic Monitoring (PAM) stations in Placentia Bay. In particular, we investigated the effects of environmental conditions and the presence of vessels on the recorded noise levels at the PAM locations. In this study, we applied two novel and emerging machine learning techniques for processing large PAM datasets: Uniform Manifold Approximation and Projection for dimension reduction (UMAP) (McInnes et al., 2018); and Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) (Campello et al., 2013). These allowed us to identify samples of PAM recordings containing URN from vessels at the two monitoring stations. This, in combination with time series of fin whale (*Balaenoptera physalus*) detections and wind speed measurements, allowed us to assess how different natural and anthropogenic factors contribute to underwater acoustic environments in Placentia Bay.

We contextualize the results using available information on the negative effects that vessel noise has on the marine mammal species that are known to use the marine habitats of PB. In particular, we focused on the North Atlantic fin whale population, listed as special concern under the Canadian Species at Risk Act (SARA). We also considered how URN in Placentia Bay has the potential to affect other baleen whale species, such as North Atlantic right (*Eubalaena glacialis*) (critically endangered), blue (*Balaenoptera musculus*) (endangered), and humpback whales (*Megaptera novaeangliae*). Fin whales use low-frequency vocalizations, and their most common vocalizations are two calls centered at 20 and 40 Hz. Males produce 20 Hz calls in sequences that form songs, playing a central role in the species' reproductive behaviour (Romagosa et al., 2021; Watkins et al., 1987). Fin whales' 40 Hz calls, on the other hand, are used by both sexes, and are thought to be linked with foraging behaviour (Romagosa et al., 2021). Fin whales show variable responses to vessel noise, from fewer vocalizations when vessel noise is present (Castellote et al., 2012), to more recent evidence that fin whale responses to vessel noise might be related to behavioural context (Groenewoud, 2023). The 40 Hz call, associated with foraging, may not be affected by the presence of vessel noise, while pronounced masking effects have been observed for the 20 Hz call (Groenewoud, 2023). Other baleen whale species, such as humpback whales, do not adjust song amplitude in response to increased vessel noise, but modify their singing behaviour in response to wind noise (Girola et al., 2023). Vessel traffic in Placentia Bay has undergone significant transformations over the past five years. The closure of the oil refinery in Come By Chance caused a significant reduction in tanker traffic in the area, while its recent conversion to biofuel production might result in increased traffic in the coming years. At the same time, the opening and expansion of large-scale salmon farming operation in Marystown led to an increase in the number of small service vessels operating in the western portion of PB. A newly proposed development for the Port of Argentia aims at creating a hub for the export of wind turbines in North America, with a consequent expected increase in traffic of large vessels within the shipping lane located in the eastern portion of the bay.

The specific objectives of our study were two-fold: 1) Characterize the acoustic environment of Placentia Bay (PB) at two different locations using seasonal trends in low-frequency (63 Hz,125 Hz, and 500 Hz 1/3 octave bands) and broadband (50 Hz to 1000 Hz) sound pressure levels, with a focus on anthropogenic noise sources; and 2) describe how different anthropogenic and natural factors may be contributing to the observed trends in underwater sounds at the two stations, which are characterized by different intensity and types of vessel traffic. Information on noise pollution along the coasts of Newfoundland and Labrador is limited. Our study characterized seasonal trends in the acoustic environment of PB in 2019 and our findings, contextualized with the current known responses of baleen whales to anthropogenic noise, can help managers better understand whether vessel noise has the potential to negatively affect large marine mammals found in the bay.

3. 2. Methods

3.2.1 Study Area

Placentia Bay (PB) is a large bay located on the southeast coast of the Island of Newfoundland, Newfoundland and Labrador, Canada (Fig 8). PB is oriented on a north-northeast axis and is approximately 130 km long. It opens towards the Atlantic Ocean in the south-west, reaching a width of 100 km at the mouth of the bay. The bottom bathymetry is characterized by variability in both depth and substrate composition (Ma et al., 2012). PB has an average depth of 125 m, however, the depth of the seafloor in the channels reaches more than 400 m. Elongated islands located near the head of the bay are characterized by the presence of deep-water channels delimited by the Burin Peninsula and the Avalon Peninsula. Specifically, the Eastern Channel is delimited by the Avalon Peninsula to the east, and Long Island and Red Island to the west. The Central Channel is delimited by Merasheen Island to the west and Long Island and Red Island to the east. The Burin Peninsula to the west, and Merasheen Island to the East, delimit the Western Channel to the east. Seafloor geomorphology changes from the opening of the bay, where mud, sand and gravel are dominant, to the deep channels where bedrock formations are common (Shaw et al., 2011).

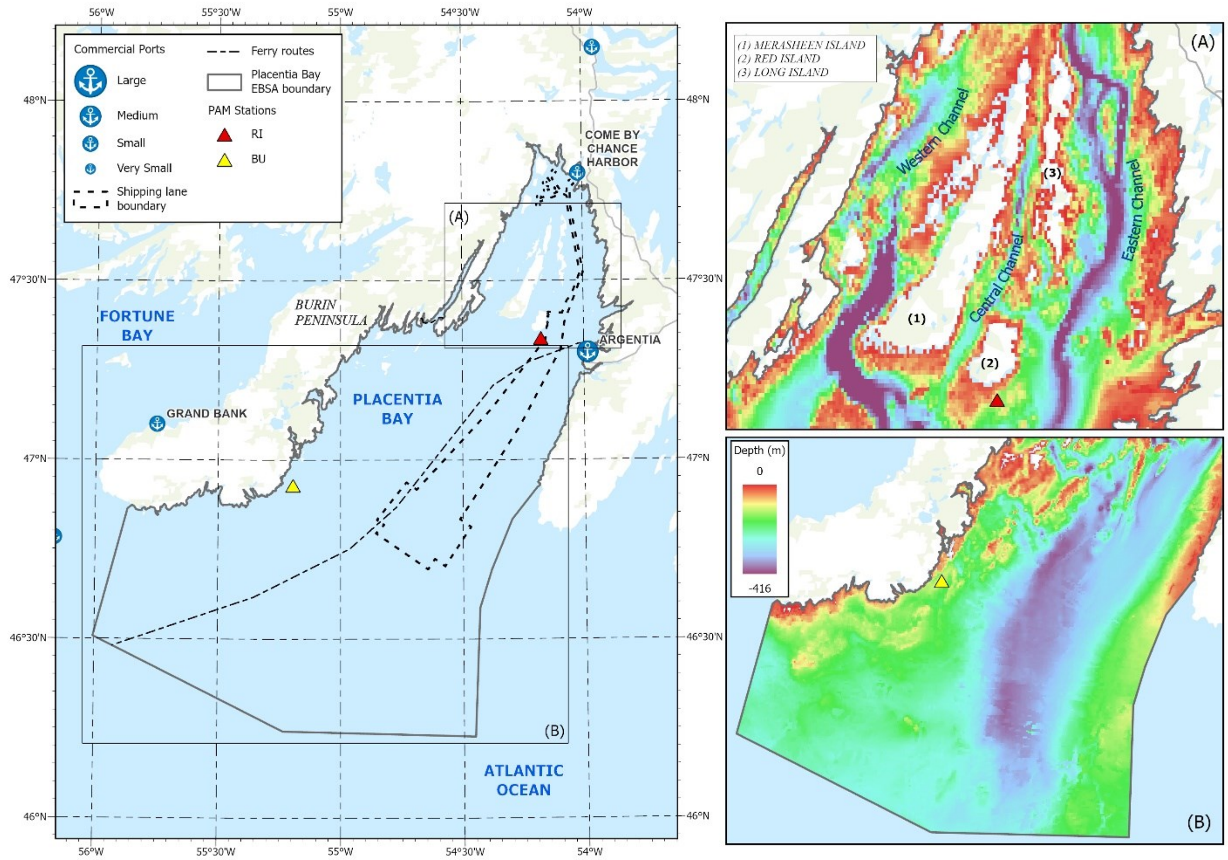

Figure 8 Study area map (left panel) showing the limits of the Placentia Bay EBSA, the location of the Red Island (RI) and Burin (BU) PAM monitoring stations, major ports, ferry routes, and the area occupied by the commercial shipping lane. The two insets show the bathymetry for the inner (A) and outer (B) portions of Placentia Bay.

The area is characterized by strong winds and frequent storms. Winds originate predominantly from the southwest direction during the spring throughout the fall, while in the winter the predominant direction of winds is from the west and northwest (Ma et al., 2012). Placentia Bay is characterized by the presence of important capelin spawning sites, aggregations of herring, seagrass meadows, and seabird colonies (Mackin-McLaughlin et al., 2022; DFO, 2019). An estimated 14 different species of aquatic mammals use the bay either seasonally or year-round, including several species of baleen and toothed whales (Table 3) (DFO, 2008).

Table 3 List of aquatic mammal species commonly found in Placentia Bay.

Common name	**Scientific name**	**Common name**	**Scientific name**
Blue whale	*Balaenoptera musculus*	Atlantic white beaked dolphin	*Lagenorhynchus albirostris*
Fin whale	*Balaenoptera physalus*	Common dolphin	*Delphinus delphis*
Sei whale	*Balaenoptera borealis*	Harbor porpoise	*Phocoena phocoena*
Minke whale	*Balaenoptera acutorostrata*	Harbor seal	*Phoca vitulina*
Humpback whale	*Megaptera novaeangliae*	Gray seal	*Halichoerus grypus*
Long finned pilot whale	*Globicephala melas*	Harp seal	*Pagophilus groenlandicus*
Atlantic white sided dolphin	*Lagenorhynchus acutus*	River otter	*Lontra canadensis*

PB has been recognized as an important foraging habitat for the endangered blue whale (Lesage et al., 2018), as the bay is characterized by the presence of significant aggregations of krill and is recognized as an important foraging area for leatherback turtles (*Dermochelys coriacea*) (DFO, 2020; Mosnier et al., 2019). Due to its ecological importance, in 2007 PB was designated as an Ecologically or Biologically Significant Area (EBSA) (DFO, 2019).

3.2.2 Hydrophone Stations

For this study, we used 5,626 hours of audio files recorded by bottom-mounted AMAR G4 hydrophones deployed at two locations in Placentia Bay. The first station was located to the south of Red Island (RI), at the entrance of the Eastern Channel, and approximately five km from the shipping lane. The RI hydrophone (47.34182; -54.17613) was deployed at a depth of 85 m. The second station was located to the south of the town of Burin (BU), away from the shipping lane and close to the mouth of PB in the southwest. The BU hydrophone (46.93156; -55.19415) was deployed at a depth of 65 m. The two instruments had sensitivities of -164.7 dBV (BU station) and -164.8 dBV (RI station). Both instruments were set to have a duty cycle of 15 minutes, a sampling frequency of 64 kHz, and operated continuously from June to November 2019.

3.2.3 Noise Measurements: Broadband & 1/3 Octave Bands SPL

To assess the regional and seasonal variability in the soundscape of PB, we processed the audio files and computed 1/3 octave band (TOL) sound pressure level (SPL) medians (L50), and two exceedance levels, L5 and L95, for four different bandwidths: broadband (50-1000 Hz), 63 Hz, 125 Hz, and 500 Hz.

The L95 exceedance level, corresponds to the 5th percentile of the distribution of SPL values for a specific band, and is a threshold for SPL values that are exceeded for 95% of the time in the recordings. L95 can be seen as an indicator of the quietest times observed in the recordings. The L5 exceedance level, on the other hand, corresponds to the 95th percentile of the distribution of SPL values, and indicates a threshold for SPL values that are exceeded for 5% of the time in the recordings. L5 captures the loudest events in the recording, and this exceedance level is often associated with close transits of vessels.

We focussed the analysis and interpretation of results on four bandwidths:

a) Broadband (50-1000 Hz), which captures seasonal and regional variability in SPL across low frequencies spanning from 50 Hz to 1,000 Hz (Halliday et al., 2021).

b) The 63 and 125 Hz TOL band, which are commonly used as indicators of underwater radiated noise from vessels (Garrett et al., 2016; Jalkanen et al., 2022; Syrjälä et al., 2020), and are recognized as an indicator of URN from vessels in the European Union (MSFD 2008/56/EC).

c) The 500 Hz TOL band, which have been suggested as an additional indicator band to measure URN from vessels in shallow waters (Merchant et al., 2014; Picciulin et al., 2016).

The raw audio WAV files were processed using the Matlab® implementation of PAMGuide (Merchant et al., 2015), a software package developed for computing noise statistics from PAM recordings. For each station, we computed 1/3 octave band sound (TOL) pressure levels (SPL) for the frequency range 25 Hz – 32 kHz at one second intervals using a Hann window with 50% overlap. All one second SPLs were averaged using a window of 30 seconds. A subset of this first dataset was later used to identify sound sources (3.2.4 Identification of Sound Sources, Vessel traffic noise). The resulting estimates of SPL were then further analyzed to compute 30 min averages for the two stations using a custom python script. The 30 min average SPLs are then used to extract L50 and exceedance levels (L95 and L5) for the entire study period (June – October 2019).

3.2.4 Identification of Sound Sources

Wind: We retrieved environmental data for the study period (June – October 2019) from an oceanographic buoy part of the SmartAtlantic Alliance project (https://www.smartatlantic.ca/) deployed in proximity of the RI station, collecting samples every 30 min. A similar buoy is deployed in proximity to the BU station; however, there were no data available for our study period. We assumed average wind speeds to be similar between the two stations, and considered this variable as the main geophonic contributor for the RI and BU stations. We assessed the effect of wind on the broadband and 1/3 octave band SPL measurements using a Quantile Generalized Additive Model (QGAM) (see Methods, QGAM Models).

Vessel traffic noise: In order to understand the distribution of vessel traffic between the two stations, we calculated the total number of vessel hours within a 5 km range from the two hydrophone deployments for six distinct classes of vessels: cargo, tanker, fishing, icebreakers, non-commercial, and passenger. We obtained the vessel hours data from the Global Maritime Traffic Density Service (GMTDS, 2022). GMTDS provides monthly maps at 1 km^2 resolution displaying the cumulative time spent by vessels in each grid cell. Cumulative times in GMTDS maps are based on Automatic Identification System (AIS) data and processed following the methods developed by the European Marine Observation and Data Network (EMODnet). We used ArcGIS software to generate a 5 km buffer around the two hydrophone deployment locations, and calculated the sum of time spent by vessels per class within the buffers for each month. This estimate has a coarse temporal resolution (i.e., monthly values) which allows comparison in vessel traffic per month between the two stations but does not provide enough information for assessing changes in ship noise over time within each month. In addition, AIS-based products do not include data for small vessels, often leading to underestimates of noise contributions of these vessels to soundscapes (Robards et al., 2016; Taconet et al., 2019).

To complement the monthly vessel traffic estimates, we applied an unsupervised density-based clustering approach to 1/3 Octave Bands SPL measurements that exceeded the broadband L25 (i.e., the 75^{th} percentile of the broadband SPL) at 30 s resolution. We selected L25 as a threshold to include all L5 estimates (3.2.1 Noise Measurements), and ensure that the measurements included not only the loudest noise produced by vessel transits, but also the noise produced by approaching, departing, and distant vessels. The Manifold Approximation and Projection for Dimension Reduction (UMAP) is a non-linear dimensionality reduction algorithm based on the concept of topological data analysis, which is particularly efficient in preserving the local structure of the original multidimensional data (McInnes et al., 2018). The Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) is a density-based unsupervised clustering technique that allows efficiently identifying clusters with varying shapes, sizes, and density (McInnes et al., 2017). Both techniques have been successfully applied to the identification of patterns in biological and environmental data, including the classification of large passive acoustic datasets from a variety of environments. For example, UMAP, has been successfully employed to identify the sex of gibbons based on their vocalizations (Clink & Klinck, 2021), and to the analysis of both terrestrial and marine soundscapes (Cominelli et al., 2024; Parcerisas et al., 2023, 2024; Sethi et al., 2020). When studying marine soundscapes, this approach allows for the identification of sound sources and for the analysis of their spatio-temporal changes, which can provide relevant information about the environment being investigated, including the presence of anthropogenic and biological sounds, as well as the presence of mooring and instrument noise in the recordings (Parcerisas et al., 2024).

We processed 29 frequency bands between 25 Hz and 25 kHz for the RI and BU stations following three steps. First, we reduced the 29 bands to two dimensions using UMAP. Second, we clustered the UMAP results using HDBSCAN. Third, we assessed the content of the clusters by inspecting the spectrograms of the corresponding audio samples, and labeled the main sound source present in the sample. As the two PAM datasets consist of a large number of passive acoustic recordings (i.e., five consecutive months for two stations), UMAP and HDBSCAN were first applied to a subset of samples covering 30 days of audio recordings (Appendix C, Table C.1). The subset consisted of 15 days of samples per station, where three days per month were selected using a random date generator scripted in Python. We then labeled the resulting clusters and generated a second UMAP projection. The second UMAP projection was generated using the full L25 dataset, this time following a semi-supervised approach where points were projected based on the clusters identified in the previous step. We then applied HDBSCAN a second time, inspected, and labeled the resulting clusters. Lastly, we aggregated the sample labels, each representing 30 s of audio recording, in 30-min intervals and summed the occurrence of the different sound sources. For a 30 min interval, a source could be represented by a maximum of 60 samples, thus occupying the entire 30 min interval. We removed all samples containing mooring noise from the analysis and used the vessel noise time series as an explanatory variable as input to the QGAM models, along with average wind speeds.

In this analysis, we used UMAP's default parameters with the exception of the min dist parameter, which was set to be equal to zero. The min dist parameter defines how tightly points will be packed in the two-dimensional space, and a value of zero is recommended for clustering applications. To ensure that the resulting UMAP plots were suitable for classification using a density-based algorithm, we used the DensMap implementation of UMAP (Narayan et al., 2021). DensMap allows better representing cluster density according to the variability of sample points: well defined, dense cluster are formed by groups of points that have low variability, while sparse and diffused clusters are formed by groups of points with higher variability. Parameters tuning for HDBSCAN was conducted by executing multiple runs of the model for varying values of parameters min cluster size, min samples, and cluster selection epsilon. Min cluster size determines the minimum expected size of a cluster, the min samples parameter defines the tolerance for HDBSCAN to declare a sample as an outlier, while the cluster selection epsilon parameter defines a threshold that prevents splitting a cluster into smaller sub-cluster based on the distances between samples in UMAP space. We then compared runs using different combinations of the three parameters using the internal clustering validation score provided by HDBSCAN, the relative validity score. Relative validity scores for HDBSCAN runs vary between -1 and +1, where larger values indicate better separation between clusters, while lover values indicate a high degree of overlap. For each optimization run of HDBSCAN, we selected the combination of parameters that maximized the clusters' relative validity score. This procedure resulted in the identification of five groups of samples containing: ship noise, ship noise with high frequency pings, noise produced by the hydrophone moorings (mooring noise hereafter), and two small clusters containing odontocete whistles and clicks and background broadband noise (see results: Identification of Sound Sources).

We carried out the analysis using a custom python script which employed the umap (McInnes et al., 2018), and the hdbscan (McInnes et al., 2017), scikit-learn (Pedregosa et al., 2011), and scikit-maad (Ulloa et al., 2021) libraries. We generated plots using the packages matplotlib (Hunter, 2007) and seaborn (Waskom, 2021).

Fin whale vocalizations: We used fin whale's 20 Hz calls as an indicator of presence for the species. As the frequency range of this call in shallow water (18-22 Hz) (Cholewiak et al., 2018) falls below the bandwidth covered by the lowest 1/3 octave band considered, 25 Hz (22.097-29.841 Hz), UMAP could not efficiently capture changes over the frequency range of fin whale vocalizations.

Instead, we processed the PAM datasets using the Low-Frequency Detection and Classification System software (LFDCS) (Baumgartner & Mussoline, 2011). LFDCS applies a workflow that first minimizes continuous (i.e., tonal) noise of the recording and removes short transient broadband signals. LFDCS then applies a contour tracing algorithm to candidate signals and extracts a set of attributes from a pitch track. The software then compares the pitch track attributes with the attributes of marine mammal calls from a library of vocalizations applying a quadratic discriminant function analysis. The similarity or dissimilarity between the pitch track and the call library for a vocalization is then expressed as Mahalanobis distance (MD). MD values represent how close of a match there is between the pitch track and the library reference calls, and lower values indicate a better match. We used a MD threshold of 3.0 and only retained LFDCS detections with MD below this value (Baumgartner et al., 2013). This resulted in 27,184 possible detections (RI: 16,586; BU: 10,526). The dataset of putative detection was then reviewed by a DFO expert in PAM and marine mammals' vocalizations that inspected all audio files and spectrograms and marked the true detections found in the LFDCS output, removing false negatives from the detections dataset.

Only one detection per day was marked as a presence, leaving the remaining detections of the day unlabeled. From the results of UMAP and HDBSCAN, we learned that both stations are affected by mooring noise overlapping with the frequency range of fin whale vocalizations. Indeed, during inspection, a large number of the possible detections contained low frequency mooring noise with a bandwidth mostly centered between 0-40 Hz. Using the results of the clustering analysis, we removed all LFDCS detections that contained samples labeled as mooring noise. We then inspected the remaining PAM recordings to confirm the presence of fin whale 20 Hz vocalizations.

QGAM Models: We used a Quantile Additive Generalize Model (QGAM) (Fasiolo et al., 2021a) to explore the relationship between noise measurements, wind speed, and the presence of vessels. We selected QGAMs as this approach allows for exploration of non-linear relationships while fitting models to specific quantiles of the response variables, making it ideal for assessing how different variables might influence the median, L5, and L95 of broadband and 1/3 Octave bands SPL measures. QGAMS estimate the distribution of responses following a non-parametric Bayesian approach, without the need of prior knowledge about the structure of relationships between response and covariates that are required in GAMs (Fasiolo et al., 2021a).

In total, we fitted four QGAMs models (Table 2). We fitted each QGAM model over three quantiles (0.05, 0.5, and 0.95) using the broadband (i.e., QGAM 1), 63 Hz (i.e., QGAM 2), 125 Hz (i.e., QGAM 3), and 500 Hz (i.e., QGAM 4) bands SPL as the response variable. The models included four independent variables: average wind speed (m/s); number of samples containing ship noise per 30 min interval; and the date and hour of the recording. In addition to these, we included station as a factor to explore differences between the two locations. We fitted all variables, except for the station, using penalized cubic splines, a step that allowed for variable selection by reducing non-significant covariates to a flat horizontal line in the model. In order to account for daily and hourly variability, we included the date and hour as covariates in the QGAM models. To check appropriate model convergence for each QGAM, we inspected the calibration loss curve of the three quantiles, where a smooth curve with a clear minimum indicates that the model converged to an optimal solution (Appendix B). In addition to this, and for each model, we used the cqcheck function provided the qgam R package (Fasiolo et al., 2021b) and generated QGAM model diagnostics, including the proportion of negative residuals as well as the model bias due to smoothed loss. The qcheck output reports the proportion of observations falling below the selected quantile, as well as an estimate of the absolute bias of the model averaged across all observations. For a QGAM fitted on quantile 0.5, approximately 50% of the predicted values are expected to fall below the model fit. By default, the average model bias is tested against a threshold error of 0.05 (Fasiolo et al., 2021a). This threshold can be increased to avoid issues with model convergence. However, models requiring considerably larger absolute bias thresholds to avoid convergence issues (e.g., >0.2), indicate that an important effect has not been taken into account (Fasiolo et al., 2021a). A summary of the predicted values falling below the selected quantiles, and the absolute bias of all QGAM models presented here are reported in Appendix D. We compared the resulting QGAM models across the three quantiles using their explained deviance as a measure of good fit to the dataset. Higher deviance explained indicate a stronger relationship between the dependent variable and the independent variables of a QGAM model. We assessed the smoothing terms by comparing the QGAMS k' dimensions with the smoothed terms effective degrees of freedom (edf). The k dimensions indicate the degrees of freedom used by the model to describe the relationship between the dependent variable and the independent variables, and larger values of k result in more complex non-linear relationships. A k value that is close to the edf of a smooth term indicates that a more complex curve might be a better descriptor of the relationship between dependent and independent variables.

We then examined the effect of all variables on the noise measurements by inspecting the significance of their smooth terms, where $p < 0.05$ was used as the threshold to determine if the fitted smooth term was significantly different from a straight horizontal line. We then assessed the presence of linear and non-linear relationships (i.e., based on models' edf values) and the direction and magnitude of such relationships.

Marine mammal's presence and vessel noise: As an indicator of potential acoustic disturbance to marine mammals, we assessed the co-occurrence of vessel noise and the presence of fin whale 20 Hz vocalizations. To minimize the effect of the wind on the noise estimates, we removed samples with an average wind speed equal to or greater than 5 m/s. We then computed the median broadband and 1/3 octave band SPLs for samples containing marine mammal vocalizations with and without the presence of vessel noise, and summarized the results using boxplots.

To explore potential changes in fin whale vocalizations when vessels are present in the environment, we tested the relationship between the maximum and minimum frequency of the 20 Hz calls and the broadband SPL. We assessed the difference in call's spectral characteristics using the Mann-Whitney-Wilcoxon test, which relaxes the assumption of normality and allows comparing distribution of groups with different sample sizes. We then quantified the magnitude of such differences by computing effect sizes for the vocalizations recorded at the two stations. As a measure of effect size, we used the Vargha-Delaney A measure, which varies between 0 and 1, where departures from 0.5 indicate increasing differences between groups. We performed all tests using R software (R Core Team, 2023).

3. 3. Results

3.3.1. Identification of Sound Sources

Underwater Radiated Noise from vessel: The two stations differed in both the type of vessels and their total hours of navigation within 5 km from the hydrophone stations (Fig 9). Traffic at the RI station exceeded 30 hr each month, with tankers being the main vessel type found in proximity of the hydrophone, followed by cargo, other vessels (i.e., no class identifier), and service vessels. Traffic in proximity to the BU station was considerably lower, peaking in June with 31.6 hours. Fishing vessels and unidentified vessels were the two most common types of vessels found at the BU station. Still at the BU station, non-commercial vessels (e.g., navy, rescue, and research) were present in all months, and displayed a a peak of traffic in July during wich non-commercial vessels totalled the highest number of navigation hours recorded (Fig 9).

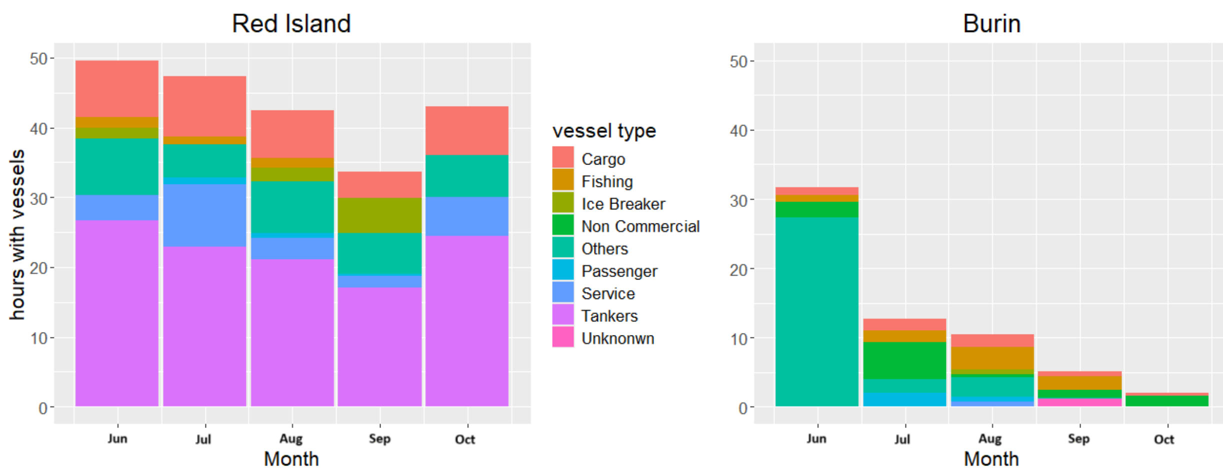

Figure 9 Summary of total hours of navigation for nine different types of vessels carrying AIS transponders within 5 km of a hydrophone station in 2019.

The first run of UMAP, performed on the L25 SPL measures for a subset of 15 days per station, resulted in a number of large and small clusters organized according to their frequency content (Appendix C, Fig C.1 and C.2). Parameter tuning for HDBSCAN performed on the two UMAP dimensions achieved a relative validity score of 0.38, indicating that not all identified clusters were well separated along the two UMAP dimensions. The selected HDBSCAN parameters were: min_samples = 60, min_cluster_size = 375, and cluster_selection_epsilon = 0.

HDBSCAN yielded 13 distinct clusters (Appendix C, Fig C.2 & Table C.1). Noise from passing vessels was the most common sound source found in the clusters. Clusters 0, 1, 2, 5, 9, 10, 11, and 12 all contained ship noise. Clusters 1 and 2 contained ship noise from samples almost entirely belonging to the BU station. Clusters 0, 9, 10, 11, and 12 all contained noise from vessels from the RI station. Cluster 5 contained URN form vessels from both stations. The remaining clusters contained mooring noise in the low frequencies, often below 50 Hz.

Following a semi-supervised approach, we used these 13 clusters as sample labels to perform UMAP dimensionality reduction on the full L25 dataset. Parameter tuning for HDBSCAN performed on this second set of UMAP dimensions achieved a relative validity score of 0.73, indicating that all clusters were well separated along the two UMAP dimensions. The selected HDBSCAN parameters were min_samples = 15, min_cluster_size = 250, and cluster_selection_epsilon = 0.1. Similar to the first run, UMAP dimensionality reduction separated the L25 samples according to their frequency content, with, for example, most samples exceeding 100 dB in the 63 Hz band from both stations plotting in the same region of the graph (Fig. 10).

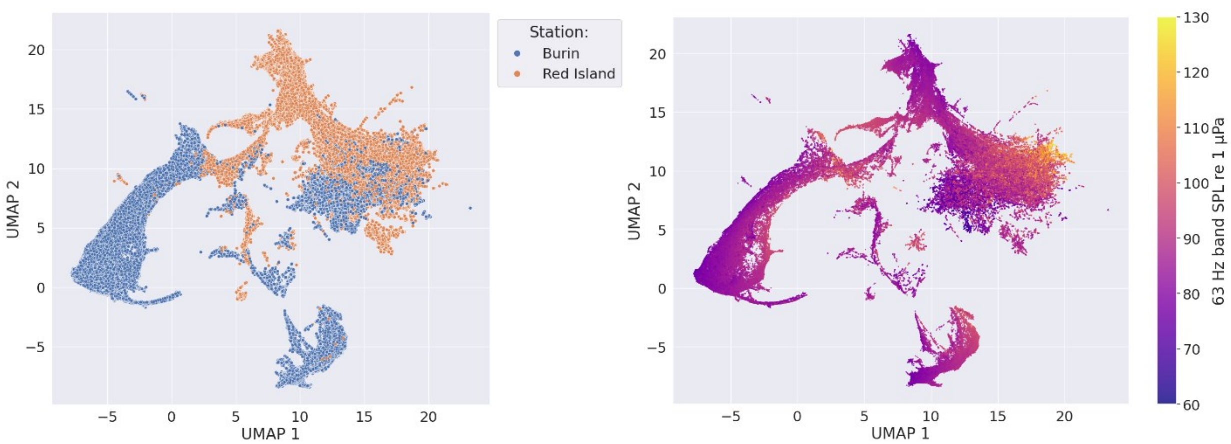

Figure 10 Results of UMAP 2D dimensionality reduction applied to the L25 samples. Samples are coloured according to the station label (Red Island, RI; Burin, BU) (left) and according to their 63 Hz band SPL (Right).

The second run of HDBSCAN yielded 20 distinct clusters (Fig 11 & Table 4). Of these, 18 clusters contained sounds belonging to sources identified from the initial run of HDBSCAN performed on the subset of L25 SPL measures. More specifically, clusters 1 to 4, 6 to 8, 13 and 17 all contained noise from vessels (Fig 13), including a cluster (cluster 1) containing propeller noise and high frequency noise (Table 4). Clusters 0, 2, 5, 11, 12, 14 to16, 18 and 19 contained low frequency noise produced by the hydrophone moorings. The remaining two clusters identified two additional sources: broadband background noise up to 2 kHz (cluster 9) and odontocete clicks and vocalizations (cluster 10). The final grouping of acoustic samples for the two stations consisted of four clusters: ship noise, mooring noise, background, and odontocete sounds (Fig 12).

Vessel noise was prevalent at the RI station, while the BU station had a lower number of samples containing vessel noise. The final ship noise cluster included 89.5 hr of audio recordings from BU and 550.5 hr from the RI station. Mooring noise was prevalent at the BU station, with 590.8 hr of audio assigned to the mooring noise cluster. RI recordings were less affected by mooring noise, which totalled 65.3 hr at this station. The background noise cluster mostly included samples from RI and totalled 14 hr. The odontocete cluster contained samples from both stations and included whistles and clicks. The RI audio recordings for this cluster consisted in 5.5 hr of odontocete vocalizations, while 1.8 hr of vocalizations were identified at the BU station.

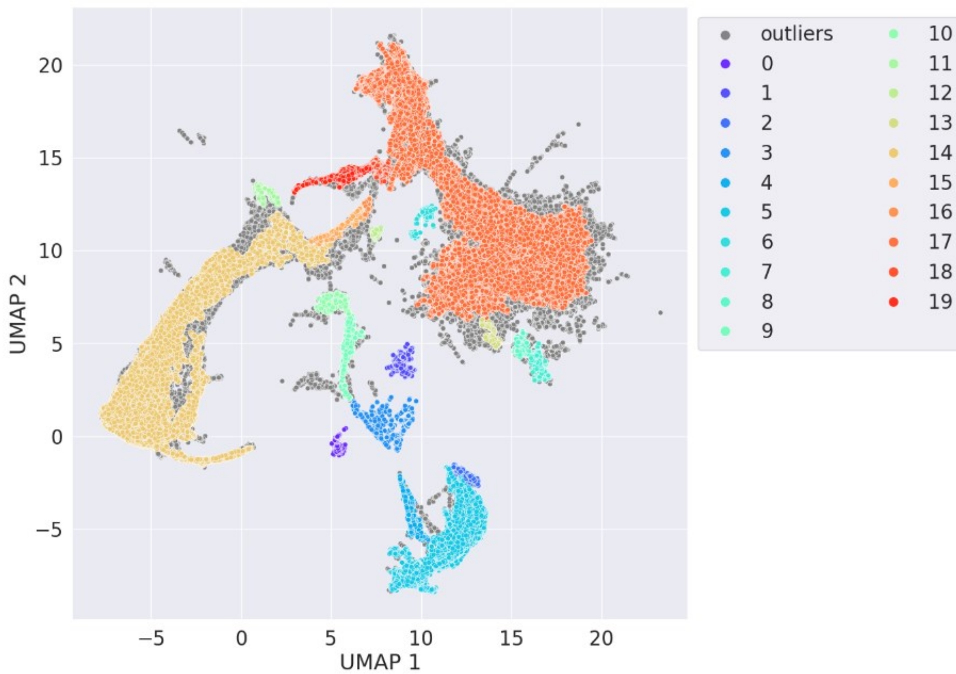

Figure 11 HDBSCAN clusters plotted over the UMAP distribution of L25 samples.

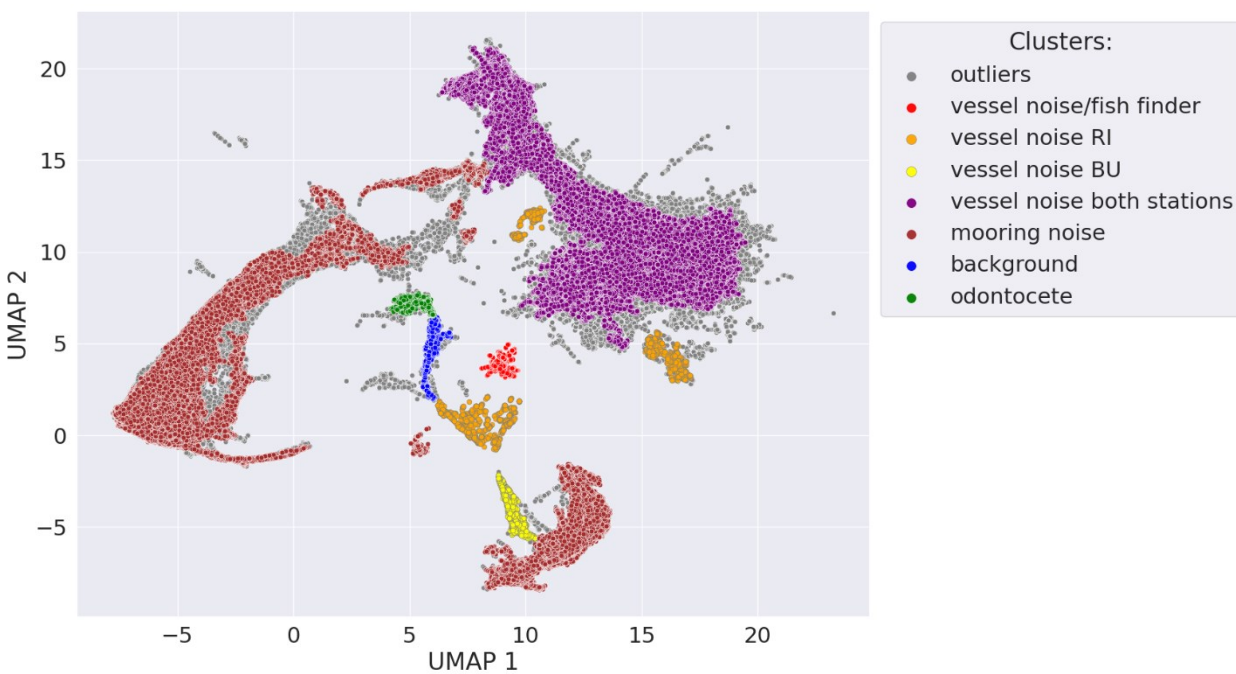

Figure 12 Final aggregated clusters plotted over the UMAP distribution of L25 samples.

Table 4 Results of HDBSCAN clustering and audio sample inspection for the L25 subset of the two PAM datasets. Cluster numbers correspond to the clusters shown in figure 11.

Clusters	Station	n samples	Label
-1	BU	6262	outliers
	RI	8080	
0	RI	554	mooring noise 1
1	BU	202	vessel noise 1*
	RI	224	
2	BU	442	mooring noise 2
	RI	6	
3	BU	1069	vessel noise 2
	RI	83	
4	BU	1106	vessel noise 3
	RI	1	
5	BU	19307	mooring noise 3
	RI	30	
6	BU	1	vessel noise 4
	RI	345	
7	RI	530	vessel noise 5
8	RI	466	vessel noise 6
9	BU	21	background
	RI	1702	
10	BU	218	odontocete whistle and clicks
	RI	653	
11	BU	336	mooring noise 4
12	BU	2	mooring noise 5
	RI	327	
13	BU	250	vessel noise 7
	RI	77	
14	BU	50497	mooring noise 6
	RI	1639	
15	BU	38	mooring noise 7
	RI	779	
16	BU	19	mooring noise 8
	RI	284	
17	BU	8107	vessel noise 8
	RI	64342	
18	RI	1027	mooring noise 9
19	BU	3	mooring noise 10
	RI	3196	

* samples containing vessel noise and high frequency noise

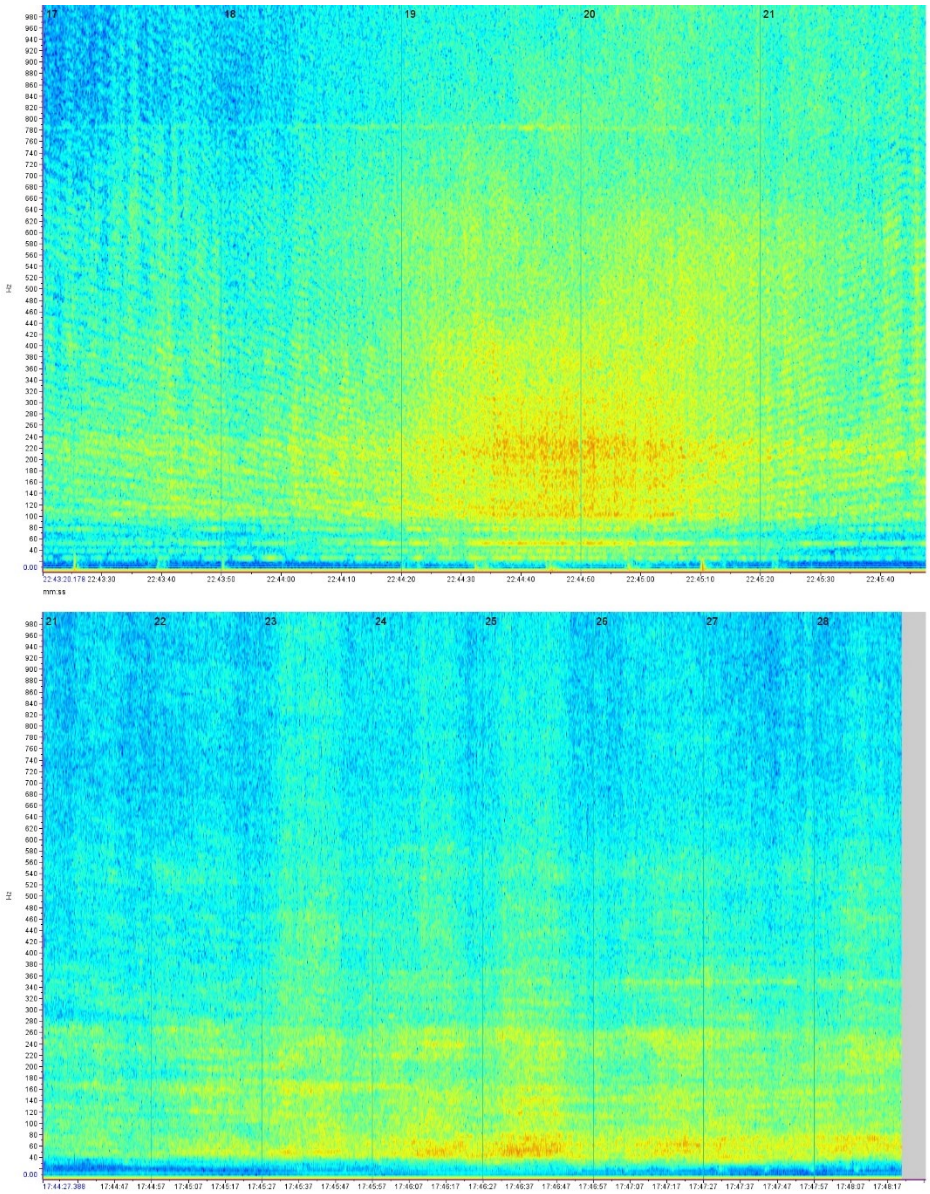

Figure 13 Two examples of audio samples containing vessel noise from both stations with frequency range 0 – 1000 Hz. Five consecutive 30 s samples recorded at the BU station containing the vessel's closest point of approach to the hydrophone location (date: 2019/09/09; time: 22:43:20) (top). Eight consecutive 30 s samples recorded at the RI station preceding the vessel's closest point of approach (date: 2019/10/18; time: 17:44:27) (bottom). Both sets of samples belong to HDBSCAN cluster 17, which contains vessel noise from both stations (Table 2). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Wind: During the study period, wind speeds ranged from a median of 2.5 m/s to a median of 7 m/s. Wind speed increased with the progressing of the seasons, with the lowest median speed recorded in June and the highest recorded in October (Fig 14).

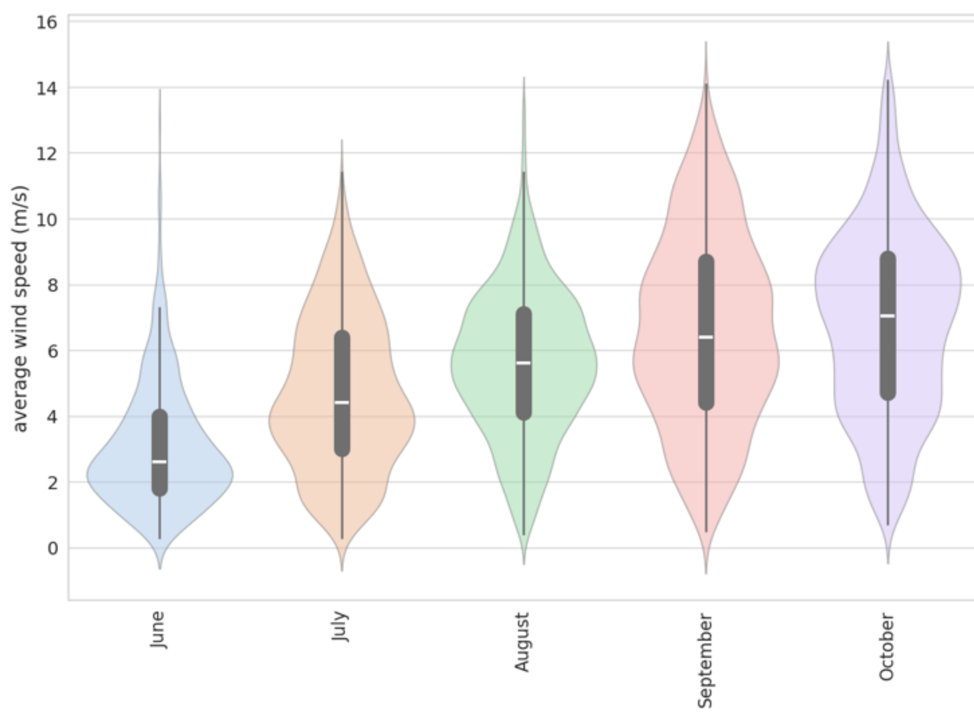

Figure 14 Violin plots showing the distribution of wind speeds recorded within the study area.

QGAM Models: All of the QGAM models achieved convergence for the three tested exceedance levels (L5, L50, and L95), and both the proportion of negative residuals and the models' absolute bias were acceptable (Appendix D, Table D.1). QGAM Model 4 for the L5 of the 500 Hz band SPL achieved the best fit with the dataset (explained deviance = 95.3%, Table 5). QGAM Model 2 for the L50 of the 63 Hz band SPL achieved the lowest deviance explained at 48.8%. Overall, QGAM models for the L5 and L95 exceedance had higher proportions of explained deviance (85-94%) than the models for the L50 exceedance level (48-72%) (Table 5).

Table 5 Summary of QGAM models fitted on the broadband (50 – 1000 Hz), 63 Hz, 125 Hz, and 500 Hz bands for three exceedance levels (L95, L50, and L5).

QGAM Model	Frequency Band	Quantile (exceedance level)	Deviance Explained	R-sq.(adj)
1	Broadband	0.05 (L95)	88.40%	0.566
		0.5 (L50)	67.60%	0.673
		0.95 (L5)	92.50%	0.575
2	63 Hz	0.05 (L95)	90.70%	0.554
		0.5 (L50)	48.80%	0.592
		0.95 (L5)	85.30%	0.527
3	125 Hz	0.05 (L95)	89.10%	0.591
		0.5 (L50)	57.40%	0.638
		0.95 (L5)	89.20%	0.571
4	500 Hz	0.05 (L95)	87.40%	0.431
		0.5 (L50)	72.60%	0.626
		0.95 (L5)	94.30%	0.464

We observed positive contributions to the measured SPL for both the presence of vessels and wind (Figs 15 and 16). However, the contribution of the two variables changed depending on the selected frequency band and station. The L95 wind speed smooth terms had a significant effect on the SPL measured at the two stations. The L50 wind smooth terms had a significant effect on SPL at both stations as well, with the only exception of the L50 for QGAM Model 4 (500 Hz band), where only the smooth term for RI had a significant effect. For the L5 smooth term, wind speed did not have a significant effect on the SPL at 63 Hz, and we observed a moderate effect of wind on the 125 Hz band. The effect of the wind was more pronounced in the L95 exceedance levels, while its contribution was smaller for the L5 exceedance level, with L50 displaying intermediate contributions between the L95 and the L5 exceedance levels. For example, the broadband L95 increased from approximately 95 dB (re 1 μPa) for very low wind speeds (<2 m/s) to approximately 115 dB (re 1 μPa) for wind speeds above 14 m/s at both stations. The broadband L5, on the other hand increased from approximately 110 dB (re 1 μPa) to 116 (re 1 μPa) for the BU station and 125 (re 1 μPa) for the RI station. We observed the largest contribution of the wind in the L95 exceedance levels for QGAM models 1 (broadband) and 4 (500 Hz band), with an increase of approximately 25 dB in SPL for both stations when winds exceeded 14 m/s, in comparison to low wind speeds (< 2 m/s).

We observed no significant differences in vessels' contributions to the broadband SPL between the two stations and across all three exceedance levels (Appendix D, Tables D.1 – D.4). With the exception of the L95 at 63 Hz at the RI station, all smooth terms for vessels had an edf close to 0, indicating that the relationship between vessel noise and the observed SPL levels was similar across the two stations. All the smooth terms for vessels, when the station is not considered as a factor, showed a positive non-linear relationship with the measured SPLs (Fig 16). Broadband median SPL (L50) levels increased from 105.7 dB when vessel noise is absent from the environment to 117.5 dB when vessel noise is present 100% of the time. An increase from 0 min of vessel noise to up to 5 min raised the broadband median level to 110.8 dB. The 63 and 125 Hz median SPL levels for 100% presence of vessel noise increased by more than 12 and 13 dB in comparison to background noise levels (i.e., in the absence of vessel noise). The increase from 0 to up to 5 min of vessel noise in the 63 and 125 Hz bands raised SPL levels by approximately 6 dB for both bands. The 500 Hz band SPL increased from 87.7 dB in the absence of vessel noise to 98.8 dB when vessel noise is present for 100% of the time. As per the previous two bands, the increase from 0 to up to 5 min of vessel noise raised the 500 Hz median SPL by approximately 6 dB.

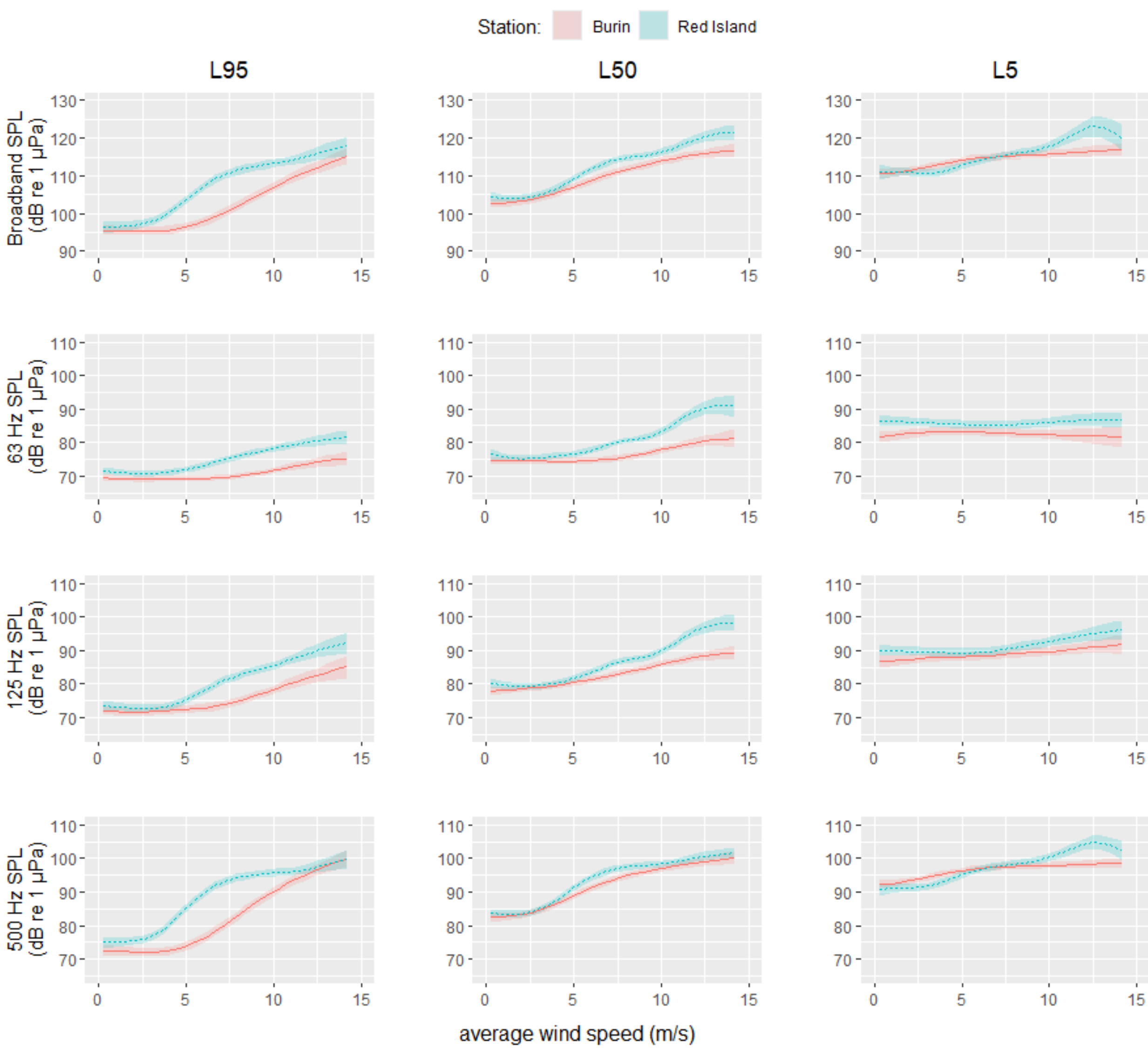

Figure 15 QGAM models partial contribution of average wind speeds to the broadband (50 – 1000 Hz) and 63 Hz, 125 Hz, and 500 Hz 1/3 octave bands for the RI and BU stations (QGAM smooth term shown on the x axis: s(wind_spd_avg, bs='cs', by=Station, m=1).

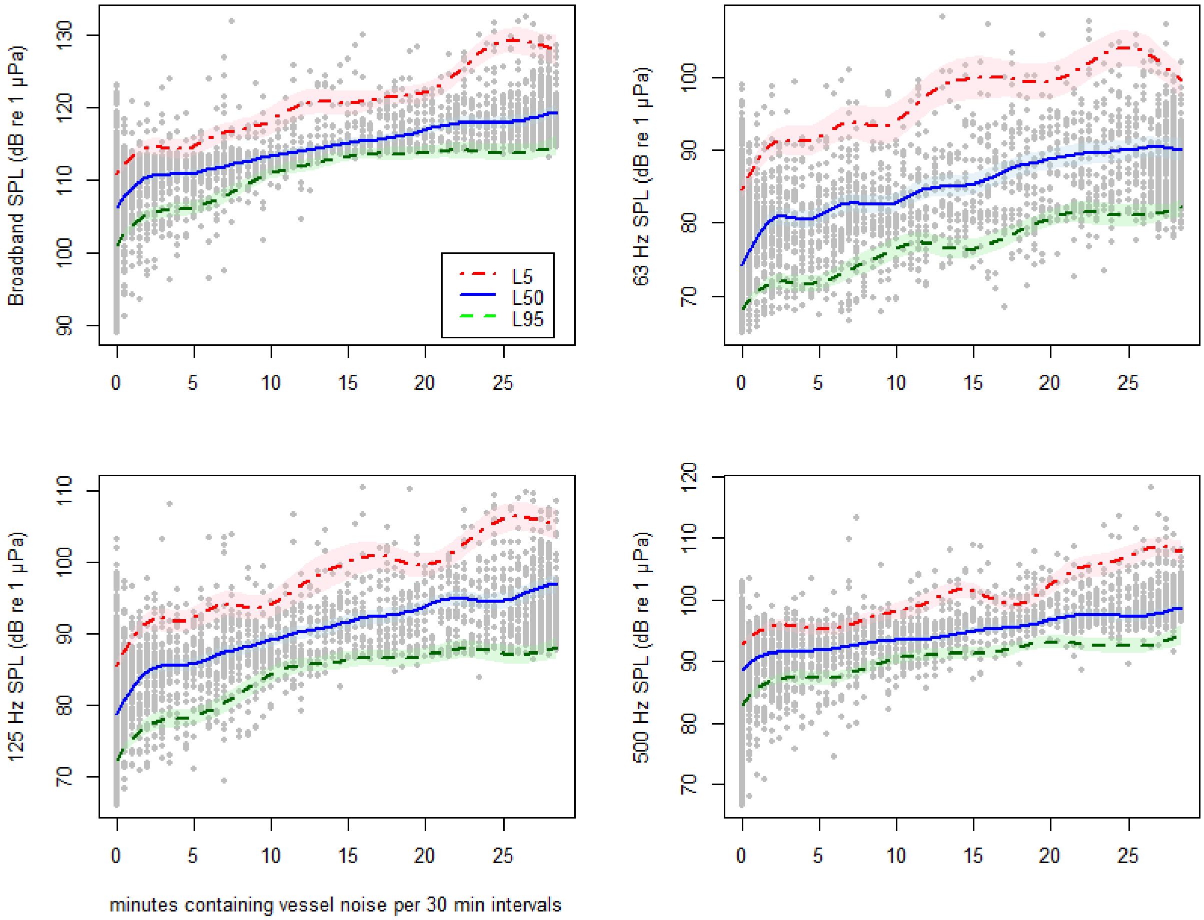

Figure 16 QGAM models partial contribution of vessel noise to the broadband (50 – 1000 Hz) and 63 Hz, 125 Hz, and 500 Hz 1/3 octave bands without considering the station factor (QGAM smooth term shown on the x axis: s(ship_label,bs='cs').

3.3.2. Fin Whales Presence & Vessel Noise

Fin whale 20 Hz vocalizations were detected at both the RI and the BU stations (Table 6). In total, we identified 65 fin whale 20 Hz vocalizations. Detections were rare in the early summer (June-July) and became more common in the late summer and fall (September-October). We observed a difference in the peak period in which fin whale detections occurred at the two stations. Overall, the RI station had a higher number of detections (n=41) than the BU station (n=24), with fin whale 20 Hz vocalizations being present in almost all recorded days in October. On the other hand, fin whale vocalizations at the BU station peaked in September, with a few detections occurring in the remaining months.

Table 6 Total fin whale LFDCS detections, and number of detections occurred in the presence and in the absence of vessel noise by station (RI and BU) and month (June – October).

		Vessel Noise	
Station	**Total**	**Absent**	**Present**
Burin (BU)	24	22 (91.5%)	2 (8.5%)
June	0	0	-
July	2	2	-
August	3	3	-
September	14	12	2
October	5	5	-
Red Island (RI)	41	23 (56%)	18 (44%)
June	0	-	-
July	3	1	2
August	2	1	1
September	10	3	7
October	26	18	8

The majority of fin whale 20 Hz vocalizations occurred during times in which no vessel noise was present (Table 6). Of the 65 detections, 45 occurred in the absence of vessel noise, while we identified 20 detections (31%) that occurred when vessel noise was present in the environment. At the BU station, which is located in an area where vessel traffic consists of passenger and fishing vessels, only two fin whale detections (8.5%) occurred in the presence of vessel noise. At the RI station, which is located in an area where vessel traffic was comprised mostly of large commercial vessels, 18 fin whale detections (44%) occurred in the presence of vessel noise.

We observed that fin whales vocalizing in proximity to the RI station are exposed to higher levels of vessel noise than fin whales vocalizing in proximity of the BU station (Fig 17). According to the QGAM results, the presence of vessel noise for more than 20 min per 30 min of audio recordings resulted in broadband SPL levels that exceeded or neared 120 dB at both stations. At the RI station, the presence of URN from vessels caused increases of up to 20 and 23 dB in the 63 and 125 Hz bands, respectively. At the BU station, the presence of vessels increased the 500 Hz band SPL from 80 dB in the absence of vessel noise to 103 dB when vessels are present for more than 80% of the time. In comparison, the contribution of vessel noise to the 500 Hz band was lower at the RI station, where the 500 Hz SPL increased from 84 dB in the absence of vessel noise to 99 dB when vessels are present for more than 80% of the time.

When vessels are present in the environment, fin whales experienced an 8 dB increase in median broadband noise levels, from 104 to 112 dB (Fig. 17). The 63 Hz band median SPL increased from 73.2 to 82.4 dB, and the 125 Hz median SPL increased from 76.5 to

88.6 dB. The smallest increase occurred in the 500 Hz median SPL, which grew from 85.6 to 92.4 dB (Fig. 17).

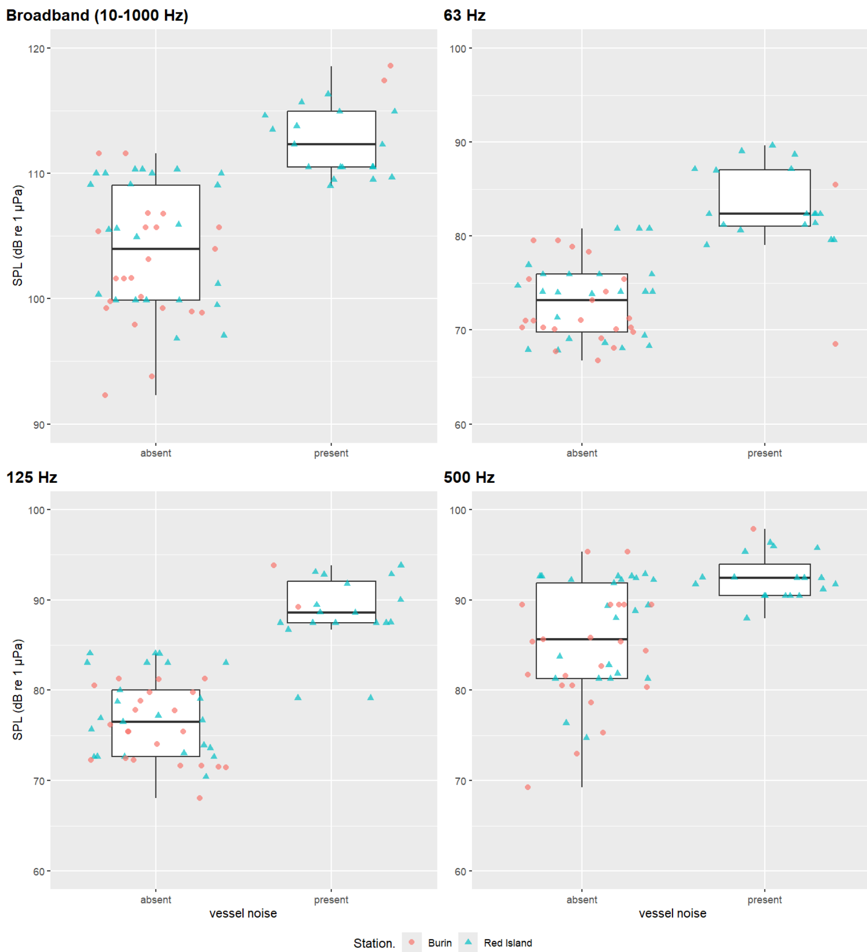

Figure 17 Boxplots showing the distribution of broadband, 63, 125, and 500 Hz band SPL measurements for fin whale detections in the presence and absence of vessel noise. The overlaid points show SPL measurements for single fin whale detections separated by station: Burin (BU) and Red Island (RI).

Table 7 Comparison of fin whale 20 Hz calls' parameters when vessel noise is absent and when vessel noise is present. The first three columns report the results of the Mann-Whitney-Wilcoxon test while the last column reports the corresponding effect sizes.

LFDCS call parameters	Mean (vessel noise absent)	Mean (vessel noise present)	Difference in location	95% CI (upper; lower)	W (p-value)	Effect size (vda)
Max F (Hz)	20.46	21.05	0.5	4.26 e^{-05}; 1	605.5 (0.02699)	0.673
Min F (Hz)	19.61	19.23	0.25	- 5.05 e-05; 0.75	575 (0.07476)	0.639

The Mann-Whitney-Wilcoxon test did not identify a significant difference in the minimum frequency of fin whale calls between detections occurring in the presence and in the absence of vessel noise (Table 7). The test, however, indicates a significant effect on the maximum frequency of calls ($p < 0.05$) with a small effect size. The presence of vessel noise resulted in a small decrease (~0.5 Hz) in the maximum frequency of the 20 Hz calls. Minimum frequencies of the 20 Hz calls were also lower when vessels are present, displayed a similar effect size to maximum frequency, and the Mann-Whitney-Wilcoxon test results were relatively close to the 0.05 significance level (Table 7).

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3. 4. Discussion

Understanding how anthropogenic noise sources overlap with biological sounds is critical to the identification of impacts and can guide the creation of effective noise monitoring and mitigation measures. Baleen whales rely on the use of long-range low-frequency vocalizations, such as to communicate and synchronize feeding (Podolskiy et al., 2024), and the presence of vessel noise in the environment can reduce their communication ranges through masking of biologically relevant signals (Erbe et al., 2019). Our results provide a first assessment of URN from vessels in Placentia Bay and suggest that anthropogenic noise along the commercial shipping lane reaches levels that have the potential to mask calls, and perhaps trigger behavioural responses in fin whales and other baleen whale species found in the area. Furthermore, our results show how different types of vessel traffic using the area result in different levels of exposure for marine species, with noise in the low frequencies (63 – 125 Hz) being dominant where large vessels are present, while noise in the 500 Hz is more pronounced in areas dominated by small vessel traffic.

Within the study area, fin whales were often detected in the presence of vessel noise. At the RI station, located in proximity of the shipping lane, 44% of fin whale detections occurred at times when vessel noise was present in the environment. Different composition and intensity of vessel traffic at the two stations resulted in changes to the noise levels experienced by marine mammals there. At the RI station, fin whales experienced the highest noise levels in the broadband, 63, 125, and 500 Hz when vessel noise was present for more than 15 min for every 30 min of recording. At the BU station, the highest noise levels for the four bands corresponded with times when vessel noise was present for 5 to 10 min every 30 min of recordings. Furthermore, noise levels in the 500 Hz tended to be higher at the BU station, reflecting the prevalence of small fishing and recreational vessels in the area. At the RI station, noise levels in the 63 Hz and 125 Hz were higher, reflecting the noise produced by large vessels transiting along the shipping lane.

When vessels are present in the environment, we observed a small reduction in the maximum frequency of fin whale 20 Hz calls compared to calls produced when vessel noise is absent. Changes of fin whales' vocalization characteristics in response to the presence of vessel noise have been documented in both the Mediterranean Sea and the Northeast Atlantic Ocean (Castellote et al., 2012). Fin whales may respond to vessel noise by decreasing the duration, bandwidth, peak, and center frequency of their 20 Hz calls. These changes are interpreted as an acoustic compensation mechanism, where vocalizations are shifted towards lower frequencies that are less affected by vessel noise. As calls shift towards suboptimal frequencies, the energetic cost of communication for the affected whales increases (Bradbury & Vehrencamp, 1998; Castellote et al., 2012). When produced in regular sequences, fin whale 20 Hz calls are thought to play a central role in reproduction, while irregular 20 Hz calls have been associated with social behaviour (Aulich et al., 2023). Changes in the frequency of fin whale songs might reduce their effectiveness as reproductive and social signals, resulting, in the long term, in negative effects at the population level. The difference we observed in the frequency of fin whale calls suggests that low-frequency vessel noise may be triggering similar behavioural responses, where fin whales are modifying the frequency of their calls due to the presence of vessel noise in the environment.

The minimum frequency of fin whale calls, on the other hand, did not change in the presence of vessel noise, in contrast to a study conducted in the Mediterranean Sea (Castellote et al., 2012). Our results, however, are based on a small sample size (n= 65), and did not account for the position of the vocalizing animals in respect to the PAM stations. These limitations prevented us from concluding with certainty that fin whales in Placentia Bay are adapting their vocal behaviour in response to the presence of vessel noise. Increasing the scope of the analysis by including additional stations and multiple years could help better understand if vessel noise in Placentia Bay is triggering changes in fin whales' vocalizations. Increasing sample size would also allow exploring dose-response relationships between fin whale 20 Hz calls and the presence of vessel noise in the environment.

Once mooring noise was removed from the PAM dataset, vessel noise and wind emerged as the main contributors to the observed SPL exceedance levels in the broadband (50-1,000 Hz), 63, 125, and 500 Hz bands. The contribution of wind was prevalent in the L50 and L95 exceedance level, while it became less important in the L5 exceedance level, which captures the 5% loudest periods in the PAM recordings. The presence of vessels, on the other hand, had the largest effect on the L5 exceedance level, indicating that anthropogenic rather than natural sound sources are responsible for changes in SPL for the loudest 5% of the audio recordings.

Overall, noise levels at the two stations increased in a quasi-linear fashion for increasing presence of vessel noise in the recordings. The presence of vessel noise for five minutes every 30 minutes or less is enough to increase background noise levels by approximately 5 to 6 dB, which is expected to reduce the range of marine mammal calls by 50% (Terhune & Killorn, 2021). When vessel noise is present 100% of the time, we found that noise levels increased approximately 12 to 13 dB, resulting in a potential further halving of marine mammals' communication ranges within the study area. The broadband (50-1000 Hz) L5 exceedance level surpassed 120 dB when vessel noise was prevalent in the recordings, indicating that such level of noise exposure might be triggering behavioural responses in fin whales and other baleen whale species found in Placentia Bay.

Acoustic compensation strategies analogous to what has been observed in fin whales have also been documented for North Atlantic right, blue, and humpback whales. Responses to vessel noise in blue whales include increases in the source level of calls (Melcón et al., 2012) and changes in call rates when ship noise is present (Groenewoud, 2023; McKenna, 2011; Melcón et al., 2012). North Atlantic right whales show evidence of vocal adaptation to increasing noise levels, with responses that involve shifting vocalization frequency and duration to compensate for reductions in communication space. Two of the most common calls emitted by North Atlantic Right Whales have been found to be affected by the presence of ship noise: upcalls (Tennessen & Parks, 2016) and gunshots (Cunningham & Mountain, 2014). Humpback whales respond to both large and small vessels by interrupting vocalizations, reducing the frequency of communication, or modifying the spectral characteristics of their calls (Brown et al., 2023; Tsujii et al., 2018). These results indicate the need for a comprehensive study focused on assessing how the presence of vessel noise might be affecting marine mammal species in Placentia Bay.

The results of the QGAM models show how both environmental and anthropogenic factors, such as the presence of wind and vessels, contribute to the observed variability of soundscapes in Placentia Bay. The use of QGAM allowed us to explore how exceedance levels (i.e., L5, L50, and L95), which are commonly used metrics for assessing underwater noise levels (Jalkanen et al., 2022), relate to the presence of noise sources in the environment. For speeds below 5-6 m/s, the contribution of wind to SPL was relatively low when compared to higher speeds. This result suggests that future assessments of vessel noise in the area should either be limited to times when wind speeds are below this threshold, or include a correction factor to remove the acoustic energy contribution of wind from the overall noise estimates. The effect of wind was lower at the BU station, though, this difference may be a result of assuming that wind speeds measured close to the RI station are similar to wind speeds at the BU station.

Lastly, we showed how the use of unsupervised dimensionality reduction (UMAP) and clustering techniques (HDBSCAN) applied to 1/3 octave band SPL measurements allowed us exploring the content of a large multi-station PAM datasets, leading to the identification of anthropogenic and biological sound sources. This approach also allowed us to identify samples containing noise generated by the instrument mooring to be removed from further analysis. In recent years, UMAP and HDBSCAN have been applied to the study of animals' communication and for the characterization of different acoustic environments (Sainburg et al., 2020; Sethi et al., 2020). Although this approach still requires review and validation of the resulting clustered sounds, we found that combining UMAP and HDBSCAN could greatly reduce the time required to analyze large PAM datasets.

Passive acoustic monitoring is now an important tool for managers and decision makers to monitor the health of marine species and acoustic environments in Canada and internationally. Pre-processing audio recordings using unsupervised machine learning techniques can greatly improve the capacity to rapidly analyze multiple years of PAM recordings, and identify and characterize specific sound sources (Parcerisas et al., 2024). Our analysis, however, did not lead to the identification of an analytical cluster containing fin whale vocalizations. This could be due to some of the limitations of the analytical approach whereby selecting only the loudest 25% of the samples might have removed the majority of audio recordings containing fin whale vocalizations from the UMAP and HDBSCAN analysis. Repeating the analysis by including the full dataset might result in the identification of additional clusters containing biological sounds of interest. Another factor limiting our ability to identify biological sounds using this approach is linked to the temporal resolution used to summarize the SPL measurements. In order to identify vessel noise, we used a resolution of 30 s for the 1/3 octave bands used as input for UMAP and HDBSCAN. A similar study conducted on PAM data collected from a towed array, using a resolution of 1 s, led to the identification of biological sounds (Parcerisas et al., 2023), suggesting that increasing the resolution to 1 s might allow for a better characterization of biological sounds. On the other hand, as a single sample equals one point being projected in UMAP space, reducing the resolution from 30 s to 1 s would result in a 30-fold increase in the number of samples to be processed, significantly increasing the required computation power and time to complete the analysis. Despite these limitations, the clustering analysis did reveal a group of samples containing odontocete whistles and clicks, indicating that the selected temporal resolution might be sufficient for the identification of mid to high frequency biological sounds. A previous study showed that a similar approach can be used for discriminating between the vocalizations of multiple species of marine mammals and identify humpback whale social vocalizations in PAM datasets (Cominelli et al., 2024). Further studies could explore how UMAP and HDBSCAN applied to 1/3 octave band SPL measurement can be used for the identification of odontocete vocalizations as well.

3. 5. Conclusion

Our aim was to contribute to the assessment of the potential exposure of baleen whales to noise in Placentia Bay, a busy and fast-developing coastal area affected by URN from both large and small vessels. We found that the presence of vessel noise at the two stations has the potential of negatively affecting marine mammals' behaviour and communication. Our results highlight the importance of understanding how different natural and anthropogenic sources of noise affect marine environments, and speak to a need for Canada to introduce noise management and mitigation strategies in coastal areas where vessels activity and marine mammal species overlap in space and time. Furthermore, the negative effects of anthropogenic noise are not limited to marine mammal species, and affect fish and invertebrate species as well, including commercially and culturally important species such as cod, crab, and lobsters (Alissah Price, 2023; Hudson et al., 2022; Ivanova et al., 2020). The Canadian Ocean Noise Strategy, initially scheduled to be published in 2021, was delayed by three years, and the draft strategy has only recently been released for public consultation (August 2024). At the same time, due to increases in vessel traffic and in other noise-generating activities, underwater noise levels are surging in different areas of the world (Jalkanen et al., 2022). Further delays in establishing nation-wide standards to regulate underwater noise and mitigate its effects could lead to significant impacts to both endangered marine mammal and commercial fish species.

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Chapter 4: Spatial and temporal assessment of vessel noise and intensity within an ecologically and biologically significant North Atlantic marine mammal habitat

4. 1. Introduction

Environmental change prompted by anthropogenic activities poses a threat to the biodiversity and health of terrestrial and marine ecosystems (Prakash & Verma, 2022; Priya et al., 2023). Anthropogenic noise, along with other drivers such as climate change, alters natural acoustic environments and can play a role in reducing both species' diversity and abundance (Kok et al., 2023).

The mechanisms through which noise affects individuals, populations, communities, and ecosystems are complex and have only been documented for a relatively small number of species (Duarte et al., 2021; Kok et al., 2023; Kunc & Schmidt, 2019). Among the marine species known to be affected by vessel noise are mammals (Erbe et al., 2019), fish (Nedelec et al., 2015; Stanley et al., 2017), crustaceans, and mollusks (Jézéquel et al., 2021; Solé et al., 2023), including commercially important species such as crab and lobster (Hudson et al., 2022; Jézéquel et al., 2021). The documented effects of noise on cetaceans include behavioural responses, masking (i.e., the acoustic interference of noise sources with cetacean communication), stress, and temporary or permanent changes in hearing sensitivity (i.e., temporary or permanent threshold shifts) (Erbe et al., 2019).

Vessels are the most ubiquitous source of anthropogenic noise in the ocean, and marine transportation is the main cause of the progressive increase of low-frequency noise observed in many regions of the ocean (Chapman and Price, 2011; Erbe et al., 2019; Jalkanen et al., 2022). Between 2014 and 2020, the global emissions of underwater noise from vessels have doubled, with 75% of the total noise energy in the 63 Hz 1/3 octave band being released by cargo and tanker vessels (Jalkanen et al., 2022). Coastal regions hosting commercial shipping lanes and ports are often among the most affected areas (Syrjälä et al., 2020). As vessel noise is expressed across a wide range of frequencies, it has the potential of affecting the full spectrum of the sounds produced and perceived by marine mammals. Most of the acoustic energy released by vessels is concentrated at frequencies below 500 Hz, overlapping with the frequencies used for long-range communication by many species of baleen whales (Dunlop, 2019; Erbe et al., 2019). However, depending on the size and speed of a vessel, its noise emissions can range as high as 10 kHz (Haver et al., 2021), reaching the frequencies used by toothed whales for echolocation (Veirs et al., 2016).

Multiple species of baleen and toothed whales that rely on Canada’s coastal habitats are being exposed to increasing levels of vessel noise. Vessel noise has been linked to diminished foraging success in the endangered Southern Resident killer whale population (*Orcinus orca*) (Holt et al., 2021), and the introduction of noise mitigation measures in the Salish Sea, in 2018, was followed by an increase in killer whales foraging activities (Williams et al., 2021). Endangered blue whales (*Balaenoptera musculus*) are affected by communication masking when close to the shipping lanes in the Gulf of St. Lawrence

(Aulanier et al., 2016), and are exposed to low-frequency vessel noise within most of the St. Lawrence Seaway (Simard et al., 2010). Besides having masking effects on their communication, the presence of vessels has been linked to diminished feeding opportunities for blue whales in the St. Lawrence Estuary (Lesage et al., 2017). Both blue whales and critically endangered north Atlantic right whales (*Eubalaena glacialis*) are exposed to vessel noise when entering the Gulf of St. Lawrence through the Cabot Strait (Cominelli et al., 2020). Although more research is needed to understand how different noise sources may have negative impacts on the recovery of north Atlantic right whales (Marotte et al., 2022), the documented responses of right whales to vessel noise include physiological responses (i.e., increased stress) (Rolland et al., 2012) and changes in vocalization patterns (Matthews & Parks, 2021; Parks et al., 2009). In the Canadian Arctic, an increasing number of vessels are transiting through important areas for marine mammals, with noise levels sometimes exceeding thresholds for the onset of behavioural responses (Halliday et al., 2017; Kochanowicz et al., 2021). Without intervention, increasing vessel noise in the Canadian Arctic has the potential to mask both marine mammal and fish vocalizations (Pine et al., 2018).

As the magnitude of effects that vessel noise can have on marine mammals and other marine species become better understood, both national and international regulatory bodies have recognized the need for the introduction of noise mitigation measures (Chou et al., 2021; Merchant, 2019; Vakili, et al., 2020). A growing number of international organizations and agreements (e.g., the United Nations, the International Maritime Organization, and the Convention on Biological Diversity) recognize quieting technologies, operational measures and the use of policies and incentives as the main tools for monitoring and reducing anthropogenic noise sources in the ocean (Chou et al., 2021). The adoption of noise reduction technological solutions is considered to be the most effective approach for mitigating vessels' underwater noise emissions (Audoly et al., 2017; Chou et al., 2021; Merchant, 2019; Rojano-Doñate et al., 2023). Operational measures such as rerouting of vessel traffic, introducing speed limitations, establishing vessel exclusion zones, and implementing changes in vessel maintenance and navigation practices are considered to have a less substantial impact on the mitigation of vessel noise (Merchant, 2019). Introducing vessel quieting technology on a large scale may take decades, making the adoption of interim solutions necessary in areas where high volumes of vessel traffic overlap with important marine mammal habitats. Among the operational measures mentioned above, speed limits are the most widespread approach for reducing vessels' noise emissions. Reducing the speed of vessels is considered to be beneficial not only for abating noise pollution, but also for reducing the risk of lethal collisions with large marine mammals as well as emission of greenhouse gasses (Leaper, 2019). However, adopting lower speeds can result in increased cumulative exposure of marine wildlife to noise over time (Williams et al., 2021), and the effectiveness of speed regulations can be strongly dependent on operator participation rates (Guzman et al., 2020).

In order to be effective, mitigation measures require the introduction of policies, regulations, and incentives aimed at ensuring that participation is sufficient to achieve an abatement of noise pollution (Chou et al., 2021; Merchant, 2019; Vakili, Ölcer, et al., 2020). Currently, national regulations for the protection of marine mammals from excessive levels of anthropogenic noise are in effect in the US and in the European Union. In the US, the Marine Mammal Protection Act (MMPA) and the Endangered Species Act (ESA) consider acoustic impacts at the level of individual animals and require proposed activities to limit the number of animals that will be adversely affected by noise-producing activities. Such assessment relies on the use of specific acoustic thresholds and criteria to assess behavioural responses and the onset of auditory damage in marine mammals (NOAA, 2018; Southall et al., 2019). More recently, the National Oceanic and Atmospheric Administration (NOAA) has introduced recommendations to remove the impact of anthropogenic noise within National Marine Sanctuaries and developed a strategy for managing ocean noise in the US over the long term (Colbert, 2020). In the European Union, underwater noise is regulated under the Marine Strategy Framework Directive (MSFD) (Directive 2014/89/EU). Descriptor 11 of the MSFD prescribes that to achieve and maintain good environmental status within the waters of the EU, the noise emitted by anthropogenic sources should be below levels that can adversely affect marine environments. In 2022 the EU became the first international body to adopt specific targets for the mitigation of underwater noise from vessels. Rather than focusing on harm caused to individuals, the EU targets focus on the extent of area that could be affected by noise originating from different types of activities. The recommendations prescribe that continuous underwater noise – which is mostly produced by vessels – should not affect more the 20% of a given marine area over a year.

In Canada, the potential effects of noise pollution on marine mammals and fish are addressed through the Ocean Protection Plan (OPP). One of the key objectives of OPP is monitoring and improving the health of marine environments. In 2016, under the umbrella of OPP, the federal government started drafting the Ocean Noise Strategy (ONS) (DFO, 2024). The goal of ONS is the development of regulations and management measures addressing noise pollution in Canadian waters. In support of the development of ONS, Fisheries and Oceans Canada's (DFO) Marine Environmental Quality (MEQ) program aims at increasing current knowledge on the impact of underwater noise pollution on marine ecosystems and at identifying suitable mitigation measures to reduce such impacts. MEQ initiatives span Canada, with study areas located in the Pacific, Arctic, and Atlantic Oceans. Placentia Bay, a large bay located in the southeast region of the island of Newfoundland (Newfoundland and Labrador, Canada) is one of MEQ's key study sites in the Atlantic. Due to its importance for marine species and the concurrent presence of multiple commercial and recreational activities, in 2007, Placentia Bay was designated as an Ecologically or Biologically Significant Marine Area (EBSA). The EBSA has the objective of protecting the habitats and marine fauna found in Placentia Bay and adjacent waters (DFO, 2019). The bay hosts different seabird colonies, capelin spawning sites, herring aggregations, and seagrass meadows (Mackin-McLaughlin et al., 2022; DFO 2019). At least 14 species of marine mammals are found in Placentia Bay either year-round or seasonally, and the bay is recognized as an important foraging area for the endangered blue whale (Lesage et al., 2018). Placentia Bay hosts a variety of commercial and recreational activities (e.g., marine tourism, fishing). The area includes a refinery located in Come by Chance in operation since 1973. The refinery was expected to close in 2020 but was subsequently converted into a biofuel production facility. Since 2019, an expanding aquaculture presence has opened multiple sea pens for salmon farming (Fig 18). The port of Argentia, the largest in the region, includes a ferry terminal connecting Newfoundland to Nova Scotia as well as commercial docks. In the coming years the port will be further expanded, to accommodate facilities for the export of hydrogen produced using wind energy. In addition to these activities, both commercial and recreational fishing occur in the area. The majority of vessels carrying Automated Information Systems (AIS) transiting within Placentia Bay in 2013 travelled at speeds between 5-10 knots, with the exception of vessels transiting within the shipping lane reaching between 10 and 15 knots (Simard et al., 2014).

In support to the goals of Canada's OPP and to the development of regulatory and managerial tools for the upcoming ONS, our study provides a first assessment of the distribution of noise sources and their overlap with marine mammal areas within the Placentia Bay EBSA. More specifically, the objectives of our research are to:

i) Assess how vessel traffic changed in Placentia Bay over the past five years;
ii) Estimate how such changes in vessels traffic have affected the distribution and intensity of noise sources within the study area; and
iii) Estimate the distribution and intensity of noise sources within areas that are regularly visited by marine mammals.

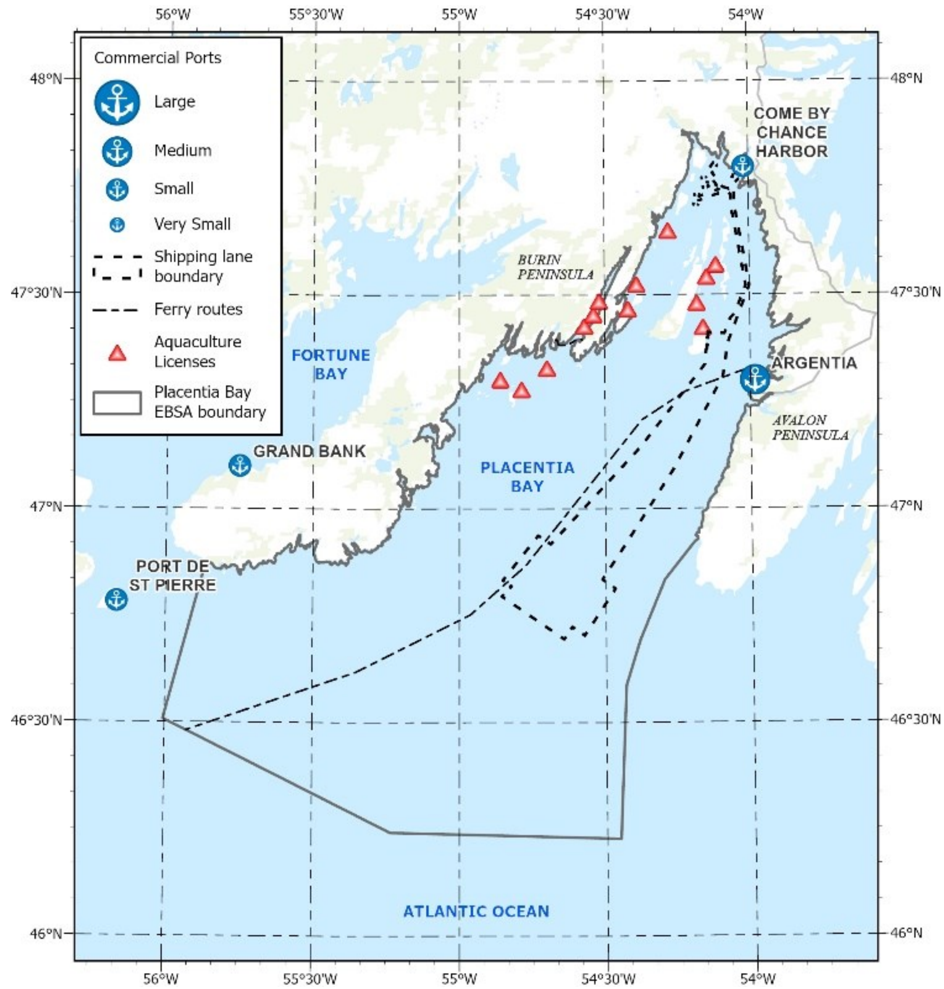

Figure 18 Map of the study area showing the border of Placentia Bay's EBSA with major ports, ferry routes, aquaculture licenses, and the limits of the commercial shipping lane.

We used density maps of total navigation time per km^2 and a vessel source level (SL) model to assess how vessel traffic and noise emissions have changed within the Placentia Bay EBSA between 2019 and 2023. In addition to the full study area assessment, we used observations collected from line transect surveys to estimate how changes in the distribution of noise sources have affected hotspots of aggregation of marine mammals (i.e., baleen and toothed whales) over the study period.

The results of our research show that the area affected by vessel noise sources in Placentia Bay has increased over the past five years, including within areas regularly visited by baleen and toothed whales. Our results can support the design of management and mitigation solutions aimed at addressing vessel noise pollution in Placentia Bay.

4. 2. Methods

4.2.1 Vessel Traffic and Vessel Source Levels.

The Global Maritime Traffic Density Service (GMTDS, 2022) provides data and maps on the distribution of vessels based on information collected through the Automatic Identification System (AIS). AIS signals in the GMTDS maps are used to calculate an index of the global temporal and spatial distribution of vessels expressed as total hours of navigation per km2 per month T_{Vessel} (GMTDS, 2022). We used T_{Vessel} as a measure of vessel presence within the study area focusing on five different classes: cargo, tanker, passenger (e.g., Roll-on Roll-off ferries), service (e.g., tugs, pilot boats), and fishing vessels. We summarized T_{Vessel} within the limits of the Placentia Bay EBSA limits (Fig 18) for each distinct vessel class and for all classes together and used the results to describe how vessel traffic has changed in the area over the period 2019-2023 (Figs 22, 23, and 24).

As direct measures of Source Levels (SLs) for vessels navigating in Placentia Bay are not available, we estimated vessel source levels for each class using the functional regression model developed by MacGillivray et al. (2022). This regression model estimates SLs based on vessels' technical specifications and operational conditions, such as: vessel draft (m); speed through water (kn) and design speed (kn); overall length (m); main engine RPM (1/minutes), main engine installed power (kW); age (years). The functional regression is based on more than 14,500 SLs measurements collected in the Salish Sea (British Columbia, Canada) for the Enhancing Cetacean Habitat and Observation (ECHO) program. This dataset has been used in a number of studies to assess the impacts of vessel noise on marine environments and species in Canada. Halliday et al. (2022, 2021a; 2021b) used median SLs obtained from the ECHO program to model underwater radiated noise from ships and estimate noise exposure risk for narwhals, beluga, and bowhead whales in the Canadian Arctic. Cominelli et al. (2020) used the ECHO program's SLs to model the acoustic footprint of large vessels transiting through the Cabot Strait (Eastern Canada). A recent study by Lagrois et al. (2024) tested the use of the regression model on the Eastern Atlantic fleet, providing support for its application to the estimation of source levels for commercial vessels found in the Atlantic Ocean.

In this study, we estimated source levels using the functional regression equation from MacGillivray et al. (2022) for four of the vessel classes: cargo, tanker, passenger, and service (Table 8). We extracted Monopole Source Levels (MSLs) for the 1/3 octave (or decidecade band) with a center frequency of 63 Hz for all classes setting their speed through water to be 10 kn. Monopole sound sources can be described as single, spherical sources radiating sound equally in all directions.

Table 8 Summary of vessel characteristics and estimated Monopole Source Levels (MSLs) for the 63 Hz band for five vessel classes: cargo, tanker, passenger, service, and fishing vessels.

	Units	Cargo	Tanker	Passeng	Service	Fishing*
Vessel Draft	m	5	15	5	3	N/A
Overall Length	m	54	267	186	35.5	10.3
Engine RPMs	1/minute	100	100	1800	1800	2200
Max Engine Power	kilowatts (KW)	749	14600	21600	4060	500
Design Speed	knots (kn)	11	14.5	22	12.5	12
MSL 63 Hz - 10 kn	dB re 1 uPa m	167.75	177.85	186.11	177.39	164

* Vessel characteristics and MSL at 63 Hz obtained from Helal et al. (2024).

We selected the 63 Hz 1/3 octave band as this frequency is a commonly used indicator to assess underwater radiated noise from ships (Garrett et al., 2016; Jalkanen et al., 2022; Syrjälä et al., 2020) as well as one of the indicators for continuous underwater noise adopted by the European Union for monitoring the health of marine acoustic environments (Directive 2014/89/EU). We selected a speed of 10 kn as it allowed us to assess all four vessel classes without exceeding their maximum design speeds (Table 8). We set the wind resistance factor to the square root of vessel speed through water, which corresponds to calm conditions in the absence of strong winds. All vessels were considered to have the same age of 10 years. Each vessel class was modeled using the characteristics of vessels typically found within the study area. For the tanker, cargo, passenger, and service classes, we used MarineTraffic (www.marinetraffic.com) to identify vessels that transited within the study area registered under Canadian flags and retrieved their technical specifications from Transport Canada’s Vessels Registration Query System (TC, 2018). The selected vessels included a large oil tanker (267 m in length), a small cargo vessel (54 m in length), a Roll-on-Roll-off (Ro-Ro) passenger vessel (186 m in length), a medium-sized service vessel (35.5 m in length), and a small fishing vessel (10.3 m in length) (Table 8).

As the study area is an active seasonal fishing ground for multiple commercial species, we included fishing vessels as an additional category. Since the regression equation from MacGillivray et al. (2022) does not include a model for fishing vessels, we used measured MSLs for a typical fishing vessel from the Newfoundland and Labrador fleet collected by Helal et al. (2024) (Table 8). We excluded other categories of vessels reported in the GMTDS database (unknown, others, non-commercial, and icebreakers), for which MSLs could not be estimated by applying the functional regression analysis and no measurements of MSL in the 63 Hz band are available.

We used the estimated MSLs to generate cumulative source level estimates for five years between 2019 and 2023. This was done following three steps. First, and for each vessel class separately, we computed cumulative monopole source levels ($cumMSL$) for all raster cells within the study area. We did this by combining the GMTDS AIS maps containing total navigation time per km^2 with the corresponding MSLs using the equation:

$$cumMSL_{Vessel,Month,i} = MSL_{Vessel} + 10\log_{10}(\frac{T_{Vessel,i}}{T_{Month,i}}) \qquad \text{[eq. 1]}$$

Where: MSL_{Vessel} is the estimated MSL for one of the five classes considered in this study (Table 1); $T_{Vessel,i}$ is the total navigation time for a vessel class within cell *i* of the GMTDS raster maps in seconds; $T_{Vessel,i}$ is a constant, $2.628e^{+6}$, representing the average number of seconds in a month; and i identifies a cell in the raster dataset. As the GMTDS AIS maps have a resolution of 1 km^2, the cumulative $cumMSL$ estimates we derived from them express the total acoustic energy emitted at the source by a vessel class in a month, expressed as dB re 1 μPa m over a standardized area of 1 km^2.

We then summed the monthly contributions of all vessel classes by year. This was done by converting the $cumMSL$ estimates to the linear scale, adding them together, and returning the values to the dB scale to compute yearly cumulative source levels ($cumMSL_{year}$) for the study area at a resolution of 1 km^2. Finally, we calculated the percentage contribution of the five vessel classes to the estimated $cumMSL_{year}$ for 2019 and 2023. These steps allowed us to generate sets of raster maps and summary statistics (max, min, median, and quantiles) capturing the spatial and temporal distribution as well as the intensity of sound sources in Placentia Bay. In particular, we focused on how the area affected by different types of vessel noise sources has changed over time.

4.2.2 Marine Mammal Presence

Marine mammal observations were collected from vessel-based line transects surveys conducted by DFO in Placentia Bay during the summer and fall over four years (2018 – 2021). Surveys occurred once per month and completing the entire survey track required approximately one week. The survey followed the protocol used in distance sampling studies. During the survey, two dedicated observers scanned the sea and recorded the species, number of animals, bearings and distance relative to the survey transect for each encounter with marine mammals. The survey track only covered a portion of the Placentia

Bay EBSA, excluding the outer portion of the bay and the inner channel, for which no observations are available.

We used the line transect survey observations to identify areas of aggregation for two broad taxonomic groups of marine mammals: baleen whales (mysticete) and toothed whales (odontocete). We aggregated observations of baleen and toothed whales recorded in the area, including unidentified species when the record included the taxonomic group, for the four years of visual surveys. The identified baleen whale species included minke (*Balaenoptera acutorostrata*), fin (*Balaenoptera physalus*), and humpback whales (*Megaptera novaeangliae*). The identified odontocete species included Atlantic white-sided (*Lagenorhynchus acutus*), white-beaked (*Lagenorhynchus albirostris*), and common (*Delphinus delphis*) dolphins as well as long-finned pilot whales (*Globicephala melas*) (Table 9).

Table 9 Summary of marine mammal observations (Fig. 7) showing the total number of sightings (n) and total number of animals seen for baleen and toothed whales.

Group	Species	Number of Sighting Events (%)	Number of Animals Seen
Baleen whales	Minke whale	16 (5.7)	17
	Fin whale	14 (5.0)	18
	Humpback whale	14 (5.0)	18
	Unknown whale	34 (12.2)	52
Toothed whales	White-beaked dolphin	101 (36.2)	642
	Atlantic white-sided dolphin	6 (2.2)	93
	Long-finned pilot whale	1 (0.4)	1
	Common dolphin	30 (10.8)	327
	Unknown dolphin	62 (22.2)	324
	Unknown porpoise	1 (0.4)	1
Total	Marine mammals	279	1,493

From the observations dataset, we computed encounter rates for baleen and toothed whales by dividing the recorded pod sizes by effort measured as the number of km surveyed during a day (Awbery et al., 2022; Secchi et al., 2020). This allowed us to produce a simple estimate of the distribution of marine mammals within the study area while accounting for the differences in the coverage of the survey from year to year. We then converted the effort-weighted observations into density maps using Kernel Density Estimation (KDE) with an output cell size of 1 km^2, matching the spatial resolution of the $cumMSL_{year}$ maps. We generated the KDEs using the Kernel Density tool from the Spatial Analyst toolbox in ArcGIS Pro® software. We conducted all area calculations in ArcGIS Pro ® software using the NAD 1983 UTM projection for zone 21N with its central meridian set at 55W. We computed the KDEs for baleen and toothed whales using 279 observations of marine mammals in total (Table 9). Among the identified species, white-beaked dolphins were the most commonly sighted marine mammal within the study area, followed by common dolphins and, in almost equal proportions, fin, humpback, and minke whales (Table 9). Two species included a single observation (i.e., long-finned pilot whales and unidentified porpoise), and unidentified cetaceans represented almost 35% of the observations (Table 9).

To estimate the overlap of vessel noise sources with areas used by baleen and toothed whales, we extracted the 50^{th} and 95^{th} percentile contours of the KDEs and used their boundaries to calculate the area affected by noise sources exceeding the median and 95^{th} percentile of the $cumMSL_{year}$ of the full study area.

We tested changes in the total area affected by $cumMSL_{year}$ exceeding the 50^{th} percentile for all years using linear regression models (Table 13).

4. 3. Results

4.3.1 Vessel Traffic.

When considering all five classes together, vessel traffic in Placentia Bay has increased steadily over the period 2019-2023 (Figs. 19, 20, and 21). With the exclusion of tankers, the total hours of navigation increased for all vessel classes we considered in this study. The median hours of navigation in 2023 have doubled when compared to 2019, increasing from approximately 1,000 hr of navigation per month to 2,000 hr, with the largest increase recorded between 2022 and 2023 (Fig 19). With more than 4,000 hr of navigation per month, tankers were the main vessel class navigating within the study area in 2019, and during the first three months of 2020 (Fig 20). In 2019, cargo vessels totaled between 1,000 and 2,000 hr of navigation, followed by service vessels with approximately 1,000 hr of navigation per month, while fishing and passenger vessels rarely exceeded 500 hr (Fig 20). Over the period 2021-2023, however, tanker traffic progressively declined while all other classes increased their total hours of navigation, with service vessels reaching and sometimes surpassing the total hours of navigation of tankers. In particular, service vessels had comparable total hours of navigation to tankers in 2022 and 2023. The decline in tanker traffic was due to the closure and repurposing of the Come By Chance refinery, although this did not result in a cessation of tanker traffic but rather in halving their total navigation time. On the other hand, with the opening and expansion of salmon farming activities, service vessels significantly increased their total hours of navigation over the five-year period, from a median of approximately 1,000 hr of navigation in 2019 to more than 2,500 hr in 2023. Navigation hours increased for fishing vessels as well, from less than 500 hr per month in 2019 to more than 1,000 hr in 2023. Passenger vessels, which totaled the smallest number of total hours of navigation among all five classes, displayed year-to-year changes that departed from the trends observed for the other four vessel classes, which displayed steady increases (or decreases in the case of tankers) from one year to the next. Passenger vessel traffic dropped in 2020 and remained very low in 2021, while it increased in 2022 and 2023, surpassing the hour of navigation recorded in 2019.

In addition to the year-to-year increase in total hours of navigation, we observed seasonal changes for all five categories (Fig 21). Fishing vessels presence generally increased in the spring and summer months between 2019 and 2023, with 2022 and 2023 showing peaks in traffic in the winter months as well (Fig 21). Service vessels navigation time in 2019 was low and with moderate month-to-month variability, while over the period 2020-2023, their activity increased in all months, with peaks emerging during the spring, summer, and fall seasons between 2021 and 2023. We observed regular trends in cargo vessels, with lower total navigation times during the winter in comparison to the spring, summer, and fall seasons (Fig 21). Lastly, passenger vessels had low presence throughout the year between 2019 and 2021, most likely due to the interruption of ferry traffic during the COVID 19 pandemic. In 2022 and 2023, however, we observed a seasonal peak in passenger vessel traffic between June and October (Fig 21).

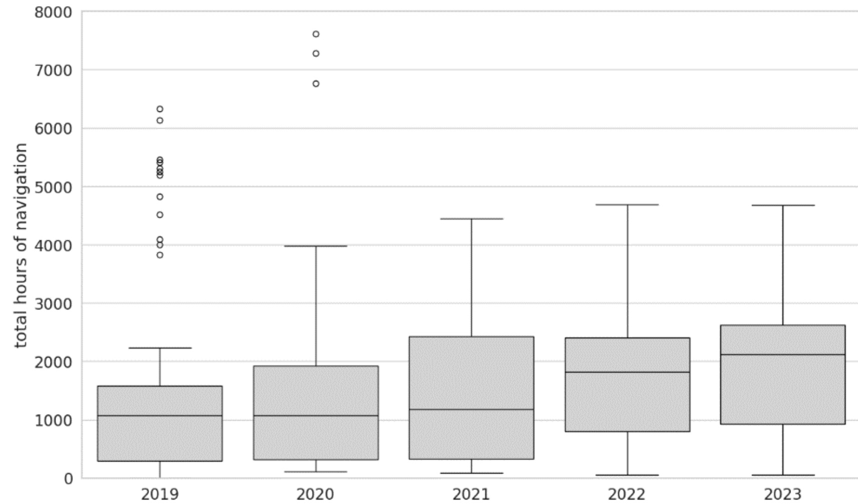

Figure 19 Distribution of total hours of navigation per km^2 per year for all five vessel types summed together (i.e., tanker, cargo, passenger, service, fishing) within the Placentia Bay EBSA boundaries between 2019 and 2023. The boxes outline upper (75th) and lower (25th) quartiles, the horizontal lines crossing the boxes indicate median values, and the whiskers delimit the minimum and maximum of the distribution.

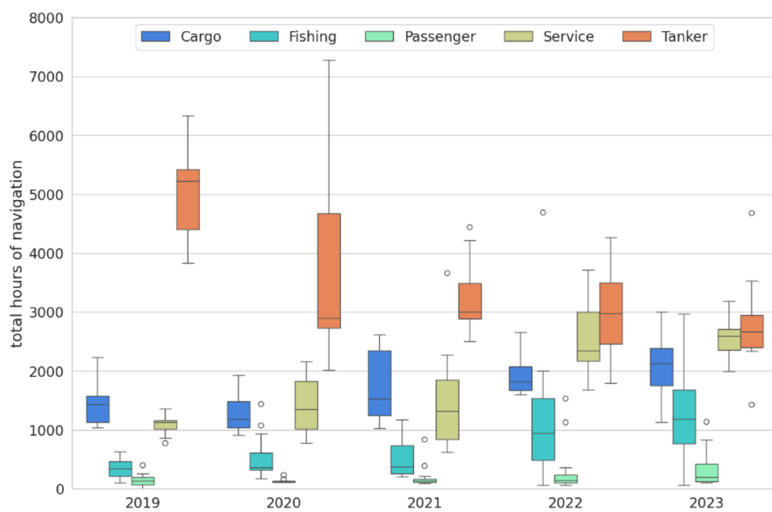

Figure 20 Distribution of navigation hours per km^2 per year for tanker, cargo, passenger, service, fishing vessels within the Placentia Bay EBSA boundaries between 2019 and 2023.

Figure 21 Seasonal changes in total navigation hours per km² per month for tanker, cargo, passenger, service, and fishing vessels within the Placentia Bay EBSA boundaries between 2019 and 2023.

4.3.2 Cumulative Noise Sources.

The yearly cumulative noise sources maps illustrate how vessel traffic has changed in Placentia Bay over the five years considered in this study (Figs 22, 23, and 24). The eastern portion of the inner bay emerged as an area where $cumMSL$ reached the highest levels across all five years considered (Figs 22 A-E). This area encompasses several ports (e.g., Argentia; Come By Chance) and traffic mainly consists of tanker and service vessels (Fig 23). While the progressive decline in tanker traffic over the years resulted in reduced $cumMSL$ along the southern portion of the commercial shipping lane, with the limits of the 95th percentile contours receding towards the port of Argentia, other areas have experienced increases in $cumMSL$ (Figs 22 F-J and 23 A-D). In particular, vessel traffic increased along the western portion of Placentia Bay, with new regular routes emerging in 2022 and 2023 (Figs. 22 D,E and 24 C,D), resulting in additional areas exceeding the 95th percentile of the estimated $cumMSL$ (Fig. 22 I, J). Over the five-year period, the median $cumMSL$ remained almost unchanged, ranging between 147 and 148 dB, and we observed similarly small variations (i.e. ≤ 1 dB) in the remaining percentiles (Table 10). Maximum and minimum $cumMSL$ both increased from year to year. The lowest $cumMSL$, less than 90 dB, occurred in 2019 and 2020, while over the period 2021-2023 the minimum ranged between 96 and 100 dB (Table 10). The maximum $cumMSL$ values for the study area increased at slightly slower pace, going from 192 dB in 2019 to 198 in 2023. Over the years, the portion of study area affected by the presence of vessel noise sources, including all non-zero $cumMSL$ estimates, increased from 83% to 89% (Table 10). The area exceeding median $cumMSL$ increased from 39% in 2019 to 48% in 2023, while the area exceeding the 95th percentile showed small changes and ranged between

3 and 5% coverage (Table 10). The total area exposed to $cumMSL$ above the median increased significantly each year, with an estimated increase of 251 km^2 per year (Tables 10 & 13).

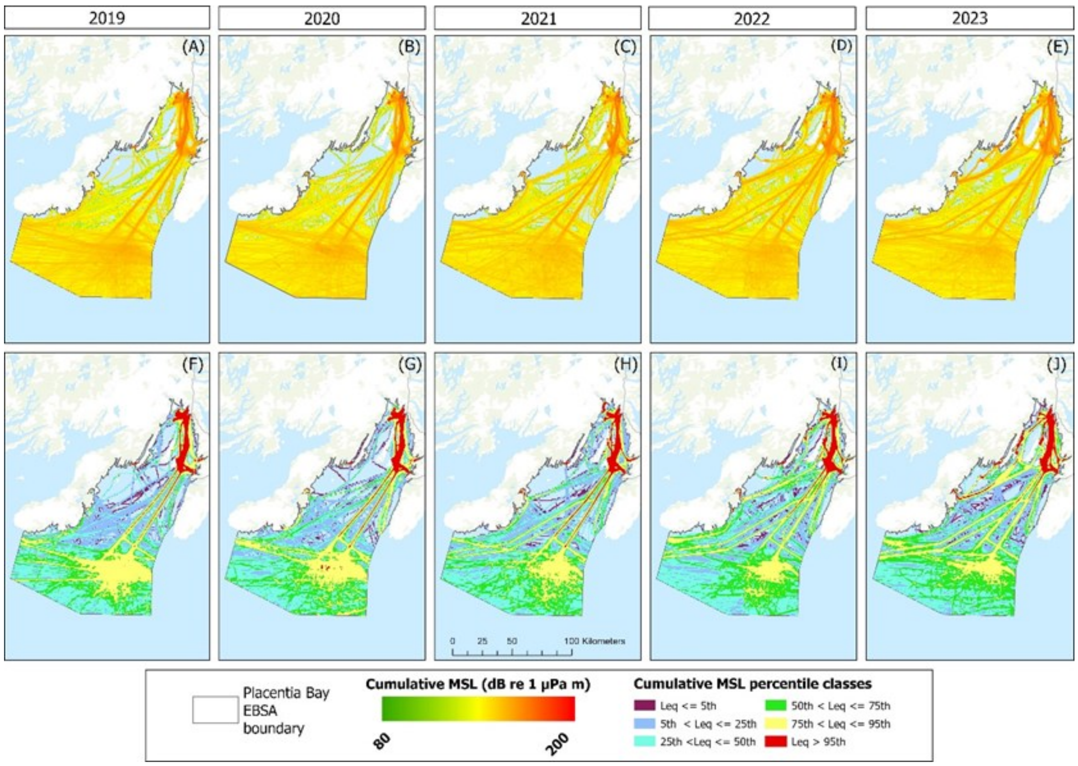

Figure 22 Cumulative Monopole Source Lelvels ($cumMSL$) per km^2 per year (A-E), and corresponding percentile classes for the period 2019-2023 (F-J).

Table 10 Percentile intervals of the mapped $cumMSL$ estimates (Fig. 22), area covered by each percentile, and corresponding percentage of the study area affected by vessel noise sources (total area = 13,538.68 km^2), and total area above the 50th percentile of the estimated $cumMSL$.

Year	Percentile interval	$cumMSL$ range (dB re 1 µPa m)	Area (km^2)	Proportion	Total area above MSL 50th percentile (km^2)
2019	MSL ≤ 5th	83.62 - 126.20	392.20	2.90%	5327.57
	5th < MSL ≤ 25th	126.20 - 143.44	2,349.85	17.36%	
	25th < MSL ≤ 50th	143.44 - 147.94	3,191.35	23.57%	
	50th < MSL ≤ 75th	147.94 - 151.72	2237.73	16.53%	
	75th < MSL ≤ 95th	151.72 - 159.86	2,576.60	19.03%	
	MSL > 95th	159.86 - 192.90	513.24	3.79%	
2020	MSL ≤ 5th	86.12 - 125.61	361.09	2.67%	5548.35
	5th < MSL ≤ 25th	125.61 - 142.51	2,250.26	16.62%	
	25th < MSL ≤ 50th	142.51 - 147.18	3,075.83	22.72%	
	50th < MSL ≤ 75th	147.18 - 150.77	2,439.14	18.02%	
	75th < MSL ≤ 95th	150.77 - 159.36	2,558.49	18.90%	
	MSL > 95th	159.36 - 194.6	550.73	4.07%	
2021	MSL ≤ 5th	97.65 - 126.59	381.51	2.82%	5582.60
	5th < MSL ≤ 25 th	126.59 - 143.63	2,329.31	17.20%	
	25th < MSL ≤ 50th	143.63 - 147.96	3,324.74	24.56%	
	50th < MSL ≤ 75th	147.96 - 151.35	2,667.92	19.71%	
	75th < MSL ≤ 95th	150.58 - 159.63	2,336.74	17.26%	
	MSL > 95th	159.63 - 194.03	577.95	4.27%	
2022	MSL ≤ 5th	100.42 - 129.46	383.27	2.83%	5783.60
	5th < MSL ≤ 25th	129.46 - 143.85	2,139.75	15.80%	
	25th < MSL ≤ 50th	143.85 - 147.94	3,774.46	27.88%	
	50th < MSL ≤ 75th	147.94 - 151.93	2,971.02	21.94%	
	75th < MSL ≤ 95th	151.93 - 160.33	2,262.94	16.71%	
	MSL > 95th	160.33 - 198.91	549.64	4.06%	
2023	MSL ≤ 5th	96.21 - 128.90	376.48	2.78%	6466.26
	5th < MSL ≤ 25th	128.90 - 143.91	2,056.85	15.19%	
	25th < MSL ≤ 50th	143.91 - 147.66	3,134.29	23.15%	
	50th < MSL ≤ 75th	147.66 - 151.52	3,250.42	24.01%	
	75th < MSL ≤ 95th	151.52 - 160.87	2,589.70	19.13%	
	MSL > 95th	160.87 - 198.59	626.14	4.62%	

Contributions to estimated total $cumMSL$ between 2019 and 2023 varied among the five vessel classes (Fig 23). The area impacted by the presence of cargo, fishing, and passenger ships increased between 2019 (Fig 23 A, B, and C) and 2023 (Fig 23 F, G, and H). In 2019, cargo vessels had the highest contributions within the southwestern portion of Placentia Bay, while in 2023 the areas of highest contribution to $cumMSL$ from cargo moved towards the central portion of the bay. Fishing vessels' contributions to $cumMSL$, on the other hand reached the highest values (i.e., close to 100% contribution) in the northern portion of Placentia Bay, did not show strong changes in their distribution, but rather increased their presence in the area when compared to the other classes. Passenger vessels had relatively low presence in 2019, and their contributions to $cumMSL$ was limited to coastal areas and to the portion of the EBSA extending south of the mouth of Placentia Bay. In 2023, however, their contribution increased, with the Argentia (NL) to Sydney (NS) ferry route emerging as a region of Placentia Bay where passenger vessels are the main source of anthropogenic noise. Service vessels are the class that showed the most dramatic changes in spatial distribution as well as in their contributions to $cumMSL$ estimates (Fig 23 D-I). In 2019, service vessels' contribution to $cumMSL$ was high in the northwestern portion of Placentia Bay, between the ports of Argentia and Come By Chance (Fig 18), with additional high-contribution areas located along the commercial shipping lane and in the waters south of the Burin Peninsula. In 2023, the northwestern portion of the bay, previously almost free of traffic from service vessels, became one of the areas receiving the highest contribution to $cumMSL$ from such vessels. Service vessels' contributions changed within the northeastern portion of the bay as well, with an increase in the area where service vessels are the main contributors to the estimated $cumMSL$. The overall contribution of tanker traffic to $cumMSL$ decreased between 2019 and 2023, with a corresponding reduction in the area where tankers represent close to 100% of the total $cumMSL$ (Fig 23 E, J). The southern portion of the Placentia Bay EBSA, however, remained an area where tanker traffic is the main contributor to $cumMSL$, followed by passenger (Fig 23 H) and cargo vessels (Fig 23 A).

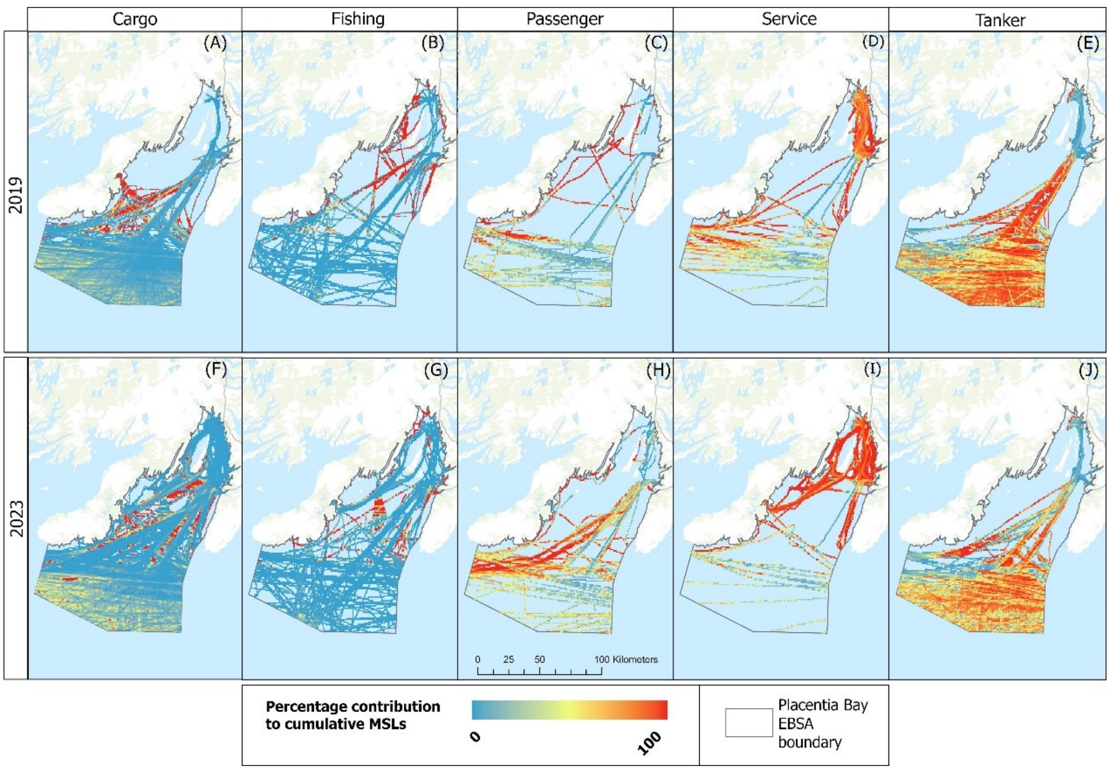

Figure 23 Percentage contributions of cargo, fishing, passenger, service, and tanker vessels to the mapped total $cumMSL$ per km^2 for 2019 (A-E) and 2023 (F-J). Contributions ranged from > 0% (blue) to ≤ 100% (red), while cells with a 0% contribution are set as null values (no color).

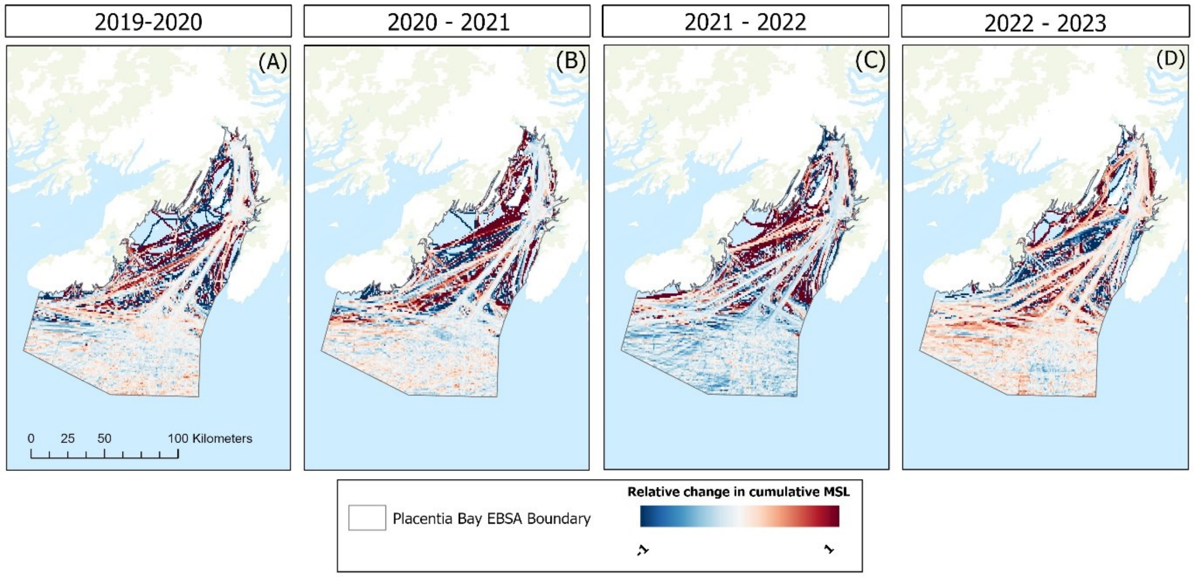

Figure 24 Year to year difference in $cumMSL$ per km^2, starting from the difference between 2019 and 2020 (A) and ending with the difference between 2022 and 2023 (D). Positive changes (relative change > 0) indicate a year-to-year increase in $cumMSL$. Negative changes (relative change <0) indicate a year-to-year decrease in $cumMSL$. A relative change of 1 indicates a cell of the raster where sources were not present in the previous year but were present in the following year (dark red). A relative change of -1 indicates a cell of the raster where sources were present in the previous year but were not present in the following year (dark blue).

4.3.3 Noise Sources within Marine Mammal Presence Hotspots.

The 95th percentile KDE contours for baleen whales delineated an area of approximately 338 km^2 located at the Southern end of the commercial shipping lane as a hotspot of aggregation for the animals (Fig 25). The 50th percentile KDE contour for baleen whales (3,340 km^2) encompassed most of the lower portion of Placentia Bay and proximately half of the inner bay. The 95th percentile contours for toothed whales showed four hotspots distributed along the commercial shipping lane, covering a total area of 285.4 km^2 (Fig. 25). The 50th percentile contour for toothed whales overlapped the baleen whales contour, but was more fragmented and covered a smaller area (2,882 km^2) (Fig. 25).

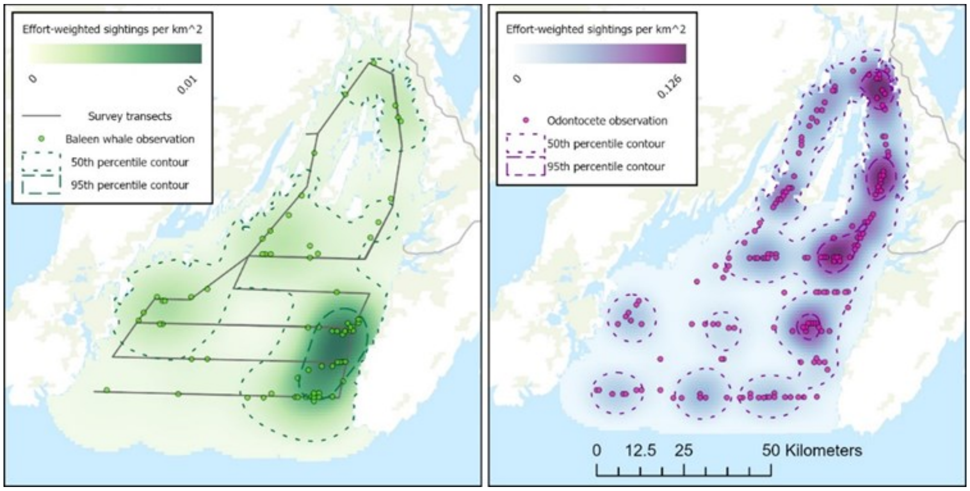

Figure 25 KDE surfaces for baleen and toothed whales (raster surfaces). Dashed lines indicate the boundaries of the 50^{th} and 95^{th} percentile contours (dashed lines) of the KDEs, points indicate marine mammal observations, and the gray solid line delineates the visual survey transects.

The presence of vessel noise sources increased within the 50^{th} percentile contours of both baleen and toothed whale occurrence. The presence contour for baleen whales saw a 18% increase in area exposed to vessel sounds from 63% in 2019 to 81% in 2023, while for toothed whales the exposed area increased by 14%, going from 77% to 91%. Vessel noise presence also increased within the 95^{th} percentile presence contours of the two taxonomic groups. Baleen whale presence areas saw the largest increase in noise sources, from 65% in 2019 to 83% in 2023, while toothed whales saw only a 5% increase over the same period. However, the presence of noise sources was highest within the 95^{th} percentile presence contours for toothed whales, ranging from 95% to 99%.

The total area above the median $cumMSL$ within the 50^{th} percentile presence contour for baleen whales increased significantly each year, with an estimated increase of 173.5 km^2

per year (Tables 11 & 13). Similarly, the total area above the median $cumMSL$ within the 50^{th} percentile presence contour for toothed whales increased by 130 km^2 per year.

The area above the median $cumMSL$ within the 95^{th} percentile presence contour for baleen whales fluctuated over the years (range 22 - 37%), with the highest percentage coverage estimated for 2022 (37%) (Table 11). However, the year-to-year changes did not result in a significant increase in the affected area (Table 13).

The area above the median $cumMSL$ within the 95^{th} percentile presence contour for toothed whales was approximately 14% in 2019, 2021, and 2022. Both 2020 and 2023 had larger portions of affected areas, totaling 22% and 17%, respectively (Table 12). However, the year-to-year changes did not result in a significant increase in the affected area (Table 13).

Table 11 Percentile intervals of the mapped $cumMSL$ estimates (Fig. 22) overlapping with the presence KDE percentile contours for baleen whales (Fig. 25), presence contour area covered by each percentile, and corresponding percentage of the presence contour areas affected by vessel noise sources (total area: 50th percentile contour = 3,340.36 km^2; 95th percentile contour = 338.57 km^2), and total area above the 50th percentile of the estimated $cumMSL$.

		Baleen whales' percentile contours					
		50th			95th		
Year	**Percentile interval**	**Area (Km^2)**	**Proportion**	**Total area above MSL 50th percentile (km^2)**	**Area (Km^2)**	**Proportion**	**Total area above MSL 50th percentile (km^2)**
2019	MSL ≤ 5th	224.72	6.7%	782.63	22.32	6.6%	76.48
	5th < MSL ≤ 25th	716.20	21.4%		69.22	20.4%	
	25th < MSL ≤ 50th	373.17	11.2%		50.87	15.0%	
	50th < MSL ≤ 75th	178.33	5.3%		49.07	14.5%	
	75th < MSL ≤ 95th	317.37	9.5%		21.84	6.5%	
	MSL > 95th	286.93	8.6%		5.57	1.6%	
2020	MSL ≤ 5th	167.71	5.0%	957.93	16.03	4.7%	118.81
	5th < MSL ≤ 25th	680.92	20.4%		65.45	19.3%	
	25th < MSL ≤ 50th	330.05	9.9%		39.24	11.6%	
	50th < MSL ≤ 75th	228.90	6.9%		33.34	9.8%	
	75th < MSL ≤ 95th	429.37	12.9%		79.47	23.5%	
	MSL > 95th	299.66	9.0%		6.00	1.8%	
2021	MSL ≤ 5th	182.68	5.5%	951.18	12.58	3.7%	91.2
	5th < MSL ≤ 25th	725.16	21.7%		73.28	21.6%	
	25th < MSL ≤ 50th	481.49	14.4%		77.37	22.9%	
	50th < MSL ≤ 75th	269.27	8.1%		47.28	14.0%	
	75th < MSL ≤ 95th	375.51	11.2%		36.53	10.8%	
	MSL > 95th	306.40	9.2%		7.39	2.2%	
2022	MSL ≤ 5th	164.61	4.9%	1396.59	14.10	4.2%	124.06
	5th < MSL ≤ 25th	624.85	18.7%		85.78	25.3%	
	25th < MSL ≤ 50th	558.82	16.7%		46.93	13.9%	
	50th < MSL ≤ 75th	471.95	14.1%		54.55	16.1%	
	75th < MSL ≤ 95th	634.65	19.0%		68.60	20.3%	
	MSL > 95th	289.99	8.7%		0.91	0.3%	
2023	MSL ≤ 5th	216.95	6.5%	1431.00	18.46	5.5%	115.57
	5th < MSL ≤ 25th	734.26	22.0%		110.94	32.8%	
	25th < MSL ≤ 50th	319.60	9.6%		35.01	10.3%	
	50th < MSL ≤ 75th	343.70	10.3%		55.15	16.3%	
	75th < MSL ≤ 95th	754.72	22.6%		59.82	17.7%	
	MSL > 95th	332.58	10.0%		0.60	0.2%	

Table 12 Percentile intervals of the mapped $cumMSL$ estimates (Fig. 22) overlapping with the KDE percentile presence contours for toothed whales (Fig. 25), presence contour area covered by each percentile, and corresponding percentage of the presence contour areas affected by vessel noise sources (total area: 50^{th} percentile contour = 2,282.17 km^2; 95^{th} percentile contour = 285.4 km^2), and total area above the 50^{th} percentile of the estimated $cumMSL$.

		Toothed whales' percentile contours					
		50th			95th		
Year	**Percentile interval**	**Area (Km^2)**	**Proportion**	**Total area above MSL 50^{th} percentile (km^2)**	**Area (Km^2)**	**Proportion**	**Total area above MSL 50^{th} percentile (km^2)**
2019	MSL ≤ 5^{th}	153.70	5.3%	970.55	4.25	1.5%	214.62
	5^{th} < MSL ≤ 25^{th}	736.96	25.6%		23.33	8.2%	
	25^{th} < MSL ≤ 50^{th}	351.01	12.2%		29.50	10.3%	
	50^{th} < MSL ≤ 75^{th}	175.55	6.1%		21.24	7.4%	
	75^{th} < MSL ≤ 95^{th}	387.49	13.4%		84.21	29.5%	
	MSL > 95^{th}	407.51	14.1%		109.17	38.3%	
2020	MSL ≤ 5^{th}	136.75	4.7%	1546.08	0.66	0.2%	231.68
	5^{th} < MSL ≤ 25^{th}	227.44	7.9%		25.35	8.9%	
	25^{th} < MSL ≤ 50^{th}	338.11	11.7%		25.46	8.9%	
	50^{th} < MSL ≤ 75^{th}	419.60	14.6%		21.73	7.6%	
	75^{th} < MSL ≤ 95^{th}	475.97	16.5%		96.40	33.8%	
	MSL > 95^{th}	650.51	22.6%		113.55	39.8%	
2021	MSL ≤ 5^{th}	112.82	3.9%	1142.16	1.23	0.4%	225.17
	5^{th} < MSL ≤ 25^{th}	772.95	26.8%		24.04	8.4%	
	25^{th} < MSL ≤ 50^{th}	450.04	15.6%		23.19	8.1%	
	50^{th} < MSL ≤ 75^{th}	252.09	8.7%		27.42	9.6%	
	75^{th} < MSL ≤ 95^{th}	461.42	16.0%		80.18	28.1%	
	MSL > 95^{th}	428.65	14.9%		117.57	41.2%	
2022	MSL ≤ 5^{th}	105.43	3.7%	1537.86	1.00	0.4%	251.58
	5^{th} < MSL ≤ 25^{th}	504.91	17.5%		14.22	5.0%	
	25^{th} < MSL ≤ 50^{th}	447.22	15.5%		15.51	5.4%	
	50^{th} < MSL ≤ 75^{th}	422.84	14.7%		29.09	10.2%	
	75^{th} < MSL ≤ 95^{th}	691.10	24.0%		94.51	33.1%	
	MSL > 95^{th}	423.92	14.7%		127.98	44.8%	
2023	MSL ≤ 5^{th}	108.29	3.8%	1628.29	1.20	0.4%	249.68
	5^{th} < MSL ≤ 25^{th}	561.79	19.5%		15.42	5.4%	
	25^{th} < MSL ≤ 50^{th}	322.34	11.2%		13.59	4.8%	
	50^{th} < MSL ≤ 75^{th}	352.74	12.2%		25.38	8.9%	
	75^{th} < MSL ≤ 95^{th}	788.90	27.4%		88.06	30.9%	
	MSL > 95^{th}	486.65	16.9%		136.24	47.7%	

Table 13 Results of regression models testing the significance of year-to-year changes in $cumMSL$ estimates. The dependent variables for the model are: the total area of the Placentia Bay EBSA above the 50th percentile of the $cumMSL$ per year (Table 10); the total area of the baleen whales 50th and 95th percentile contours above the 50th percentile of the $cumMSL$ per year (Table 11); the total area of the toothed whales 50th and 95th percentile contours above the 50th percentile of the $cumMSL$ per year (Table 12).

		Total area above MSL 50th percentile (km2)				
		PB EBSA	**Baleen whales 50th percentile contour**	**Baleen whales 95th percentile contour**	**Toothed whales 50th percentile contour**	**Toothed whales 95th percentile contour**
Years (2019-2023)	**Estimate**	251.262	173.54	18.283	130.726	9.002
	Standard Error	65.73	36.213	18.348	74.464	2.595
	P-value	**0.032**	**0.017**	0.392	0.177	**0.04**
	F-statistic	14.612	22.965	0.993	3.082	12.035
	R2	0.83	0.884	0.249	0.507	0.8

4. 4. Discussion

With the closure and repurposing of the Come By Chance refinery, the development of aquaculture industry, the expansion of the Port of Argentia to meet the needs of an emerging hydrogen production industry, and interruption and resumption of ferry traffic during and after the COVID19 pandemic, Placentia Bay has undergone a dramatic transformation over the past five years. This transformation resulted in a doubling in the median hours of navigation for cargo, fishing, passenger, service, and tanker vessels and in the reconfiguration of vessel traffic in the area. These changes have resulted in larger portions of Placentia Bay being exposed to anthropogenic noise pollution generated by vessels, including within areas of relatively greater importance for marine mammals.

Overall, vessel traffic in Placentia Bay has increased, but this change did not lead to a corresponding increase in the estimated median $cumMSL$ which fluctuated between 147 and 148 dB over the five-year period. In addition, the range of $cumMSL$, shifted towards progressively higher minimum and maximum values. This difference between the median and the range of $cumMSL$ can be explained by changes in the composition of vessels transiting the area. Tanker, cargo, and service vessels are the three main sources of underwater anthropogenic noise in Placentia Bay. A reduction in tanker vessels traffic ($MSL_{tanker} = 177.85$, Table 1) was followed by an almost equal increase in service vessel traffic ($MSL_{service} = 177.39$), and as both categories have similar estimated MSLs, we can expect only a small change in the overall median $cumMSL$. The growth of traffic for the remaining three classes, especially passenger vessels, which were the loudest class considered in the study ($MSL_{passenger} = 186.11$, Table 1), could explain the increase in maximum and minimum values we observed over the years.

Most (83% - 89%) of the marine environment of the Placentia Bay Ecologically and Biologically Significant Area is affected by noise from vessels, and in five years, the area affected by at least one source of noise increased by 6%. The area above the median $cumMSL$ increased 5%, and the area above the 95th percentile $cumMSL$ increased by approximately 1%. Considering that our study did not include all available AIS vessel categories, and that a number of recreational vessels not carrying AIS systems use the area, the total area affected by the presence of vessel noise sources in Placentia Bay might be closer to 100%, with larger portions exceeding the median and 95th percentile $cumMSL$. The inner portion of Placentia Bay emerged as a hotspot of vessel noise sources. Over the years, this area has seen an increasing number of noise sources, and a shift in the composition of traffic from prevalently large vessels (tankers) travelling within the shipping lane, to medium and small vessels (cargo and service) often following routes outside of the shipping lane.

Our results suggest that both baleen and toothed whales within the Placentia Bay EBSA are experiencing increased underwater sound exposure and possible disturbance from vessel noise. In 2023, 43% of the areas regularly used by baleen and 56% of the areas used by toothed whales exceeded the median $cumMSL$. Of the two groups, toothed whales were exposed to higher $cumMSL$ than baleen whales, with 17% of their 50th percentile presence contour affected by $cumMSL$s >160 dB in 2023, in contrast to 10% of the 50th percentile presence contour of baleen whales for the same period. It is also of note that the area exposed to $cumMSL$ >160 dB within the baleen whales 95th percentile presence contour dropped to almost zero between 2019 and 2023. Increases in ambient noise is of particular concern for the protected baleen whale species found in Placentia Bay. North Atlantic fin whales constituted approximately one third of the baleen whales observed in the study area. The Canadian Species at Risk Act (SARA) lists the North Atlantic fin whale population as being of special concern, and the management plan for its protection recognizes noise pollution as one of the most concerning factors threatening fin whales in Atlantic Canada. Fin whales can respond to vessel noise by reducing their vocalization rates, and their songs (i.e., sequences of 20 Hz vocalizations) can be masked by the presence of nearby vessels (Castellote et al., 2012). As songs are thought to be relevant to the species’ mating behaviour (Romagosa et al., 2021; Watkins et al., 1987), vessel noise has the potential to reduce reproductive success in the population, threatening its recovery.

Considering the increase of vessel traffic that occurred in Placentia Bay between 2019 and 2023, and the consequent increase in the area affected by such noise sources, there is a potential for noise pollution to have an impact on both fin whales' communication and behaviour in the area. Broadband noise levels from continuous sources in excess of 120 dB re 1 μPa are employed in the US as a threshold for the onset of behavioural responses in most species of baleen whales (NMFS, 2023). We found that this threshold might be exceeded in Placentia Bay when vessel noise is present for at least five minutes for every 30 min of audio recording containing vessel noise.

Approximately 1/3 of the 20 Hz vocalizations observed in 2019 occurred in the presence of vessel noise, with median broadband noise levels ranging from 100 dB, when vessel noise is absent, and nearing 120 dB, when vessel noise is present (**Chapter 3**). Fin whales are not the only SARA listed species found in Placentia Bay, and the area has been recognized as an important habitat for the blue whale (Lesage al., 2018). Although no observation of blue whales occurred during the period covered by the line transect surveys (2018-2021), observations collected by DFO in previous years indicate that blue whales use the bay for foraging. Like fin whales, blue whales exhibit changes in acoustic behaviour when ship noise is present in their environment, and respond by increasing the loudness (i.e., the source level) of their calls (Melcón et al., 2012).

Placentia Bay also lays within the range of the critically endangered North Atlantic right whale population, and individuals have occasionally been detected in the bay using acoustic monitoring (DFO, 2020). North Atlantic right whales show physiological responses to chronic noise pollution, and experience increased stress levels when exposed to noise from large commercial ships (Rolland et al., 2012). Furthermore, North Atlantic right whales respond to increased noise levels by shifting the frequency of their vocalizations and increasing their duration, a mechanism that helps compensate for the loss of communication space. Two of the most common calls emitted by North Atlantic right whales have been found to be affected by the presence of ship noise: upcalls (Tennessen et al., 2014) and gunshots (Cunningham & Mountain, 2014).

The potential negative impacts of vessel noise in Placentia Bay are not limited to these protected whale species, and can affect all marine mammal species found within coastal marine environment. These include, for example, potential communication masking and disturbance for humpback and minke whales, as well as for toothed whale species found in the region, which could be experiencing reduced foraging success due to the proximity to sources of vessel noise (Holt et al., 2021).

Besides marine mammals, Placentia Bay hosts commercially important species of fish and crustaceans. Without mitigation, the progressive increase in underwater noise we observed has the potential of reducing recruitment of Atlantic cod (*Gadus morhua*) in the region. First, as vocal displays are part of the Atlantic cod mating behaviour, increasing vessel noise could affect reproduction by reducing the communication range of adult cod

(Stanley et al., 2017). Second, there is evidence that the exposure to chronic noise can reduce growth of cod larvae, affecting survival rates in the long term (Nedelec et al., 2015). The Placentia Bay EBSA includes several important spawning grounds for the Atlantic cod (DFO, 2019), and increasing noise levels could result in reduced survival for juvenile cod in this area.

The results presented in our study have several limitations, which lead us to make several recommendations for future research. We limited our analysis to a subset of vessel classes carrying AIS, and excluded all unidentified vessels and icebreakers from our vessel traffic and cumulative noise sources estimates. Considering that AIS does not capture all vessels transiting through an area (Jalkanen et al., 2022), and that small recreational vessels can be the predominant noise source in shallow coastal waters (Hermannsen et al., 2019), our results underestimate the volume of traffic actually found in Placentia Bay, and therefore likely underestimate the increase in the area affected by noise sources as well. Another limitation comes from the aggregation of multiple AIS vessel classes under the same group in the GMTDS vessel density maps. For example, the service vessel class includes pilot vessels used to aid large commercial vessels in their navigation through the inner part of the bay, as well as specialized tugs used in salmon aquaculture activities. Having a finer-grain classification of vessel classes, in combination with measurements of their source levels, would allow us to better estimate the contributions to underwater noise originating from specific anthropogenic activities.

Our assessment of $cumMSL$ for the five-year period is based on source levels estimated by applying a functional regression equation (MacGillivray et al., 2022) to a set of representative vessels for each class considered in the study. In the absence of source level measurements for the fleet found in Placentia Bay, using a single estimated source level per vessel class allowed us to gain insights on the overall distribution and intensity of noise sources in the area. However, our results do not take into account the specific characteristics of vessels and, as mentioned earlier, more accurate estimates could be achieved by measuring a subset of the Placentia Bay's fleet with known characteristics. Although the approach we adopted is suited for assessing the distribution and intensity of noise emitted by vessels at their source, it should not be considered equivalent or analogous to the estimation of ambient noise levels through the use of acoustic propagation models (e.g., Roul et al., 2019). Considering noise levels at the source allowed us to generate five years of monthly $cumMSL$ estimates and identify areas of Placentia Bay that might be affected by noise levels that are detrimental to the health of marine species. However, our analysis does not consider how noise propagates from vessels in the environment, and does not include the contribution of natural sound sources (e.g., waves and rain) to ambient noise levels, making our results less comparable with some other studies predicting how vessel noise propagates in the environment. Future studies assessing vessel noise in the area could benefit from including the contribution of additional environmental variables such as wind and currents.

Finally, the estimated overlap between vessel noise and marine mammals represents a preliminary assessment of these animals' exposure to anthropogenic noise sources in Placentia Bay. As the KDEs and contours we used in this study are based on a limited number of observations, we could not generate yearly or monthly estimates. The small number of visual detection samples also prevented us from applying more sophisticated approaches to analyze the line transect survey data, such as density estimates based on distance sampling techniques. Increasing the coverage and occurrence of the surveys would help with building more accurate estimates of the seasonal variability and density of marine mammals in Placentia Bay.

4. 5. Conclusion and Management Implications

Underwater noise from vessels can have detrimental effects on the health of marine ecosystems and species therein, posing a threat to the conservation of biodiversity in busy coastal areas. Our study adds to a growing body of literature documenting how vessel noise is pervasive within the habitat of protected marine mammals in Canada (Adams et al., 2020; Aulanier et al., 2016; Cominelli et al., 2018, 2020; Halliday et al., 2021; Halliday et al., 2017; Mérindol et al., 2024). Our results provide a first assessment of how vessel noise sources are distributed within a busy coastal area, and show how these sources overlap with the ranges of marine mammals. In particular, we show how changes in anthropogenic activity in the area resulted in a progressive increase in vessel traffic, and a consequential growth in the portion of Placentia Bay affected by anthropogenic noise sources. We also show how new developments can result in significant changes in the distribution of noise sources, with areas that were previously only marginally affected by vessel traffic progressively becoming hotspots of noise through time.

Although our results do not provide an assessment of how ambient noise levels have increased in Placentia Bay due to growing vessel traffic alone, the $cumMSL$ maps provide information on the distribution and prevalence of noise sources in the area that can support decision makers in shaping regional and national underwater noise management measures. In the absence of regulations and thresholds for the assessment and mitigation of underwater noise from vessels in Canada, drawing from existing regulations in other jurisdictions can help better situate the results of our analysis. Marine species in Placentia Bay, including marine mammal populations protected under SARA, are exposed to noise levels that likely exceed both the US and EU disturbance thresholds. Depending on the class being considered, vessels in Placentia Bay have the potential of increasing background noise levels above the US behavioural disturbance threshold in marine mammals (120 dB re 1 μPa) at distances ranging from 250 m to more than 5 km. Similar ranges (≤8 km), have been predicted for commercial vessels in the Cabot Strait, at the entrance of the Gulf of St. Lawrence, west of Placentia Bay (Cominelli et al., 2020). Our results, which underestimate the number and distribution of vessels in the area, indicate that more than 80% of Placentia Bay received noise from vessels carrying AIS at least once in 2023. Furthermore, approximately 50% of the area received cumulative noise emissions at the source in excess of 147 dB re 1 μPa m, and 25% in the excess of 150 dB re 1 μPa m. This suggests that vessel noise in Placentia Bay is currently exceeding the EU thresholds, with 20% of marine areas being exposed to these exceedance levels over a year. These results indicate that management and mitigation actions are needed in order to prevent increasing levels of vessel noise to negatively affect marine mammal species in Placentia Bay and other similarly noisy coastal areas in Canada.

The shift in the distribution of noise sources we reported highlights the importance of regular monitoring of vessel traffic for the management of underwater anthropogenic noise and the protection of marine acoustic environments. Underwater acoustic environments can undergo dramatic changes when new commercial and industrial activities are established or when existing ones are modified. Marine spatial planning (MSP) has been proposed as a tool for optimizing the spatial and temporal distribution of ships and for reducing their impacts on marine environments (Ménard et al., 2022; Rojano-Doñate et al., 2023). MSP for vessel traffic management involves designing, implementing, and monitoring the success of targeted mitigation measures (Burnham et al., 2021; Chion et al., 2018; Ménard et al., 2022). Considering the complex dynamics of vessel traffic in Placentia Bay, mitigating the impacts of vessel noise requires the adoption of a suite of management measures targeting specific classes of vessels, areas, and times of the year.

Introducing speed regulations offers the advantage of tackling multiple impacts caused by vessel traffic simultaneously (Leaper, 2019). As vessels transiting along the commercial shipping lane in Placentia Bay travel at speeds exceeding 10 kn, introducing a speed limit could result in reduced noise emissions in the area, with the caveat that lower speeds can result in increased duration of wildlife exposure to noise (Williams et al., 2021). Further reductions in noise emissions could be achieved by applying similar speed regulations to ferries and other passenger vessels transiting within Placentia Bay. Mitigating the noise emitted by vessels navigating outside of the shipping lane, in the inner portion of the bay, might be more challenging, as most of these vessels tend to travel at speeds below or close to 10 kn. No-go areas might be equally challenging to implement, as access to Placentia Bay is important for both commercial and recreational fishing, as well as aquaculture activities. An alternative solution could come from the example set by the EU regulations: adopt spatial and temporal thresholds for the presence of vessels within Placentia Bay, with time allocated to different types of users, to ensure that marine habitats are not exposed to excessive levels of vessel noise over prolonged periods.

4. 6. Chapter 4 Bibliography

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Chapter 5: Discussion & Conclusion

5.1. Key contributions, findings and future research directions

The success of national and international underwater noise strategies relies on our ability to understand the complex relationship between acoustic environments and ecological processes. PAM has emerged as central tool for measuring underwater noise pollution, monitoring marine environments and endangered species, and evaluating noise mitigation measures (Desjonquères et al., 2020; Gibb et al., 2019; Pine et al., 2018; Vagle, 2020). Despite its advantages, little of the Canadian coast has so far been assessed using PAM. Increasing the coverage of marine PAM studies is one of the recommended actions identified in the draft of Canada's Ocean Noise Strategy (ONS) (DFO, 2024, Table 2, Recommendation 8). The ONS also recognizes the technical and analytical challenges posed by the acquisition of "immense volumes of acoustic data", and encourages the adoption of innovative methods for increasing our capacity to interpret environmental acoustic information in a timely manner (ONS, DFO, 2024, Table 2, Recommendation 9).

A possible solution to these challenges comes from the integration of supervised and unsupervised machine learning techniques in the analysis of PAM datasets (Cominelli et al., 2024; Nieto-Mora et al., 2023). By allowing researchers to explore acoustic datasets at multiple temporal and spatial scales without necessarily relying on manually labeled data, unsupervised approaches in acoustic analysis can overcome some of the limitations encountered in PAM analysis (Houegnigan et al., 2017). One technique in particular, the Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018), is emerging as a versatile tool for investigating the links between PAM data and environmental processes. UMAP is a non-linear dimensionality reduction algorithm built on the concept of topological data analysis that is particularly efficient in transforming multivariate datasets (McInnes et al., 2018). In particular, UMAP uses a technique called Laplacian eigenmaps to initialize the model, which result in projections that preserve both the local and the global structure of multivariate datasets (Kobak and Linderman, 2021). A common processing step is separating sounds over their frequency spectrum (i.e., generating a spectrogram), which results in multidimensional datasets that can then be efficiently visualized, explored, and analyzed through the use of dimensionality reduction techniques. Examples of UMAP applications include predicting biodiversity and habitat quality across various acoustic environments (Sethi et al., 2020), monitoring bird communities (Morales et al., 2022), identifying individual animals through their vocalizations (Clink & Klinck, 2020), and studying the structure of animals' vocalizations across a range of different taxa (Sainburg et al., 2020). Applications to underwater recordings are still limited, but include examples that demonstrate how UMAP provides a way to explore and monitor marine coastal and freshwater acoustic environments (Parcerisas et al., 2023, 2024) as well as coral reefs (Williams et al., 2024). In these examples, UMAP is used for acoustic analysis in combination with other machine learning models as a pre-processing step prior to unsupervised clustering (e.g., Parcerisas et al., 2023), or a post-processing step following the use of other ML models, such as Convolutional Neural Networks (CNN) (e.g., Sethi et al., 2020).

Chapters 2 and 3 of this dissertation contribute to the literature discussed above, and present two applications of UMAP to the visualization, exploration, and analysis of marine PAM datasets. The results of my research show how UMAP can be a tool for monitoring changes in marine acoustic environments, allowing one to investigate the relationship between underwater recordings and environmental processes, namely:

- Environmental conditions, such as wind, currents, and surface temperature (Chapters Two and Three)
- Geographical differences between stations (Chapter Three)
- The presence of cetacean species (Chapters Two and Three)
- The quantification of anthropogenic noise sources (Chapter Three)

These findings were achieved by integrating semi-supervised machine learning techniques with more established methods used in acoustic analysis (e.g., manual inspection and labeling of audio files; computation of acoustic metrics; statistical modeling). Furthermore, when applied to 1/3 octave band SPL measurements, UMAP differentiated samples belonging to two distinct PAM monitoring stations (Fig. Chapter Three), while enabling the identification of similar acoustic events occurring at other locations and times (e.g., vessel noise and odontocete vocalizations; Chapter Three). Lastly, introducing UMAP as a processing step in PAM analysis facilitated the identification of mooring-noise in the recordings, leading to more reliable ambient noise estimates by accounting for this extraneous noise contribution.

My results also show how the presence of vessel noise contributes to increasing ambient noise levels experienced by cetaceans in the study area. The findings presented in Chapters Three and Four provide two different assessments of how anthropogenic noise in Placentia Bay has the potential to have negative impacts on cetaceans and their habitat. Chapter Three reports baseline underwater ambient noise measures collected at two PAM monitoring stations in 2019, while Chapter Four presents a five-year spatial assessment of the distribution of anthropogenic noise sources in Placentia Bay.

Chapter Three focuses on the Atlantic fin whale population, and shows how approximately 30% of fin whale vocalizations recorded at the two study sites occur in the presence of vessel noise. Furthermore, the results show how the occurrence of only five minutes of vessel noise during every 30 minutes of audio recording is sufficient for broadband noise levels to reach and exceed the threshold for the onset of behavioural responses in marine mammals (120 dB) (Southall et al., 2019). Among other baleen whales (i.e., blue, sei, minke, humpback whales), fin whales visit Placentia Bay for its plankton and fish aggregations (DFO, 2019), and their feeding and social activities in the area could be disrupted by vessel noise, especially in proximity to the commercial shipping lane. By masking important biological signals, vessel noise reduces the communication space available to cetaceans and other marine species (Eickmeier & Vallarta, 2023; Erbe et al., 2019).

The results of Chapter Three also show that vessel noise in Placentia Bay can increase broadband (50-1000 Hz) ambient noise levels by 15-25 dB, with similar increases in the low frequencies (i.e., in the 63 Hz and 125 Hz 1/3 octave bands). These frequency ranges overlap with the frequencies used by fin, blue, sei, minke, and humpback whales (Erbe, Dunlop, et al., 2018), indicating that vessel noise in the region has the potential of masking their vocalizations. Adapting the duration and frequency characteristics of vocalizations is a common response to increasing noise levels (Erbe et al., 2019; Kunc & Schmidt, 2019). Fin whales, for example, can reduce the duration and number of their calls and modify their call frequency in the presence of vessel noise. Similar vocal changes have also been observed in blue, north Atlantic right, and humpback whales. If not definitive, the results presented in Chapter Three warrant further investigation into how baleen whales in Placentia Bay might be adjusting their vocalizations in response to vessel noise. Vessel noise has the potential of eliciting physiological reactions, increasing the production of stress-related hormones in baleen whales (Lemos et al., 2022; Pallin et al., 2022; Rolland et al., 2012). So far, evidence of stress responses to underwater noise exposure is limited to north Atlantic right (Rolland et al., 2012), gray (Lemos et al., 2022), and humpback whales (Pallin et al., 2022). My research did not address the physiological effects of vessel noise on cetaceans. However, our current knowledge indicates that physiological stress reactions to vessel noise in cetaceans might be more common in baleen whales than previously thought. Over time, cetaceans visiting busy and fast-developing coastal areas such as Placentia Bay might experience increasing levels of stress.

By disrupting behaviours, masking biologically important sounds, driving changes in vocal activity, and eliciting stress responses, noise pollution can increase the energetic expenditures of individuals, and reduce both their health and reproductive potential in the long time (Kunc et al., 2016). This, in turn, could hinder the recovery of federally protected whale species (Breeze et al., 2022). Chapter Four provides a first estimate of how vessel noise sources are distributed in Placentia Bay, allowing the identification of areas where noise pollution has the potential of triggering the chain of effects described above. A significant portion of the bay is affected by the presence of vessel noise sources, with hotspots of noise emissions located along the commercial shipping lane, within the area used by the salmon aquaculture industry, and along the routes followed by ferries. These hotspots overlap with habitats where cetaceans are frequently observed, highlighting areas of Placentia Bay where the introduction of noise mitigation measures could be most impactful. As vessel noise is directly related to the speed of a vessel, speed regulations are one of the most widespread noise mitigation measures applied to marine mammal habitats in Canada (e.g., Joy et al., 2019; Trounce et al., 2019) and the US (e.g., Laist et al., 2014; ZoBell et al., 2021). Speed regulations have the great advantage of tackling multiple vessel-related impacts at the same time, including abating noise levels at the source, reducing the risk of collisions with marine megafauna, and decreasing greenhouse gas emissions (de Jong et al., 2020; MacGillivray et al., 2020).

Despite the obvious benefits of speed limit regulations, the results I present in Chapter Four indicate that speed limits alone may not be sufficient to tackle the noise emitted by a range of diverse vessels being employed for multiple purposes. Even though all vessel source levels were estimated for a speed of 10 kn, which reduces both the risk of ship strike and noise emissions, large portions of Placentia Bay would still be affected by a high number of vessel transits. Other area based-measures, such as exclusion zones and re-routing might be needed in Placentia Bay in order to achieve a significant reduction in vessel noise. Furthermore, as vessel traffic can undergo substantial changes over a short period, implemented noise mitigation measures would need to be reassessed and possibly adjusted over time in order to preserve their efficacy. Under the expectation that the ONS will introduce thresholds for the emission of underwater noise within all Canadian waters, directing resources towards developing and maintaining a large number of site-specific noise mitigation programs might not be the best strategy for tackling this widespread pollutant at the national level. Establishing incentives for the adoption of noise-reduction technology and establishing noise emission threshold at the source for vessels navigating in Canadian waters might be a more efficient approach for tackling ocean noise pollution.

Vessel traffic and underwater noise levels have been growing globally since the 1950s. Despite the overlap of the study period with the COVID19 Pandemic, vessel traffic within the limits of Placentia Bay has doubled over a five-year period (2019-2023). Ferries were the only class of vessels that showed a decrease in traffic in 2020 and 2021, which were the peak periods of the pandemic. This rate of growth underscores the urgency of establishing a national strategy addressing ocean noise. Currently, Canada’s ONS is in its public consultation phase, and a first draft of the federal action plan will not be released until 2025. This process could result in further delays in addressing noise pollution at a time when noise emission from vessel and other activities are expected to be growing, with the potential of reducing the health of marine habitats and hindering the recovery of protected marine species. In contrast, both the EU and the US have been developing guidelines, protocols, and management products to address ocean noise over the past ten years, and both jurisdictions have already introduced regulations to minimize the impacts of noise within their national waters. In Chapter Four, I discuss the present results in light of the newly introduced EU regulations, showing that current regimes of vessel traffic in Placentia Bay, in which vessel noise exceeds recommended levels over a year, are exceeding 20% of the area. While the regulations and thresholds introduced in other jurisdictions might not be the most suited for the Canadian context, adopting them as interim thresholds could help fill the current regulatory gap, thus preventing additional damage to marine ecosystem while the Canadian strategy is under development.

5.2. Limitations and research recommendations

Integrating unsupervised machine learning techniques in PAM analysis presented several challenges and limitations (Chapter Two). Although the application of UMAP and other ML techniques facilitated the analysis of multiple PAM datasets, the results of these models cannot be interpreted directly, requiring additional data sources in order to identify relationships between characteristics of audio recordings and environmental processes. If ML techniques are to be adopted as a standard tool for marine acoustic analysis, future monitoring programs should consider pairing the deployment of acoustic recorders with other environmental monitoring sensors (e.g., CTDs) which can, for example, provide data to better predict sound propagation. Additional issues arise from limitations in the data structure required by pre-trained audio classification models (Sethi et al., 2020; Chapter Two). The pre-trained audio classification model I used in Chapter 2 (VGGish, Hershey et al., 2017) requires resampling all audio files to a frequency of 8 kHz, limiting the number of cetacean species that could be included in the analysis. However, departing from the use of a pre-trained classification model, and applying UMAP directly to the acoustic metrics of interest (i.e., 1/3 octave bands) allowed me to overcome the 8 kHz frequency limitation, and resulted in a more versatile and simplified analytical approach (Chapter Three).

The availability of marine mammal observations (both visual and acoustic) within the study area is limited. The consequences of this limitation is present in all three research chapters (Chapters Two, Three, and Four), and the analysis I conducted would benefit from more robust estimates of the distribution, abundance, and habitat use of cetaceans in Placentia Bay. In Chapter Two, the performance of VGGish and UMAP in identifying humpback whale sounds could have been improved with a larger dataset of labeled vocalizations. In Chapter Three, the small number of fin whale vocalizations detected during the study period was not sufficient to assess vocal changes in fin whale calls in response to increasing intensity of vessel noise. In Chapter Four, due to the relatively small number of marine mammal observations, I could not derive reliable species-specific population-density estimates. Future studies and conservation efforts should aim at increasing the spatial and temporal coverage of marine mammal observations in the region. One solution could be introducing and supporting a citizen science program for the systematic collection of marine mammal sightings. Citizen science programs have been successful in informing research and policy making relative to the protection of marine mammal species in different parts of the world (e.g., Embling et al., 2015; Harvey et al., 2018; Tonachella et al., 2012). In the context of Placentia Bay, establishing a regular and long-term monitoring program would help support studies assessing noise impacts and risk of ship strike for marine mammals, and inform the design of targeted mitigation measures to protect endangered marine mammal species.

The approach I followed when mapping the distribution of vessel sources within Placentia Bay (Chapter Four) is a simplified approach in comparison to other studies focused on predicting and mapping underwater noise levels from vessels. Such approaches provide ambient noise estimates obtained from the use of underwater acoustic propagation models accounting for the acoustic properties of the environment (e.g., substrates, water column properties) and for the contribution of natural factors (e.g., wind) . These models yield more accurate ambient noise estimates, however, due to their high demand in terms of data and processing power, the results are usually snapshots of vessel noise over a short period of time (e.g., one month or one year). Furthermore, the approach relies on the acquisition and processing of AIS data to extract information on the distribution and behaviour of vessels, which could not be acquired for Placentia Bay during the time of this study. Instead, I focussed on using freely available AIS-derived maps (GMTDS, 2022) and a source level predictive model (MacGillivray et al., 2022) to assess changes in the spatial distribution of vessel noise sources. These methods may be more accessible to users without access to AIS data, can be scaled to fit multiple time intervals (e.g., days, weeks, months) introducing a temporal dimension to vessel noise, and the results can be used as a starting point for more complex acoustic propagation studies. Mapping cumulative noise sources could be a valuable tool for assessing how changes in vessel traffic can result in changes in the distribution of anthropogenic noise within important marine environments, allowing regulators to adaptively modify noise mitigation measures.

My dissertation focuses on underwater radiated noise from vessels, and I did not consider other anthropogenic noise sources (e.g., seismic surveys, aircraft overflights, noise from construction sites) that might have contributed to the observed increases in ambient noise described in Chapter 3. The contribution of aircraft overflights to underwater noise pollution is becoming more apparent, especially in marine coastal environments close to airports (Erbe et al., 2018). Airplanes, helicopter traffic servicing oil and gas and other at sea operations, and military aircrafts are all contributors to underwater noise levels warranting further investigation (Luksenburg & Parsons, 2007). Future studies should investigate the potential for aircraft noise to be affecting coastal marine habitats on the island. In addition to these considerations, future research should consider the occurrence and impact of anthropogenic stressors other than underwater noise from vessels. Noise pollution has the potential to interact with other stressors (e.g., light pollution, environmental pollutants, pathogens), resulting in a range of possible outcomes, including synergistic and antagonistic effects (Halfwerk & Jerem, 2021; Simmonds, 2018; Thomsen & Popper, 2024).

5. 3. Conclusion

Addressing the global biodiversity crisis requires prompt action aimed at mitigating, and ideally eliminating, the impacts of anthropogenic activities on marine and terrestrial ecosystems. As an anthropogenic stressor, underwater noise in the ocean has the potential of driving changes in the composition of marine communities, can prevent the recovery of protected species, and affect recruitment of commercially important species. However, our understanding of the mechanisms through which noise interacts with marine animals is still limited. Only a few species of marine mammals, fish, and invertebrates have been investigated, and even fewer studies have assessed how noise can impact populations and communities. My research contributes to increasing our understanding of how noise from vessels is a pervasive pollutant in Canadian coastal environments, overlapping with important marine mammal habitats, and reaching levels that might negatively affect their behaviour and health. The single species and a single stressor (underwater vessel noise) modelling approach is a step towards describing the complex effects that noise can have on marine communities in combination with other anthropogenic stressors. Future studies should consider the possible interactions among multiple stressors (e.g., light pollution, chemical pollution), and include multi-species assessments considering not only marine mammals, but also their prey.

Without the introduction of mitigation measures, underwater noise level will most likely continue to rise globally. One of the most concerning results of my research is that vessel traffic within the study area, at least for the five vessel classes I considered, has doubled between 2019 and 2023. Considering that drafting the ONS required more than eight years (2016-2024), and that the corresponding federal action plan is not close to implementation, rising underwater noise levels will have the potential of becoming a significant threat to marine life in Placentia Bay as well as in other parts of Canada's coastal waters before national regulations are introduced. This suggests a need for the introduction of interim noise emission thresholds in combination with guidelines on how to assess and reduce anthropogenic noise pollution in the ocean. One possible direction could be the endorsement of thresholds and regulations that have already been introduced in other international jurisdictions. This would not only provide an immediate short-term response to the environmental threats posed by anthropogenic noise, but also contribute to the development of a shared international approach to its mitigation in the long term.

5. 4. Chapter 5 Bibliography

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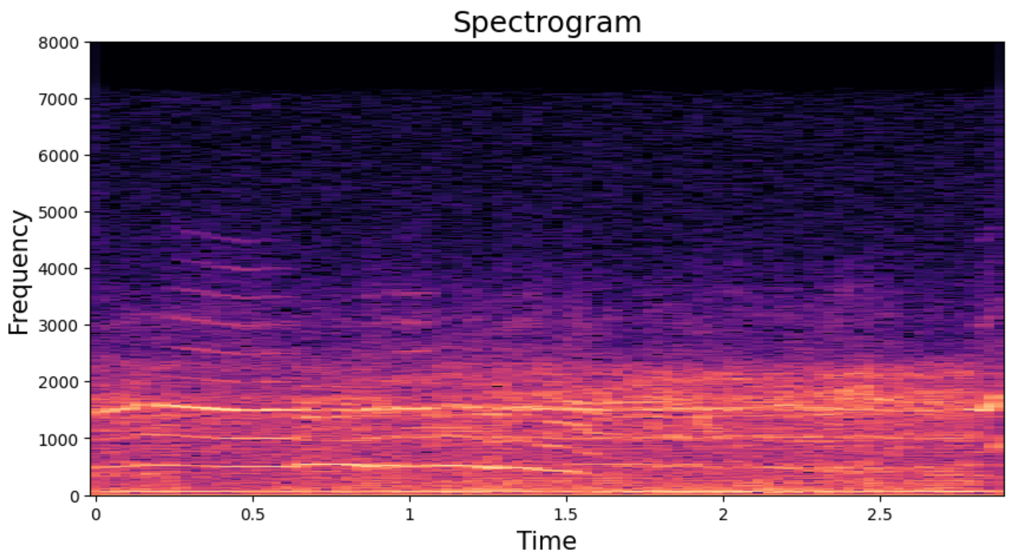
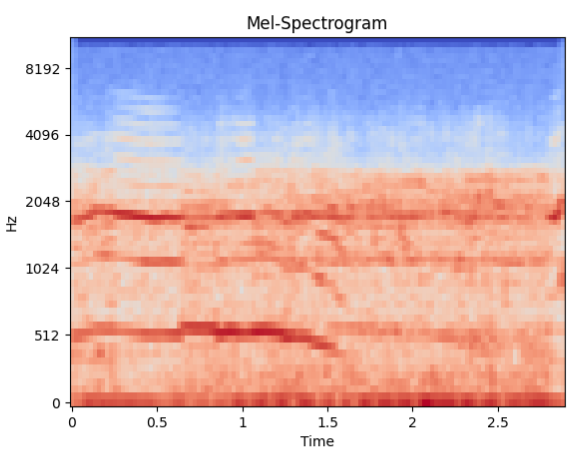
Appendix A - Spectrograms & Log-Mel Spectrograms by Species

Spectrograms and Mel-spectrograms of audio samples from the WMD dataset for 12 marine mammal species. For each example, the sample ID for the audio file corresponds to the record ID from the WMD.

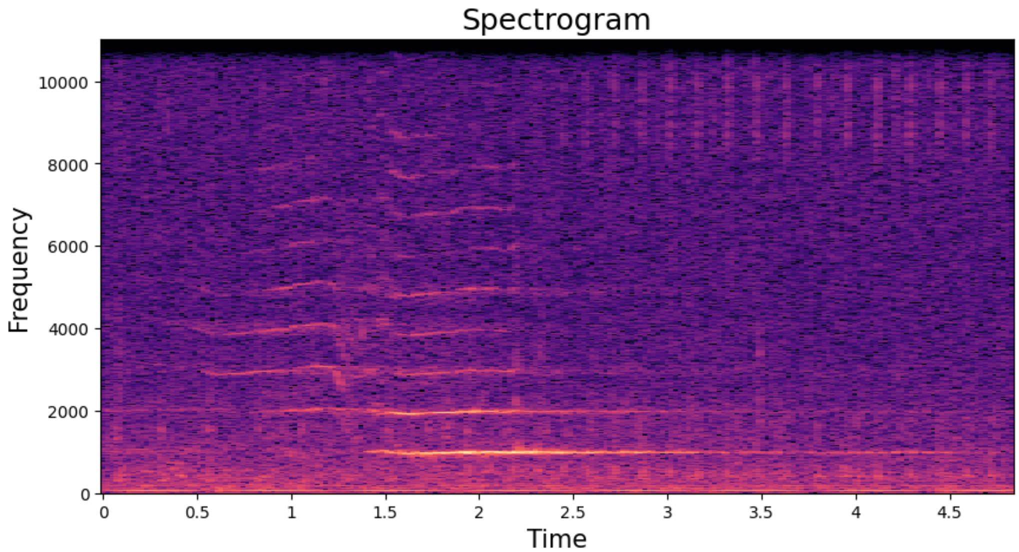
All spectrograms were computed with nftt = 2048 and hop length = 512.

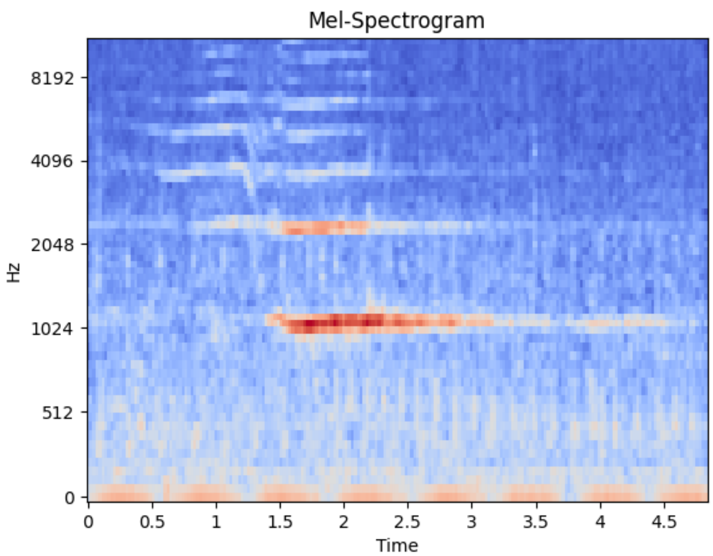
Sample 1: Humpback whale
WMD Sample ID: 5801801P



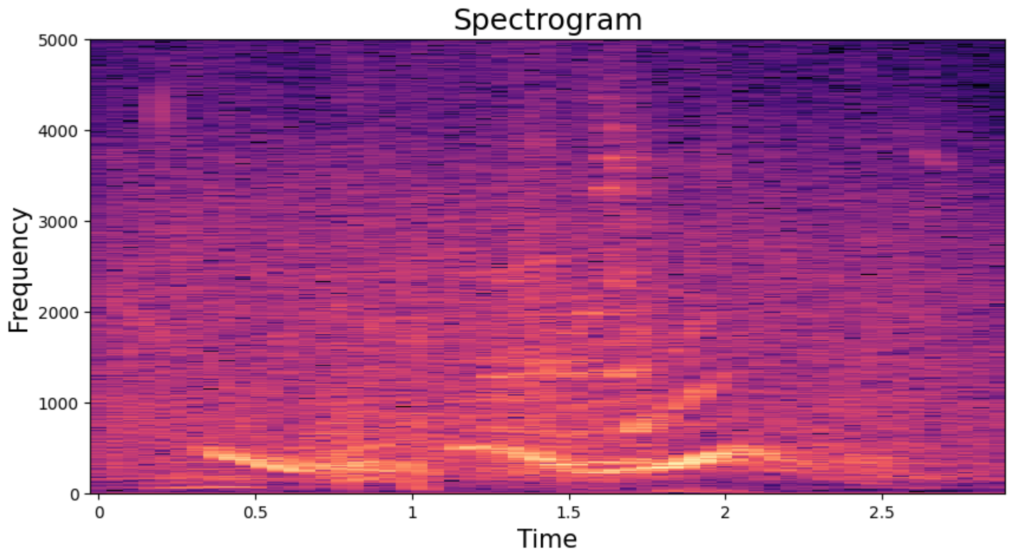


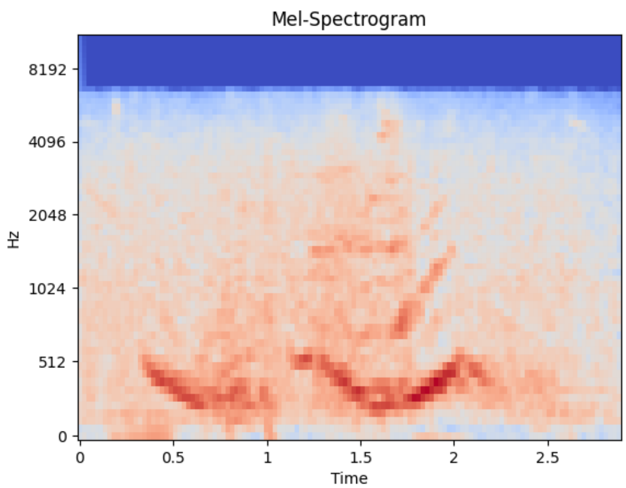
Sample 2 Killer Whale
WMD Sample ID: 6002602S



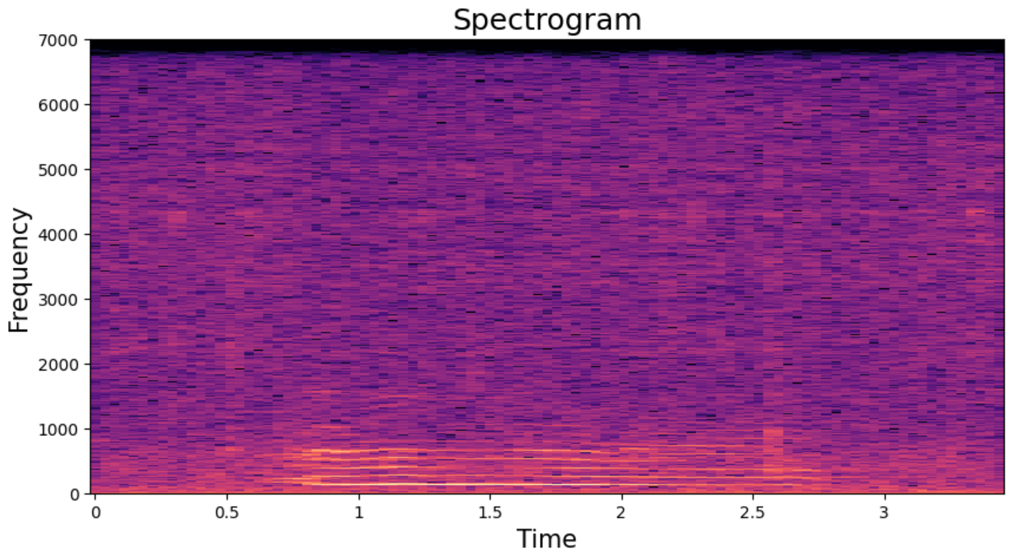


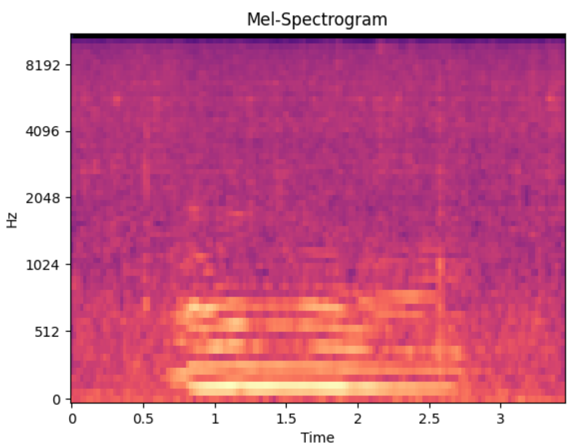
Sample 3: Bowhead Whale
WMD Sample ID: 80001004



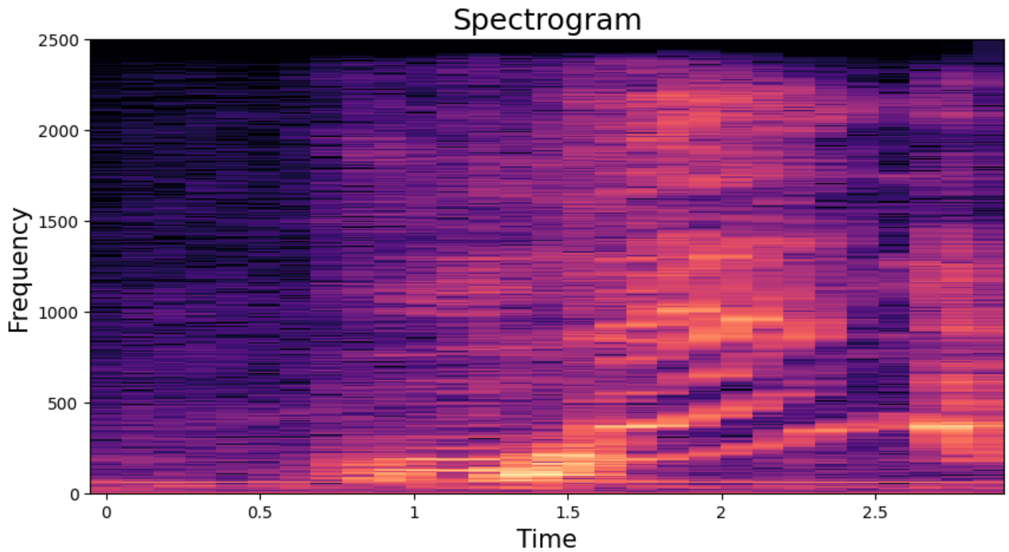


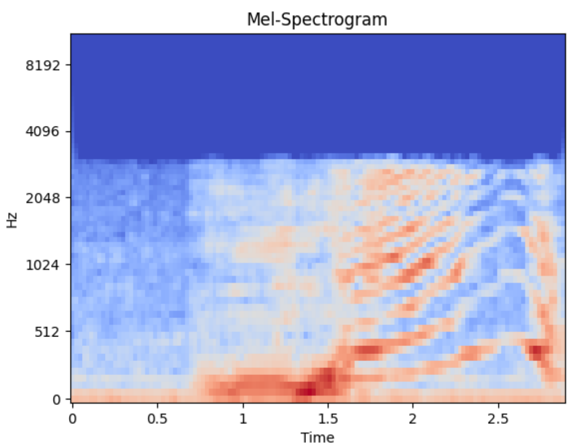
Sample 4: North Atlantic Right Whale
WMD Sample ID: 8101301D



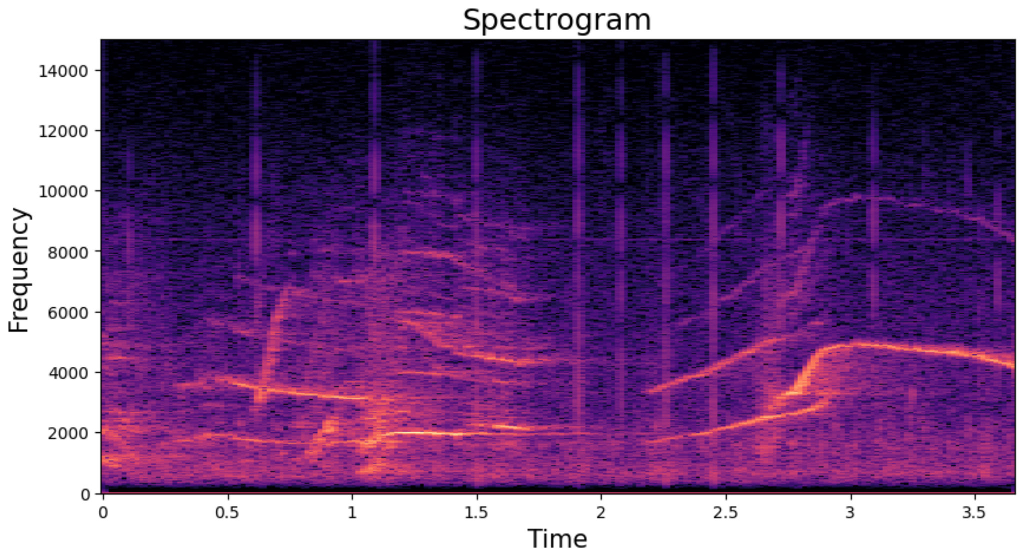


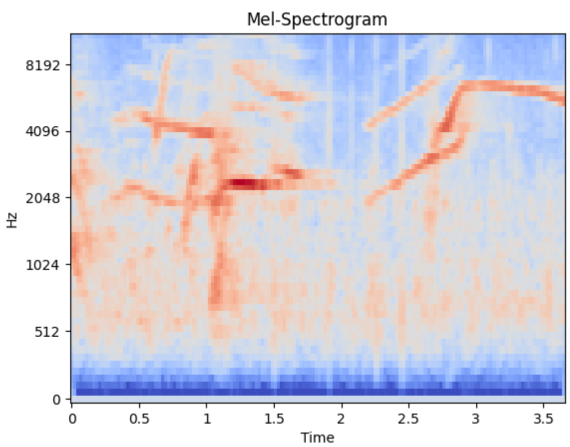
Sample 5: Southern Right Whale
WMD Sample ID: 7900200M



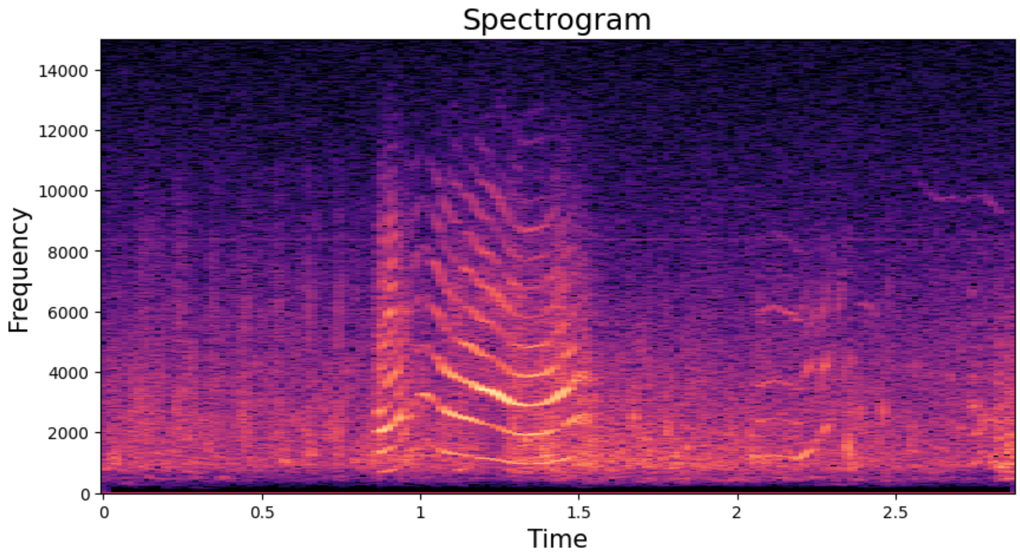


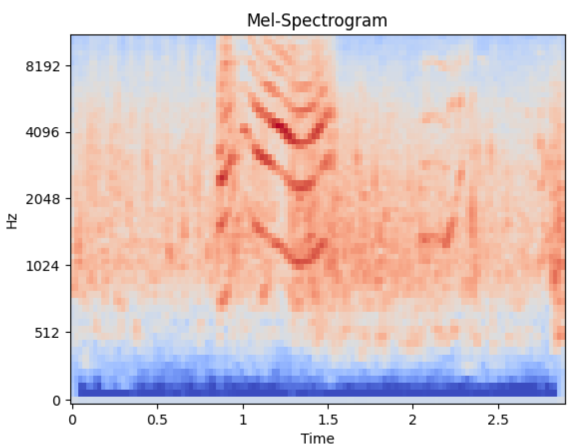
Sample 6: Long Finned Pilot Whale
WMD Sample ID: 54024003



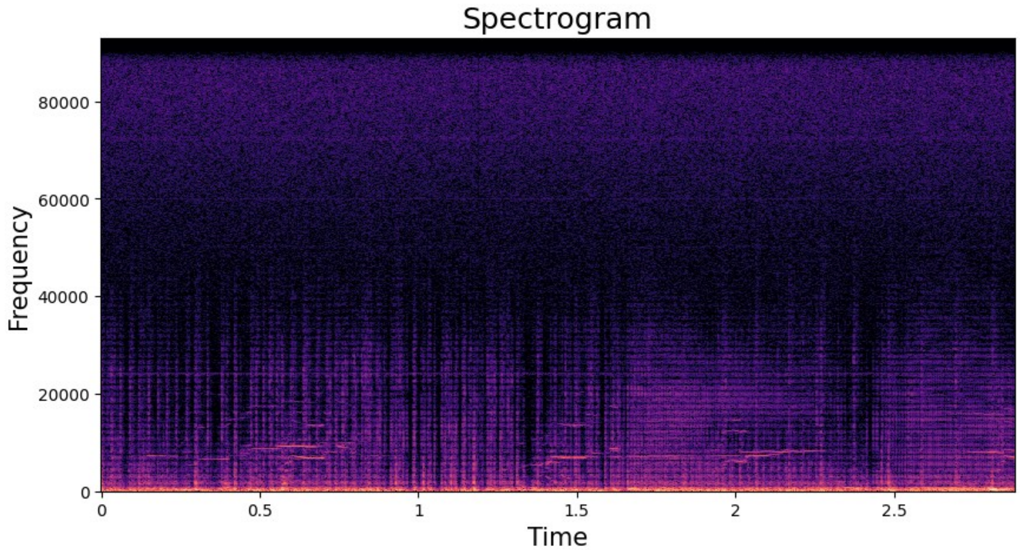


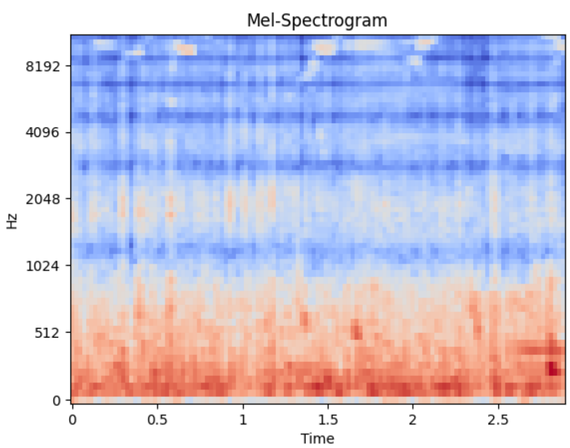
Sample 7: Short finned pilot whale
WMD Sample ID: 57021004



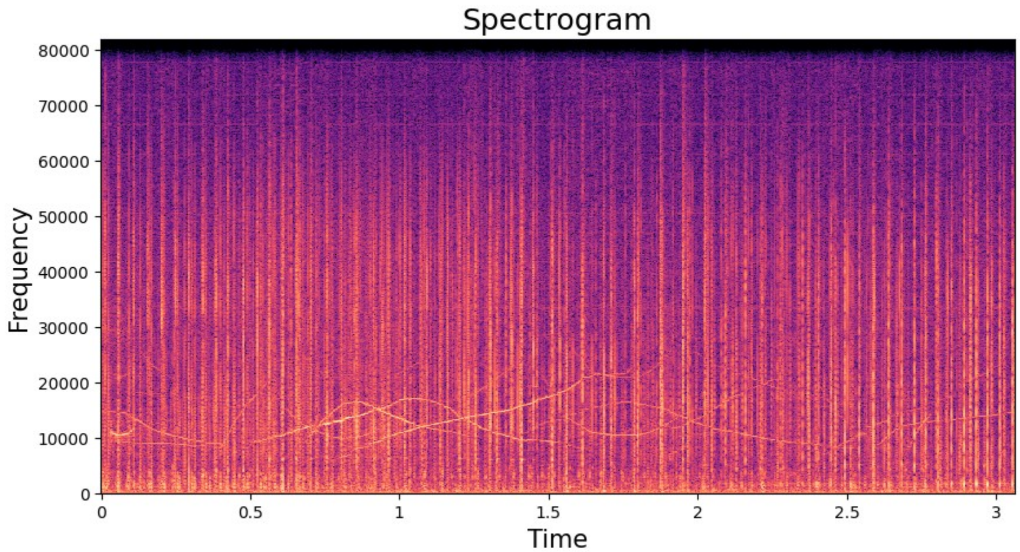


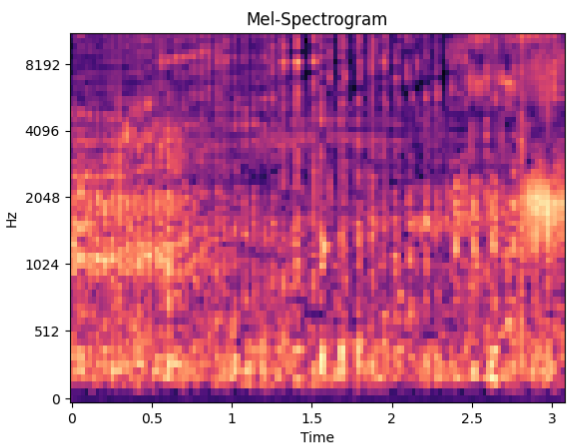
Sample 8: Rough Toothed Dolphin
WMD Sample ID: 8501301K



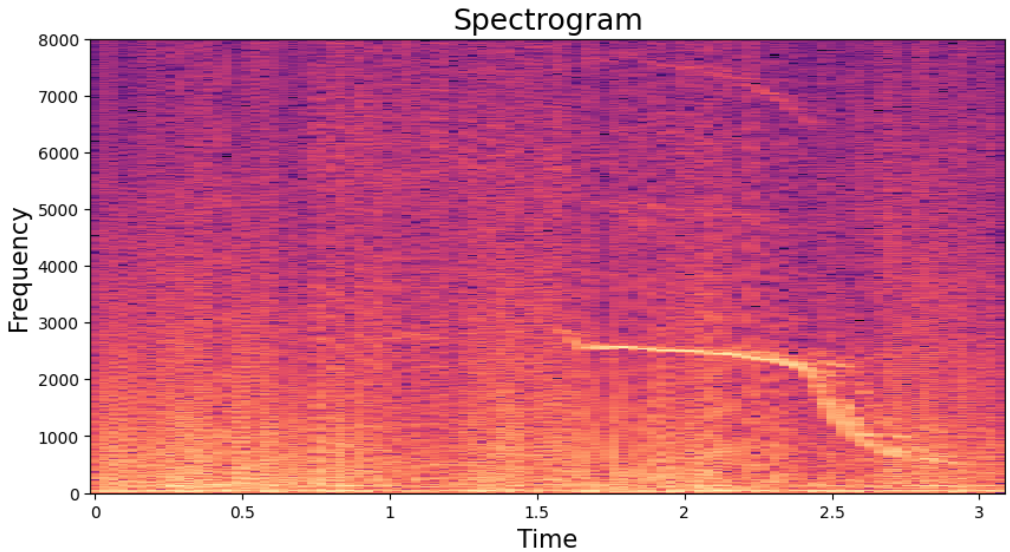


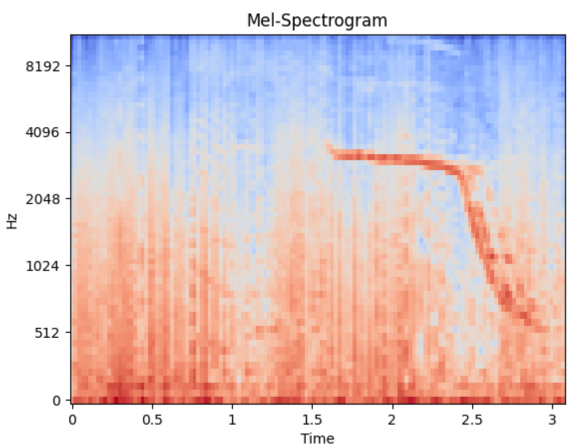
Sample 9: Clymene Dolphin
WMD Sample ID: 8300601S



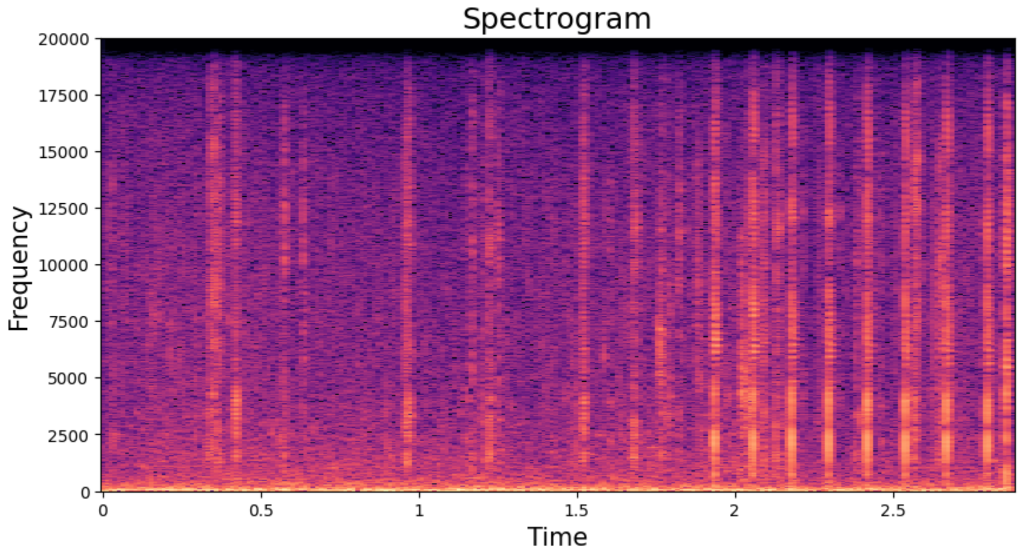


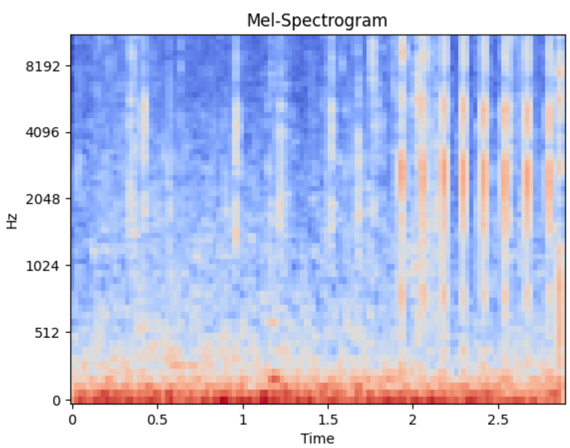
Sample 10: Beluga whale
WMD Sample ID: 62019004



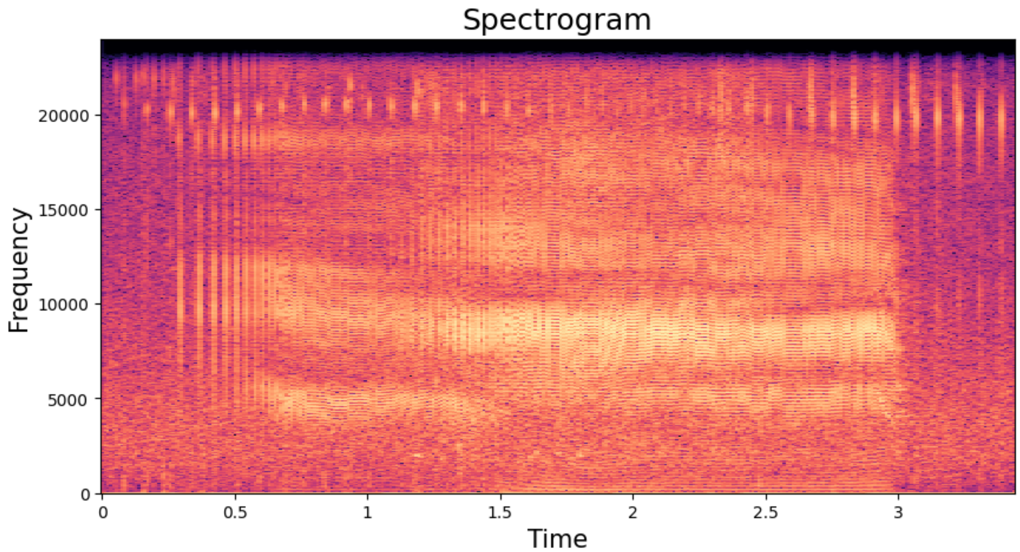


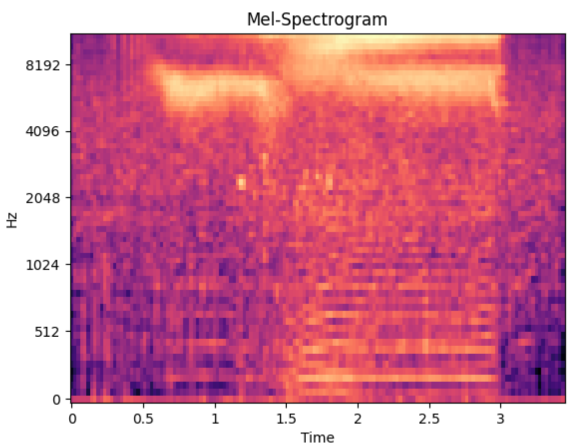
Sample 11: Sperm whale
WMD Sample ID: 72009001





Sample 12: Bottlenose dolphin
WMD Sample ID: 94201044

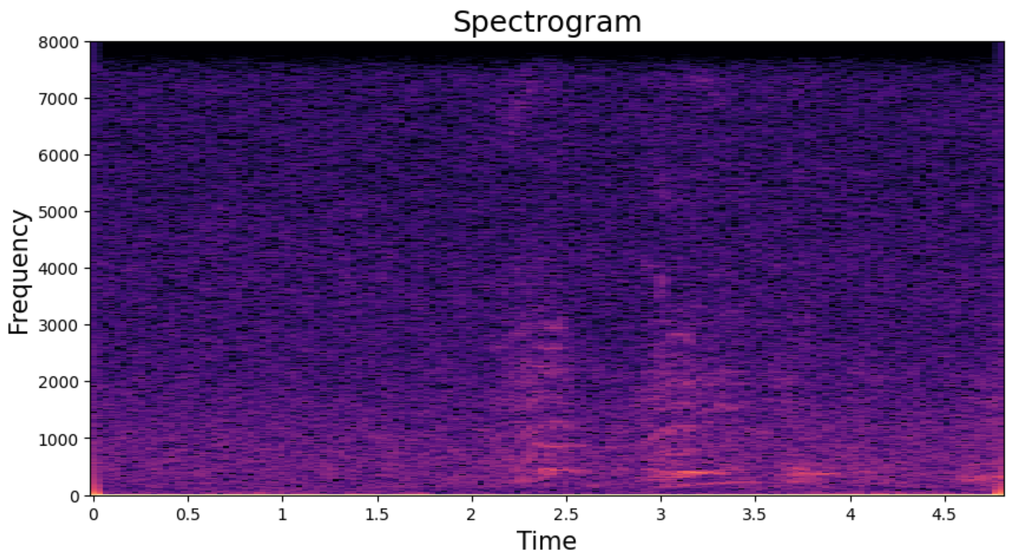


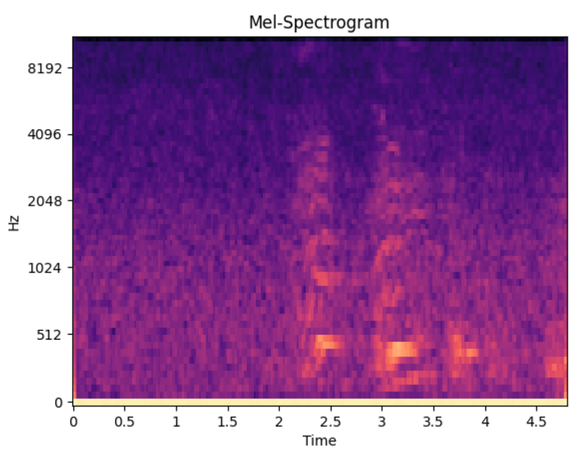


A1.2: Humpback Whale Vocalizations Spectrograms & Log-Mel Spectrograms

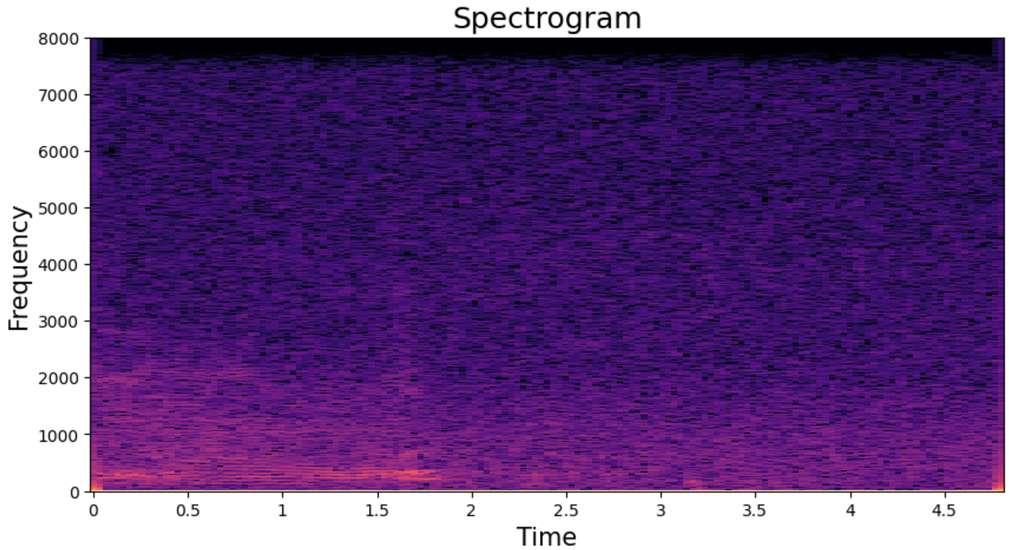
This section contains six example spectrograms of humpback whale vocalizations from the PBD dataset, and the corresponding Mel-spectrograms used as input in VGGish. The spectrograms and Mel-spectrograms are computed using the librosa python package version 0.10.1 (DOI:10.5281/zenodo.8252662) with n_ftt = 2048 and hop_size = 512.

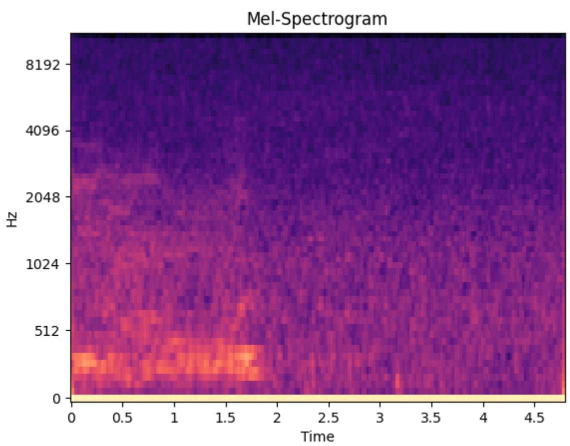
Sample 1: July 11 2019 – 3:45:30.000



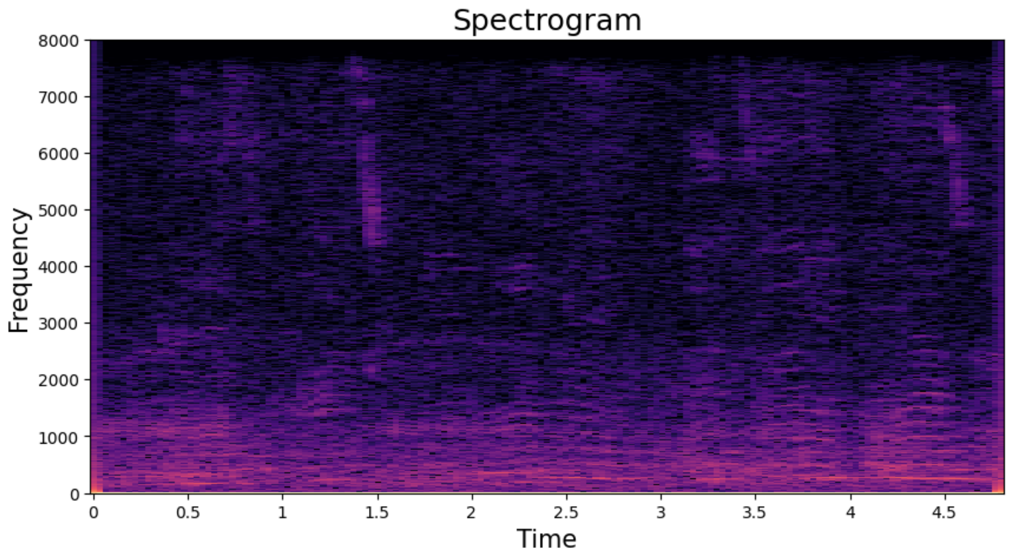


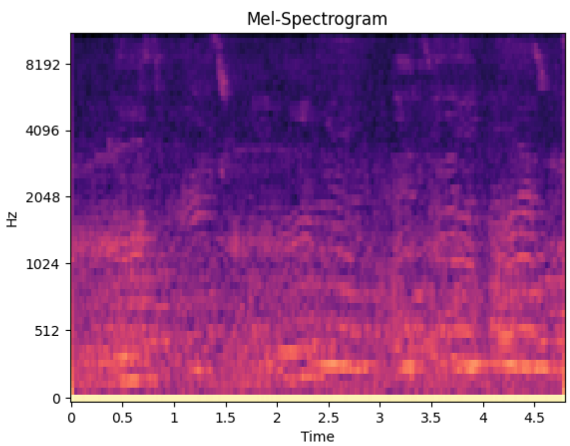
Sample 2: July 11 2019 – 3:45:34.800



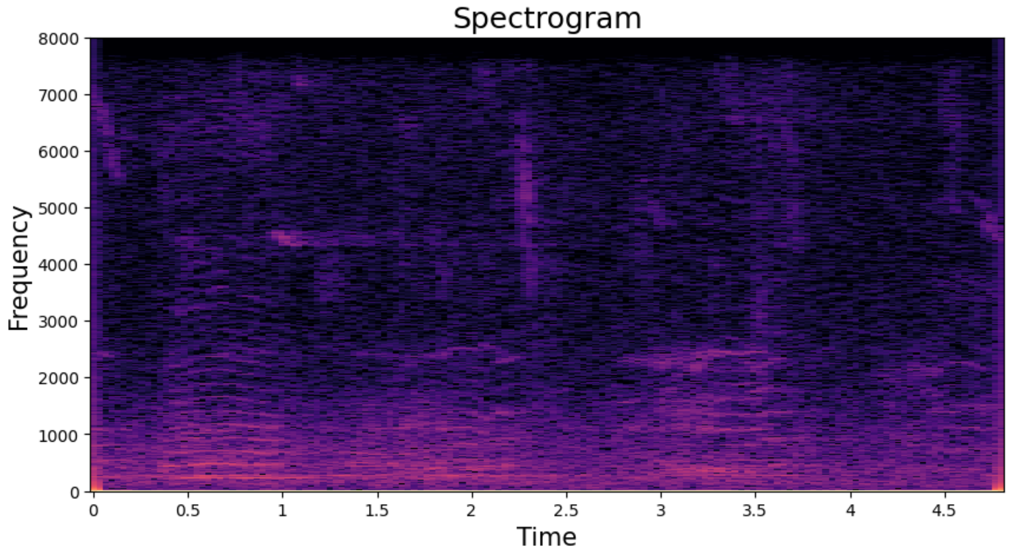


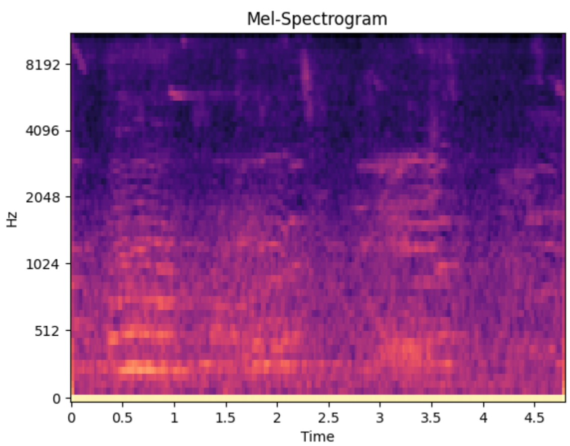
Sample 3: July 17 2019 – 2:47:13.000



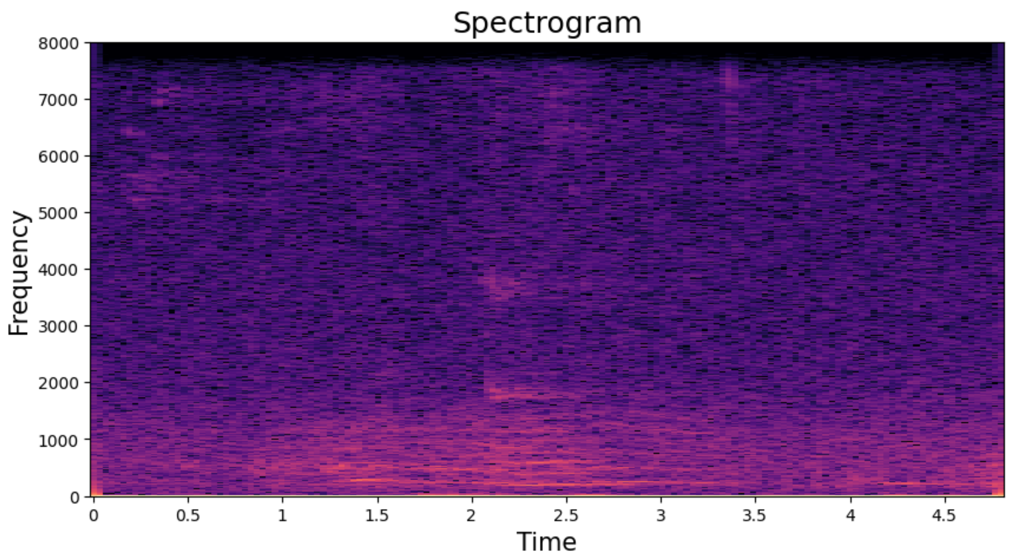


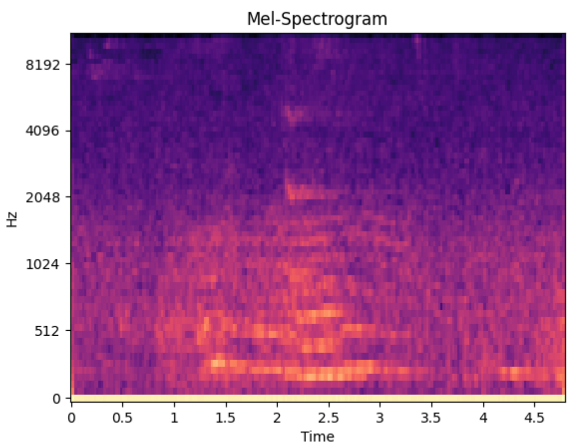
Sample 4: July 17 2019 – 2:47:17.800



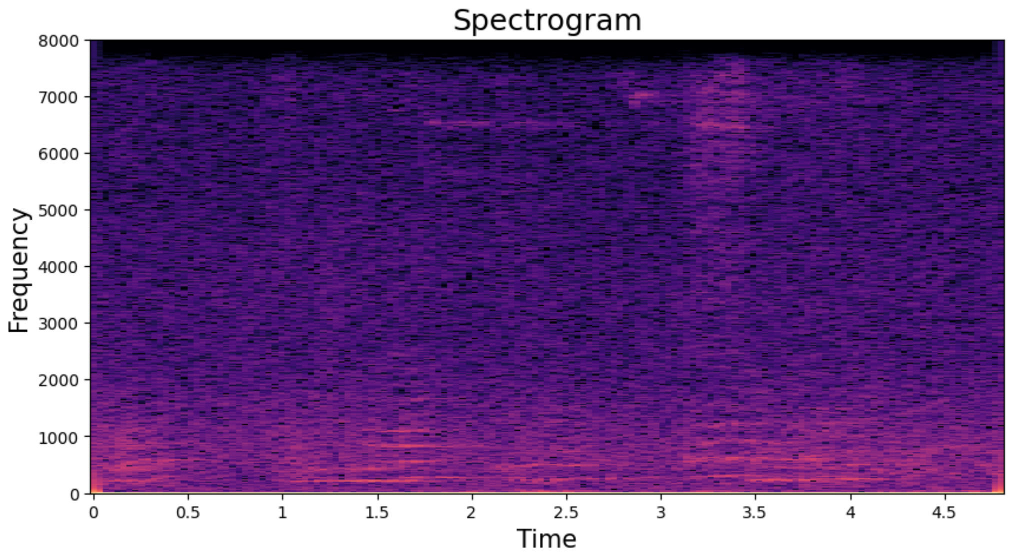


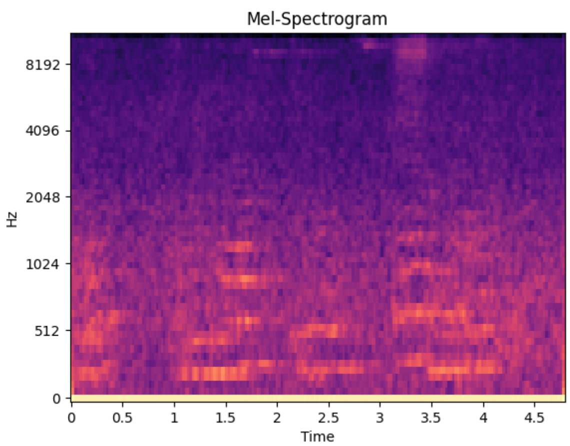
Sample 5: July 21 2019 – 21:11:19.000





Sample 6: July 21 2019 – 21:11:19.000



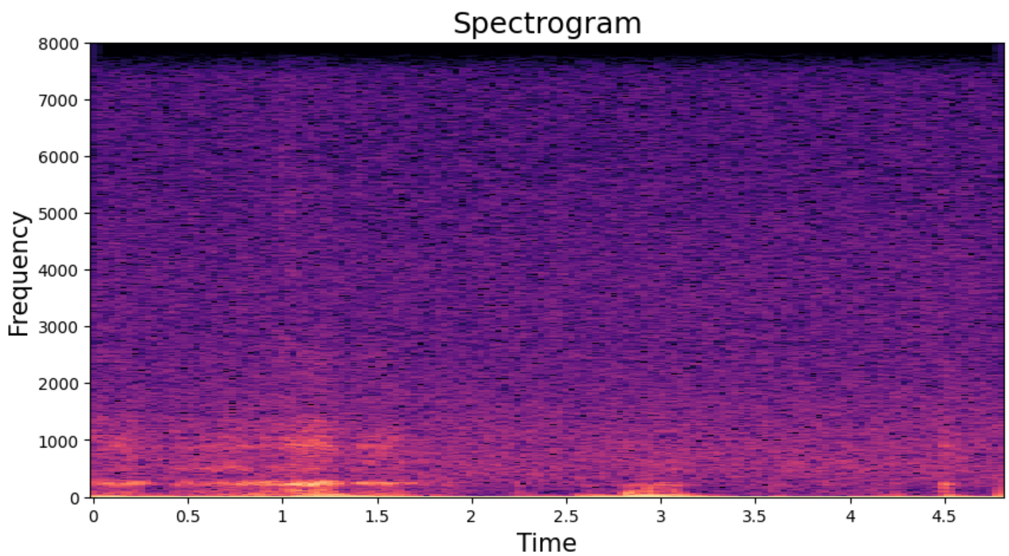


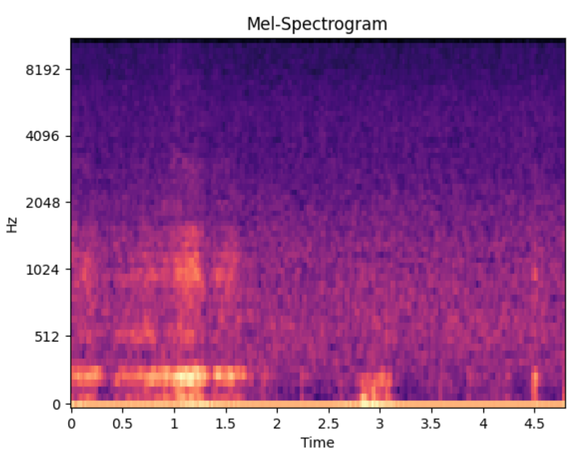
S1.3: August predictions

This section contains four example spectrograms and Mel-spectrograms of humpback whale detections from the BRF model trained on the PBD dataset: two true positives and two false positives are shown below.

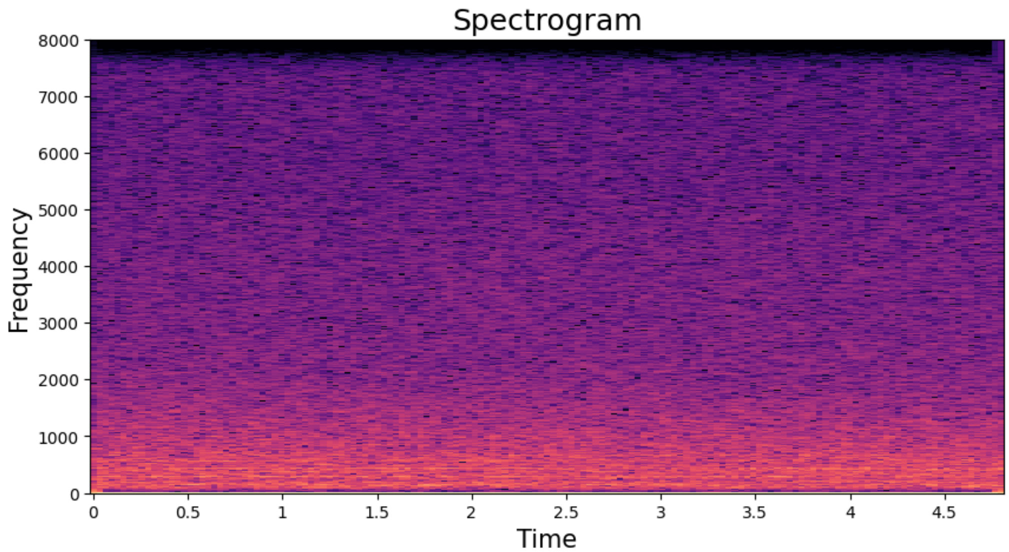
The spectrograms and Mel-spectrograms are computed using the librosa python package version 0.10.1 (DOI:10.5281/zenodo.8252662) with n_ftt = 2048 and hop_size = 512.

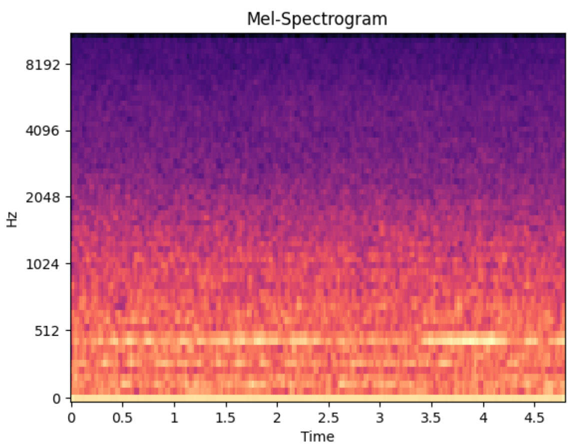
False positive 1: August 2 2019 – 19:13:53.000



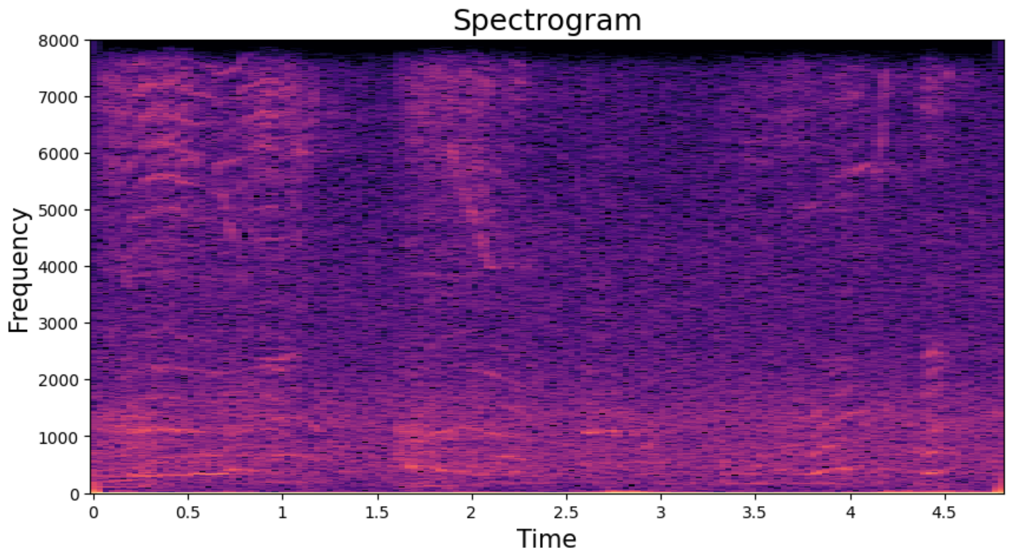


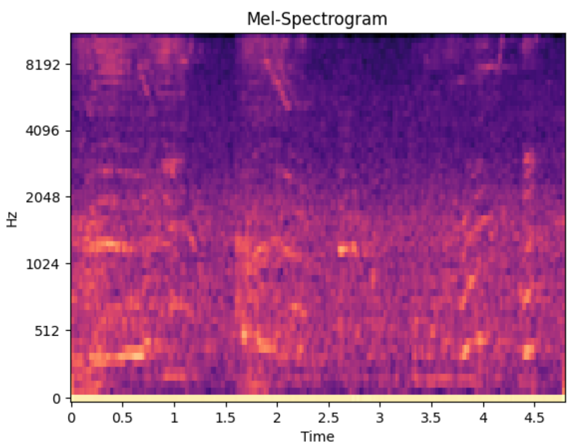
False positive 2: August 24 2019 – 18:16:58.800



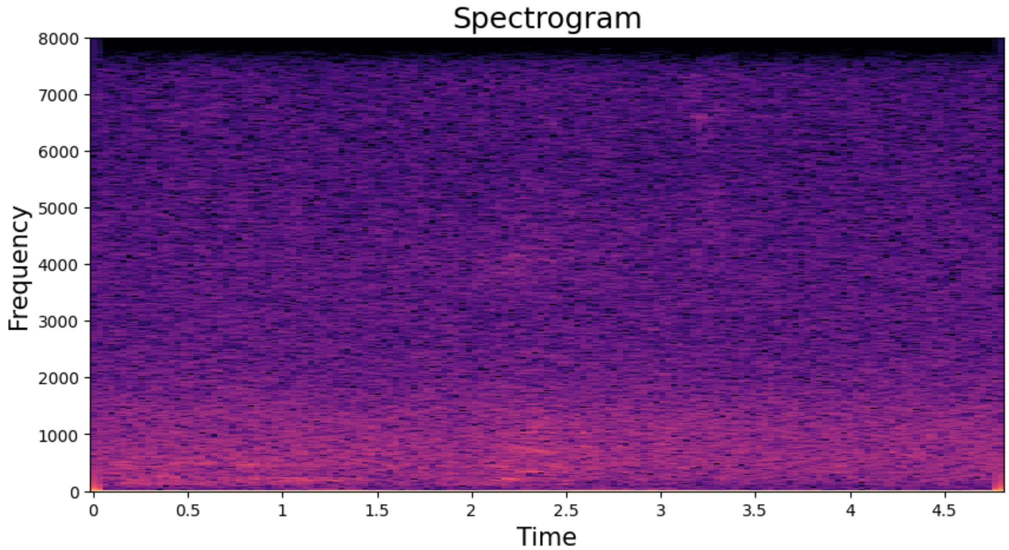


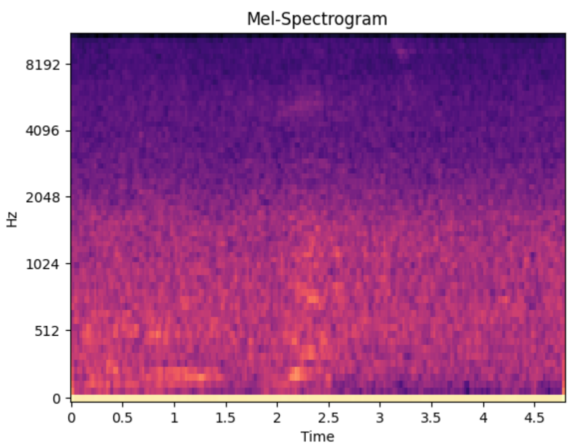
True positive 1: August 23 2019 – 8:41:09.000





True positive 2: August 23 2019 – 8:41:09.000





Appendix B - Violin Plots, Confusion Matrices, and additional UMAP visualizations.

Violin Plots

The violin plots below compare the two UMAP dimensions generated as embeddings to the acoustic features generated by VGGish for different labels assigned to the acoustic samples from the Watkins Marine Mammal Sounds Database (WMD). The labels include marine mammal taxonomic groups (Fig B.1), marine mammal species (Fig B.2), and the locations for humpback and killer whales (Fig B.3).

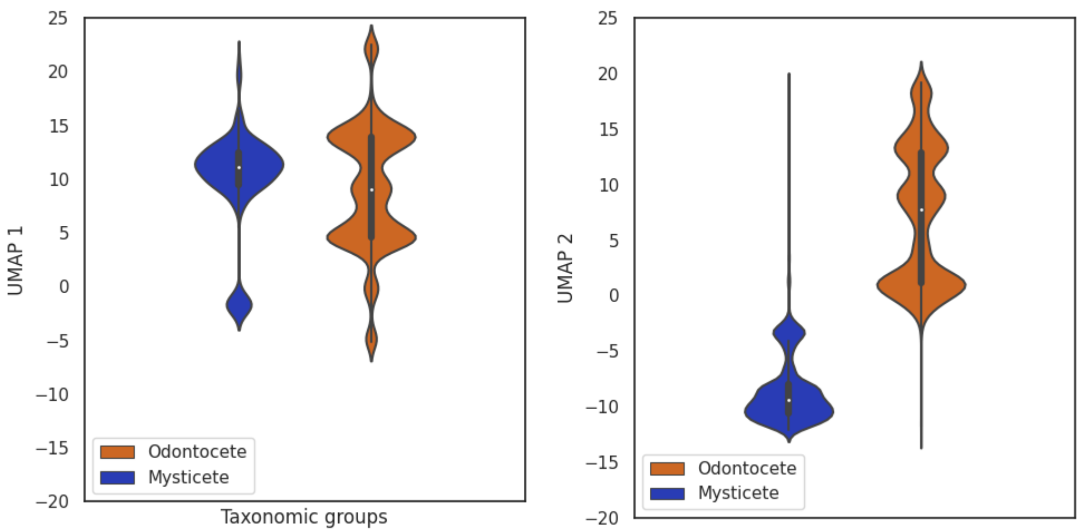


Figure B.1 Violin plots showing the distribution of UMAP dimensions for the taxonomic group label of the WMD dataset.

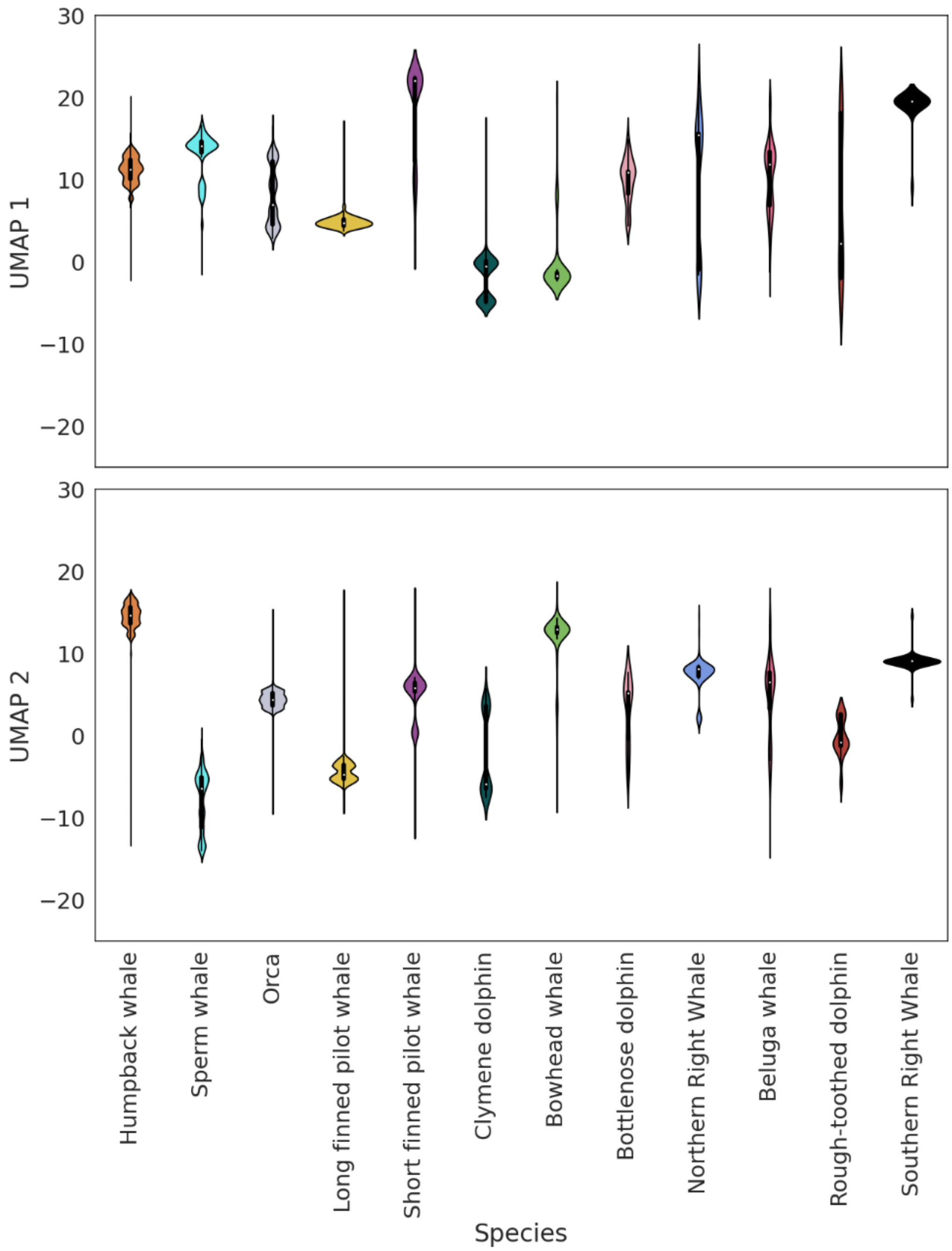


Figure B.2 Violin plots showing the distribution of UMAP dimensions for the species label of the WMD dataset.

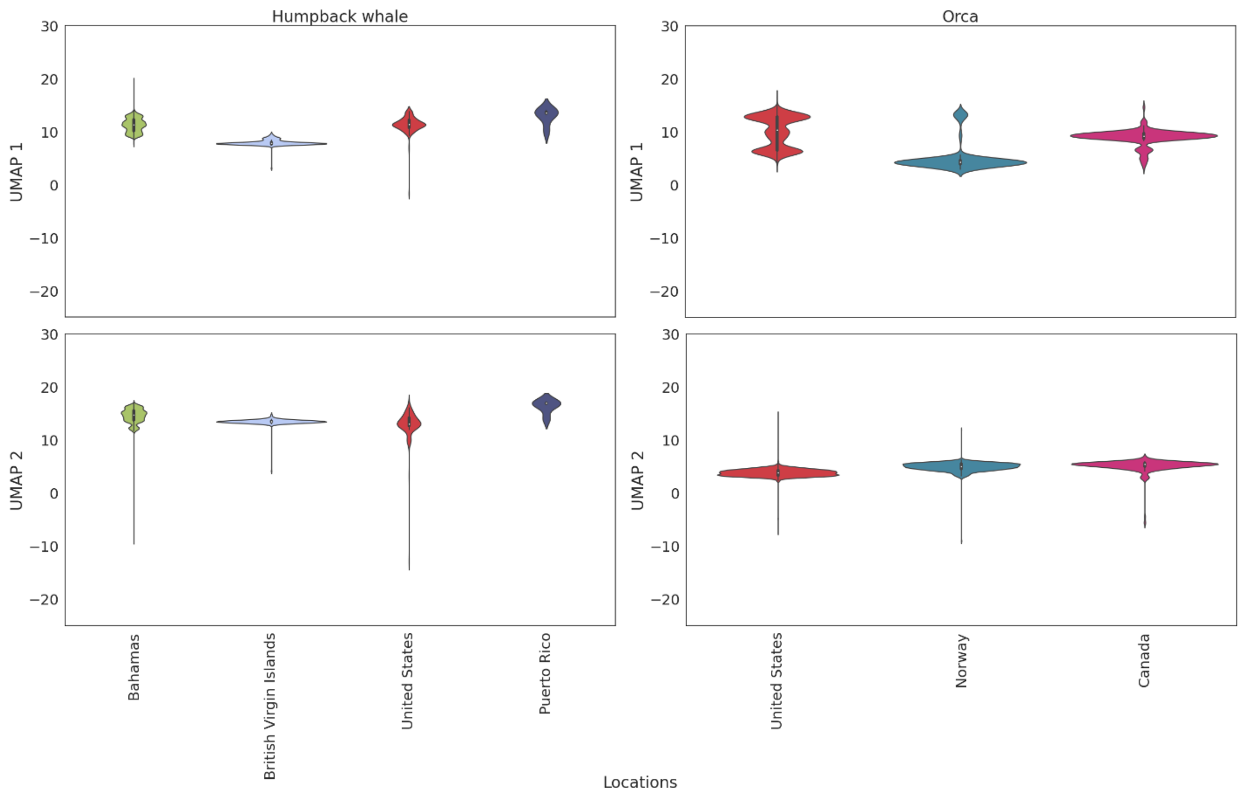


Figure B.3. Violin plots showing the distribution of UMAP dimensions for humpback whales and orcas according to their sampling location.

Confusion Matrices

The confusion matrices reported below report the performance of the balanced random forest classifiers on the testing dataset relative to wind speed (Fig B.4), surface temperature (Fig B.5), current speed (Fig B.6), and presence of humpback whales (Fig B.7).

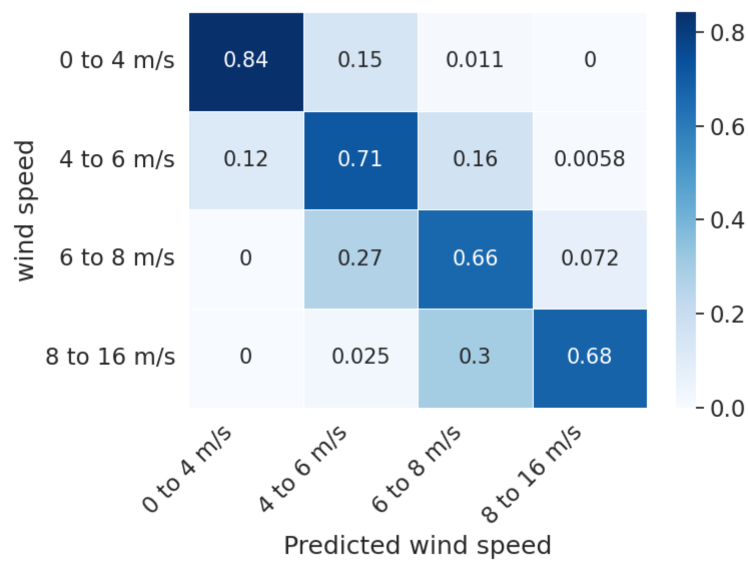


Figure B.4. Confusion matrix of the testing dataset for the wind speed labels.

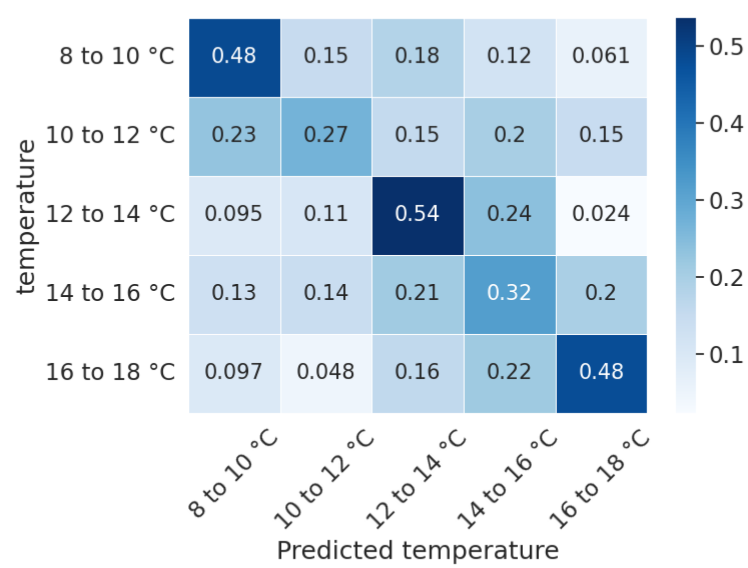


Figure B.5 Confusion matrix of the testing dataset for the surface temperature labels.

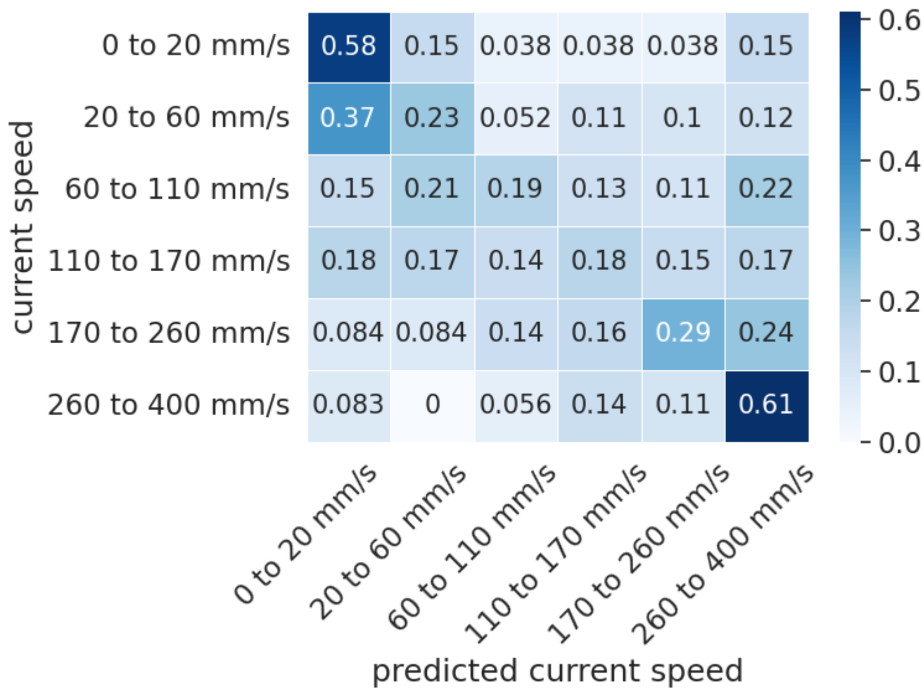


Figure B.6. Confusion matrix of the testing dataset for the current speed labels.

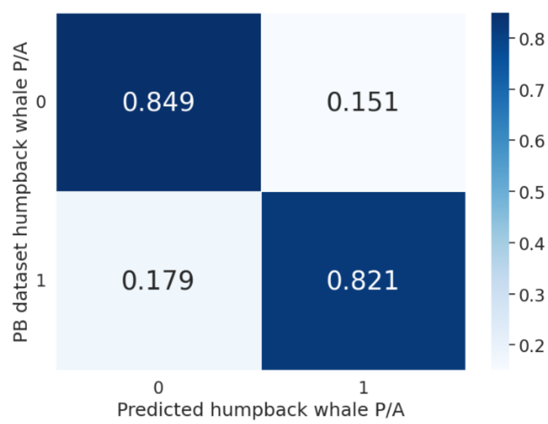


Figure B.7. Confusion matrix of the testing dataset for the humpback whale presence labels.

Additional UMAP Visualizations:

UMAP visualizations for two of the oceanographic variables (Fig 1): surface temperature (Fig B.8) and current speed (Fig B.9).

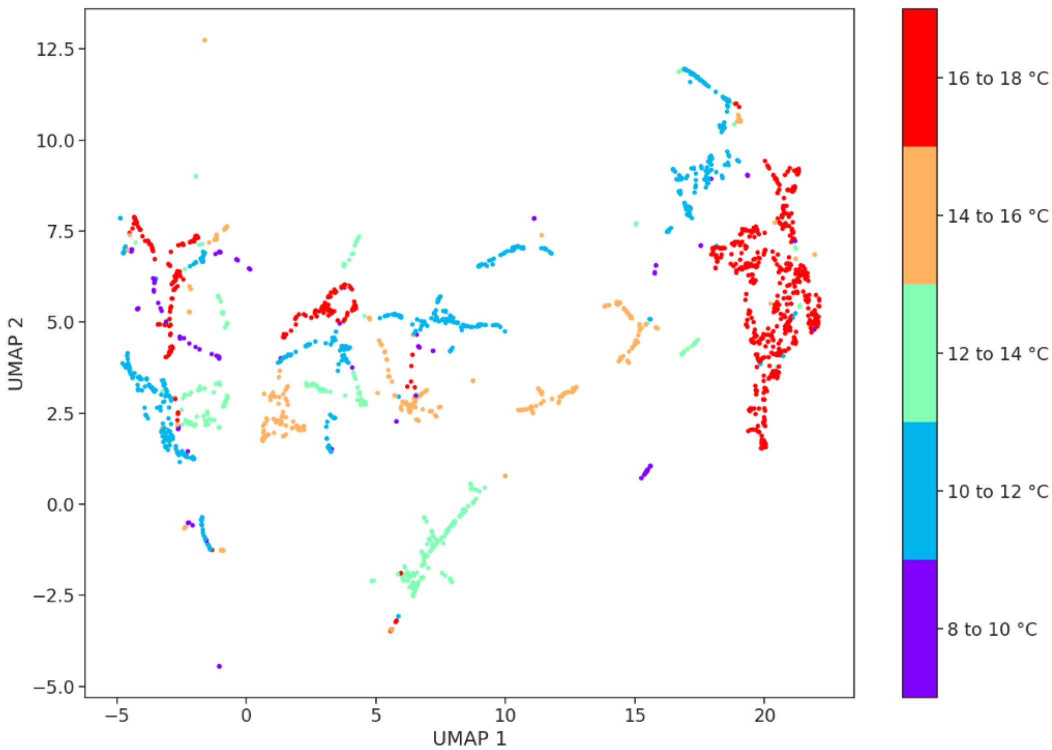


Figure B.8 UMAP visualization of the surface temperature labels.

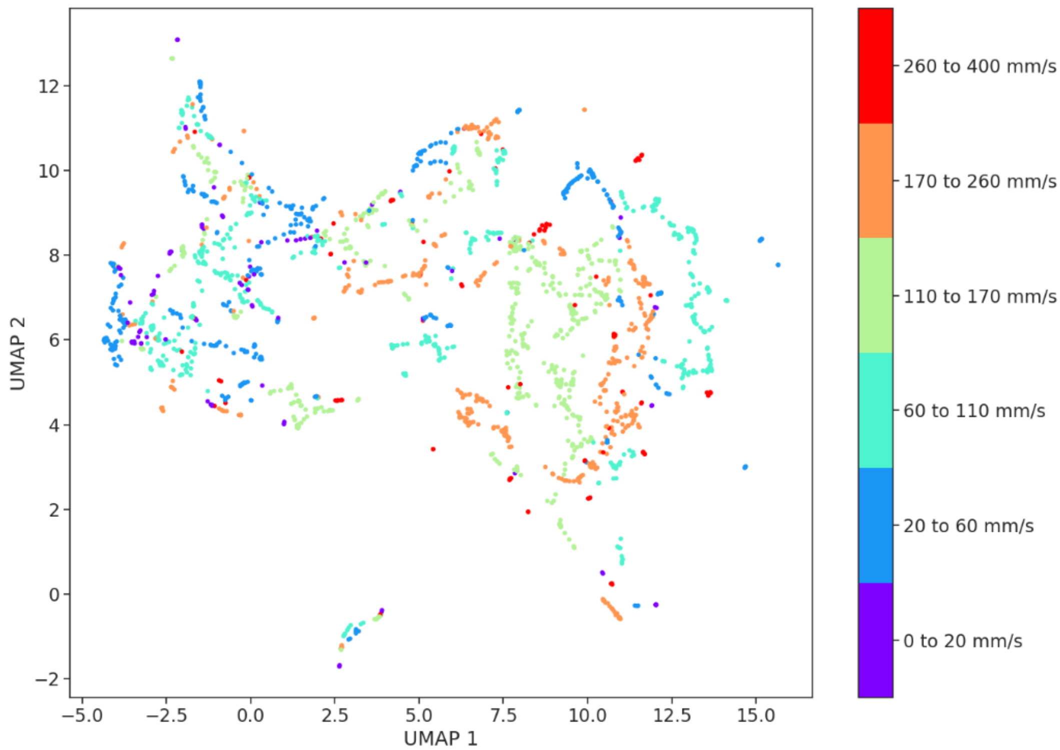


Figure B.9 UMAP visualization of the current speed labels.

Appendix C - Cluster Content Examples.

This appendix contains additional information relative to the clustering results presented in Chapter Three of the dissertation. The appendix includes plot of the UMAP visualizations and results of HDBSCAN we performed on the initial subset of 30 randomly selected days (Fig. A1, A2, & Table A1), and example spectrograms for the 19 clusters we identified in the second run of the analysis (Figs. A3 to A32).

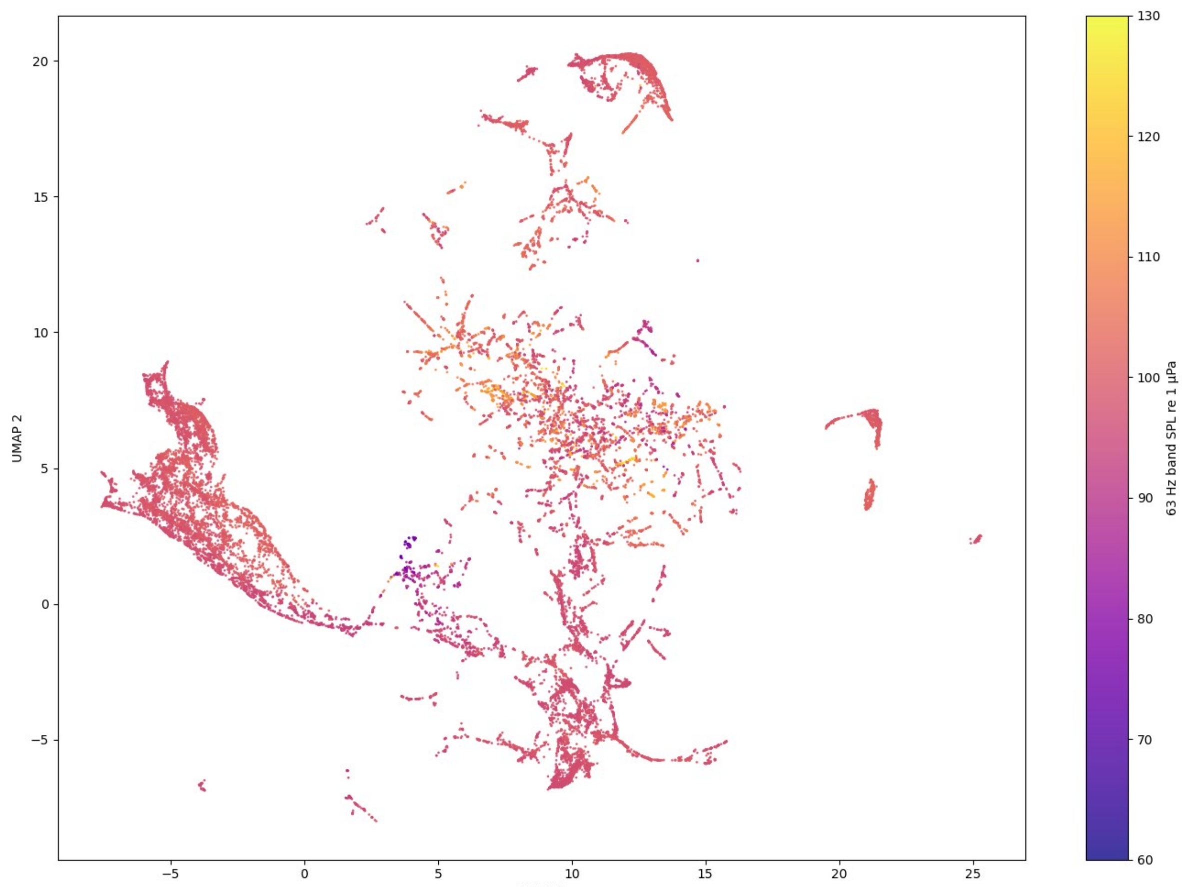


Figure C.1. Results of UMAP 2D dimensionality reduction applied to the random subset of 30 days. Samples are coloured according to their 63 Hz band SPL.

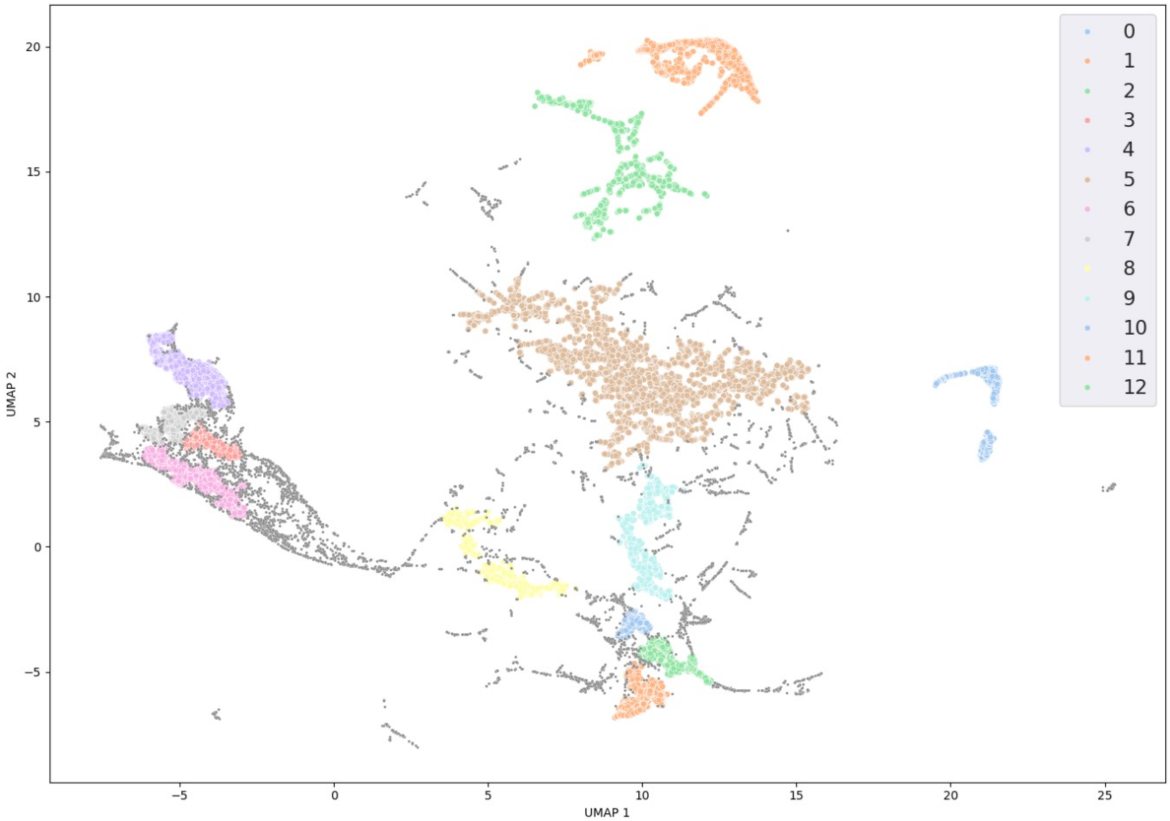


Figure C.2. HDBSCAN clusters plotted over the UMAP distribution of the random subset of 30 days. Samples are coloured according to their 63 Hz band SPL. The gray dots indicate samples identified as outliers by HDBSCAN.

Table C.1. Summary of the first round of HDBSCAN clustering performed on a 30 days subset from the two PAM monitoring stations. The clusters correspond to the HDBSCAN clusters shown in Fig. A2.

Clusters	Station	n samples	Label
-1	BU	3687	outliers
	RI	3390	
0	BU	1	vessel noise 1
	RI	821	
1	BU	2088	vessel noise 2
	RI	5	
2	BU	1087	vessel noise 3
	RI	18	
3	BU	399	mooring noise 1
4	BU	1871	mooring noise 2
5	BU	1504	vessel noise 4
	RI	2313	
6	BU	1258	mooring noise 3
7	BU	653	mooring noise 4
8	BU	22	mooring nosie 5
	RI	474	
9	BU	17	vessel noise 5
	RI	1036	
10	RI	436	vessel noise 6
11	RI	1235	vessel noise 7
12	RI	783	vessel noise 8

Cluster Example Spectrograms

Cluster 0 - Mooring Noise 1

Number of samples

BU: 0 RI: 554

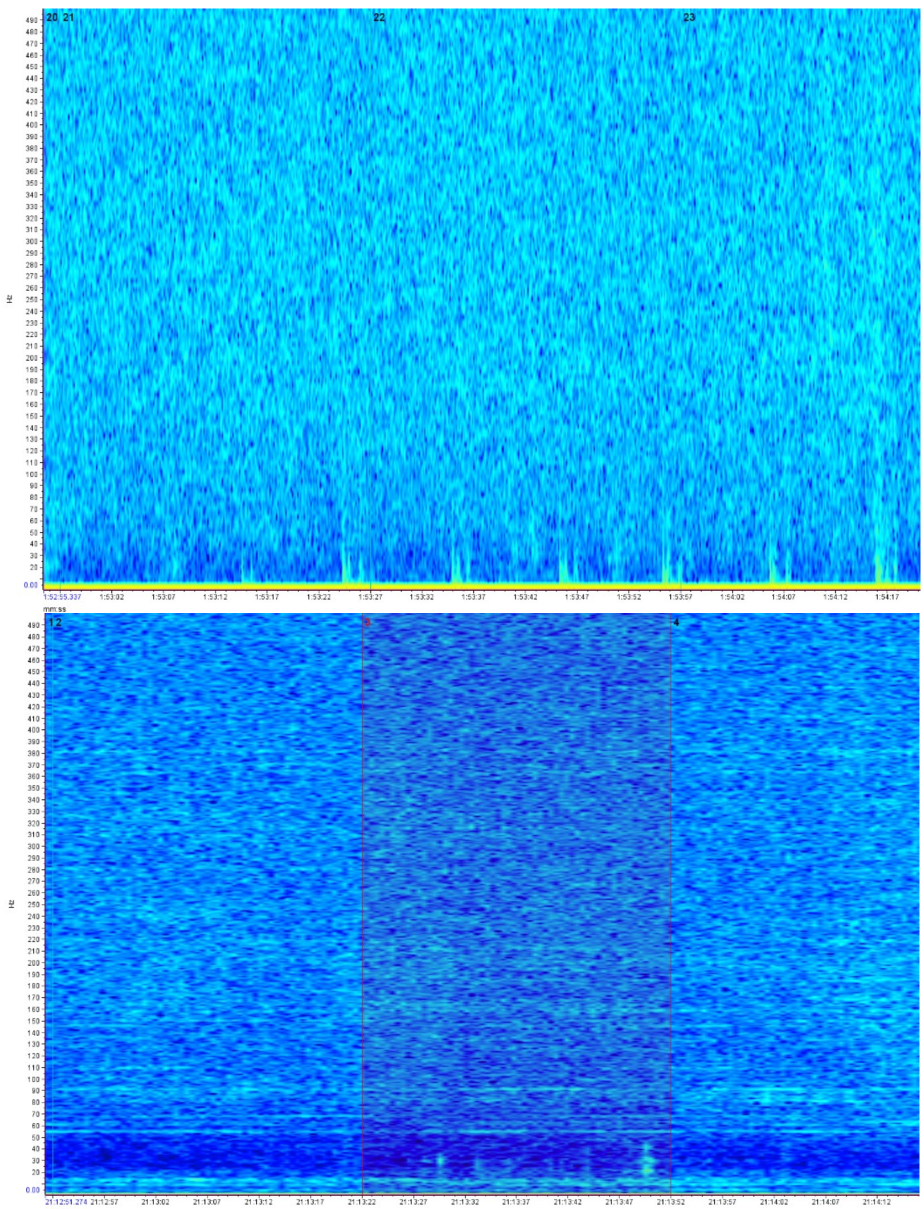


Figure C.3. Cluster 0 samples with frequency range 0 – 500 Hz. Two 30 s samples from the RI station (date: 2019/06/24; time: 01:52:57) (top); three 30 s samples from the RI station (date: 2019/10/15; time: 21:13:21) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 1 – Vessel noise 1

Number of samples

BU: 202 RI: 224

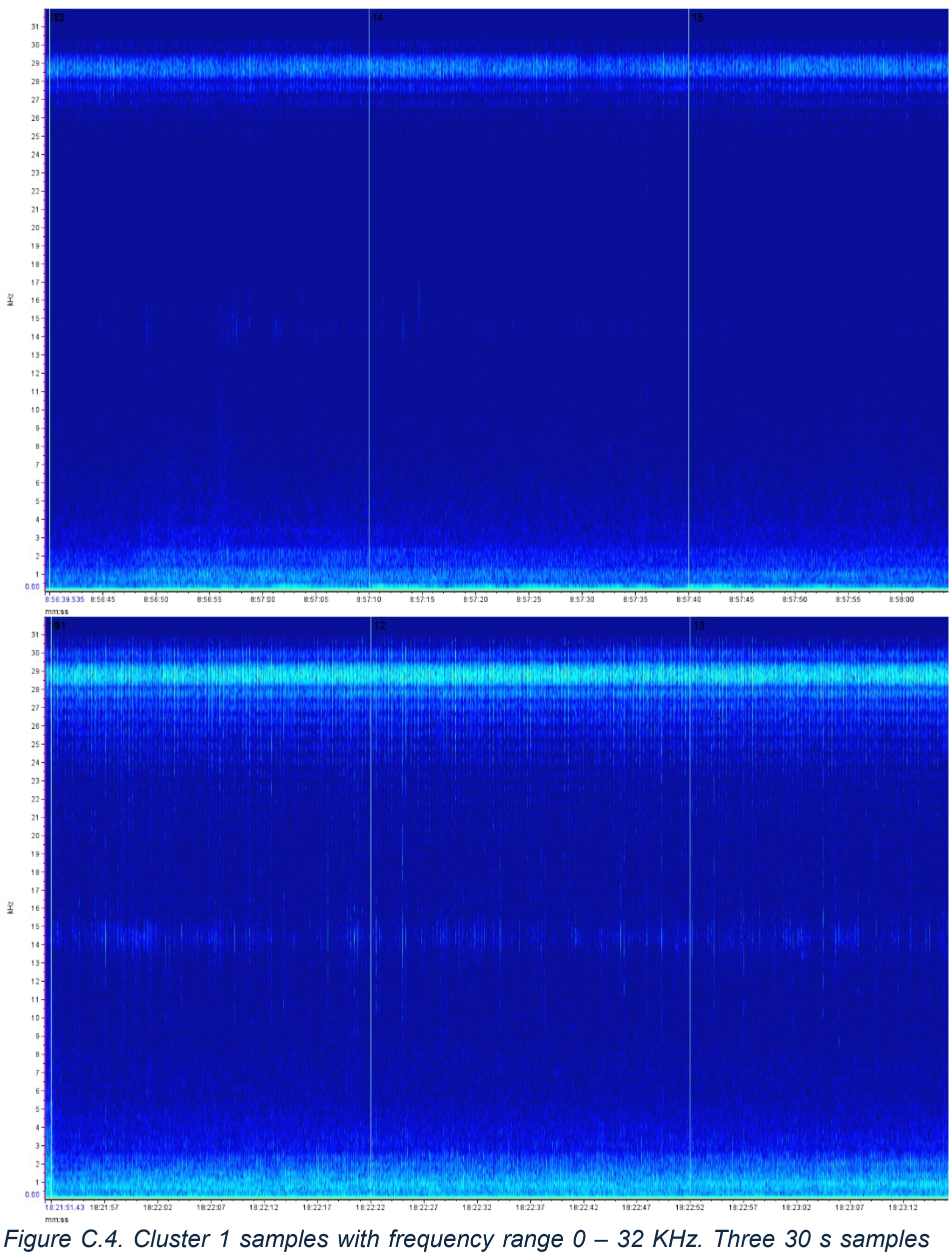


Figure C.4. Cluster 1 samples with frequency range 0 – 32 KHz. Three 30 s samples from the BU station (date: 2019/07/10; time: 08:50:40) (top); three 30 s samples from the RI station (date: 2019/09/11; time: 18:16:52) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 512.

Cluster 2 – Mooring noise 2

Number of samples

BU: 442 RI: 6

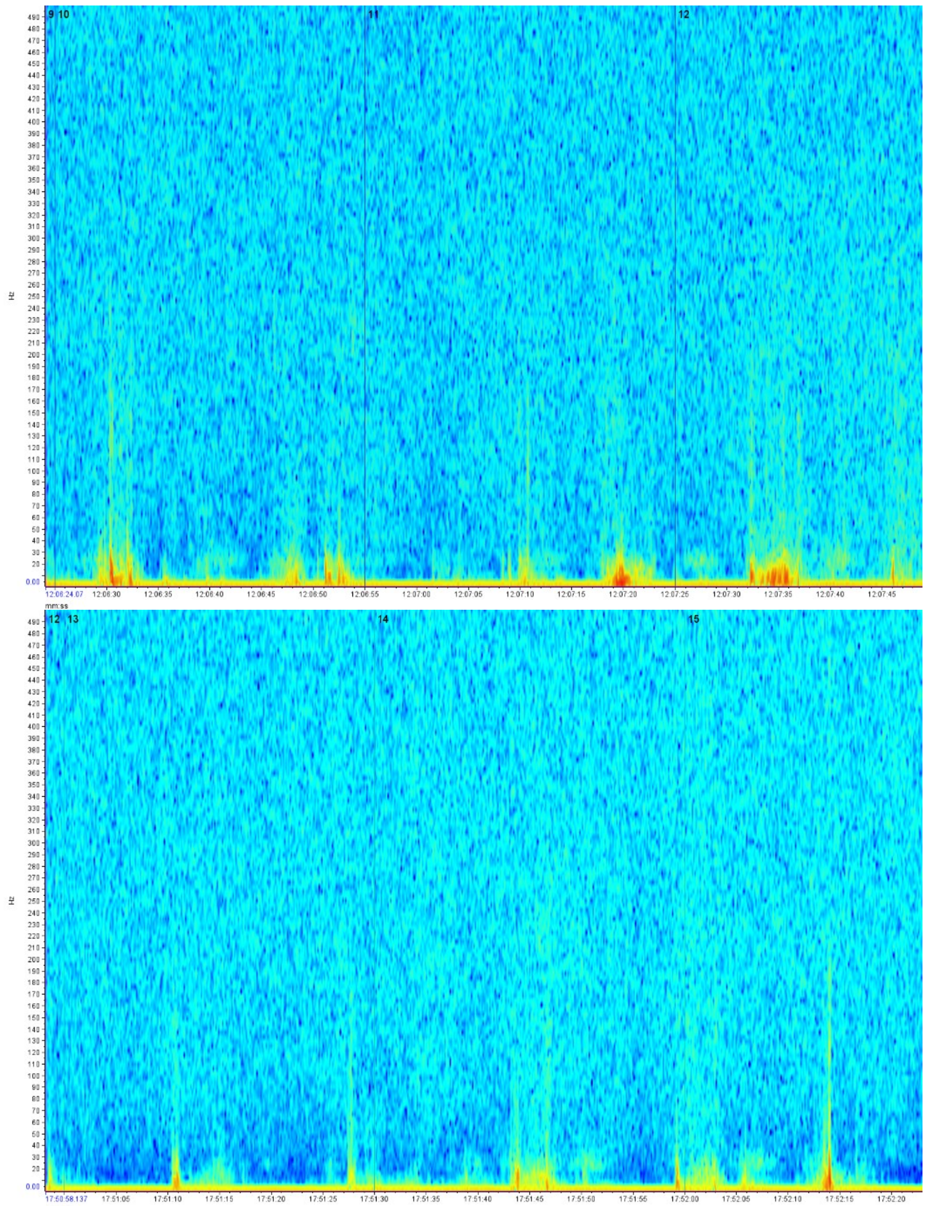


Figure C. 5. Cluster 2 samples with frequency range 0 – 500 Hz. Three 30 s samples from the BU station (date: 2019/06/25; time: 12:06:25) (top); three 30 s samples from the RI station (date: 2019/09/08; time: 17:45:00) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 3 – Vessel noise 2

Number of samples

BU: 1069 RI: 83

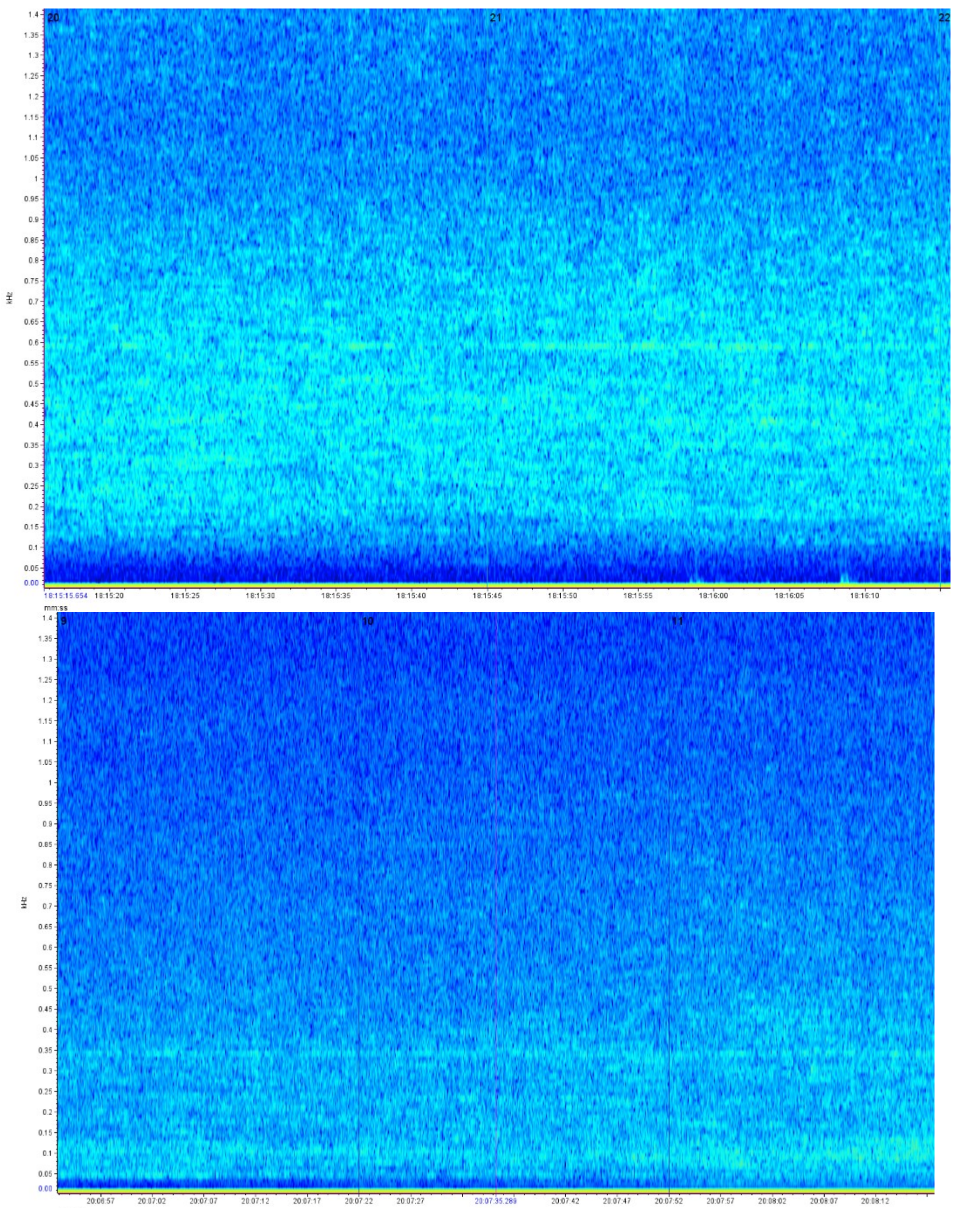


Figure C.6. Cluster 3 samples with frequency range 0 – 1500 Hz. Three 30 s samples from the BU station (date: 2019/09/11; time: 18:15:14) (top); three 30 s samples from the RI station (date: 2019/07/15; time: 20:06:51) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Cluster 4 – Vessel noise 3

Number of samples

BU: 1106 RI: 1

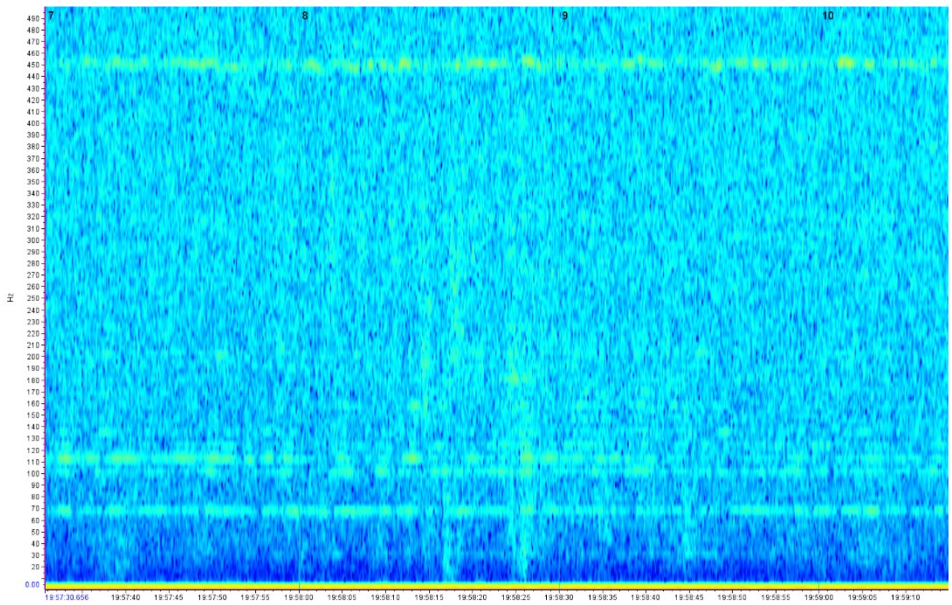


Figure C.7. Cluster 4 samples with frequency range 0 – 500 Hz. Four 30 s samples from the BU station (date: 2019/09/11; time: 18:15:14). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 5 – Mooring noise 3

Number of samples

BU: 19307 RI: 30

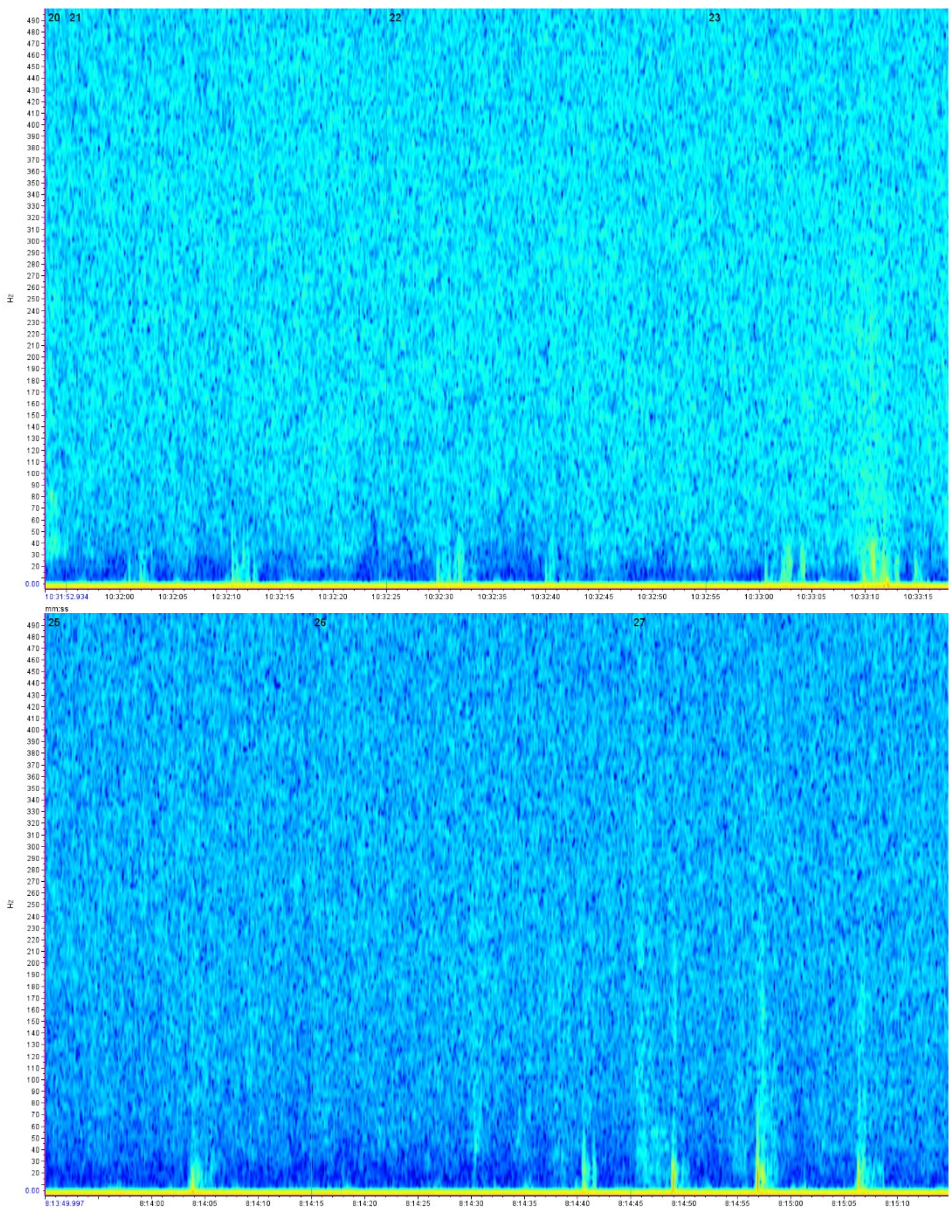


Figure C.8. Cluster 3 samples with frequency range 0 – 500 Hz. Three 30 s samples from the BU station (date: 2019/06/23; time: 10:31:54) (top); three 30 s samples from the BU station (date: 2019/08/28; time: 08:13:50) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

__Cluster 6 – Vessel noise 4__

Number of samples

BU: 1 RI: 345

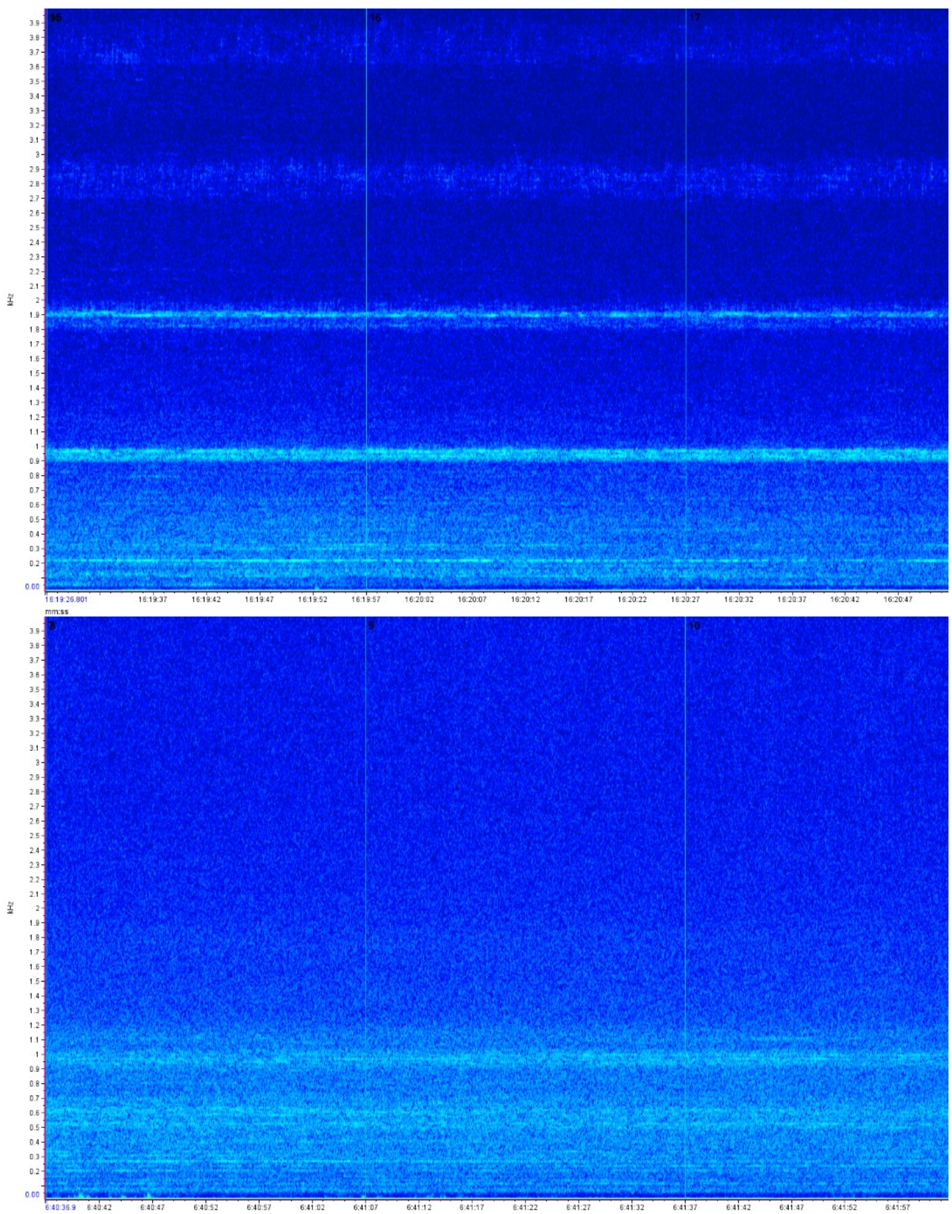


Figure C.9. Cluster 6 samples with frequency range 0 – 4 KHz. Three 30 s samples from the RI station (date: 2019/06/16; time: 16:19:26) (top); three 30 s samples from the RI station (date: 2019/08/12; time: 06:40:36) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Cluster 7 – Vessel noise 5

Number of samples

BU: 0 RI: 530

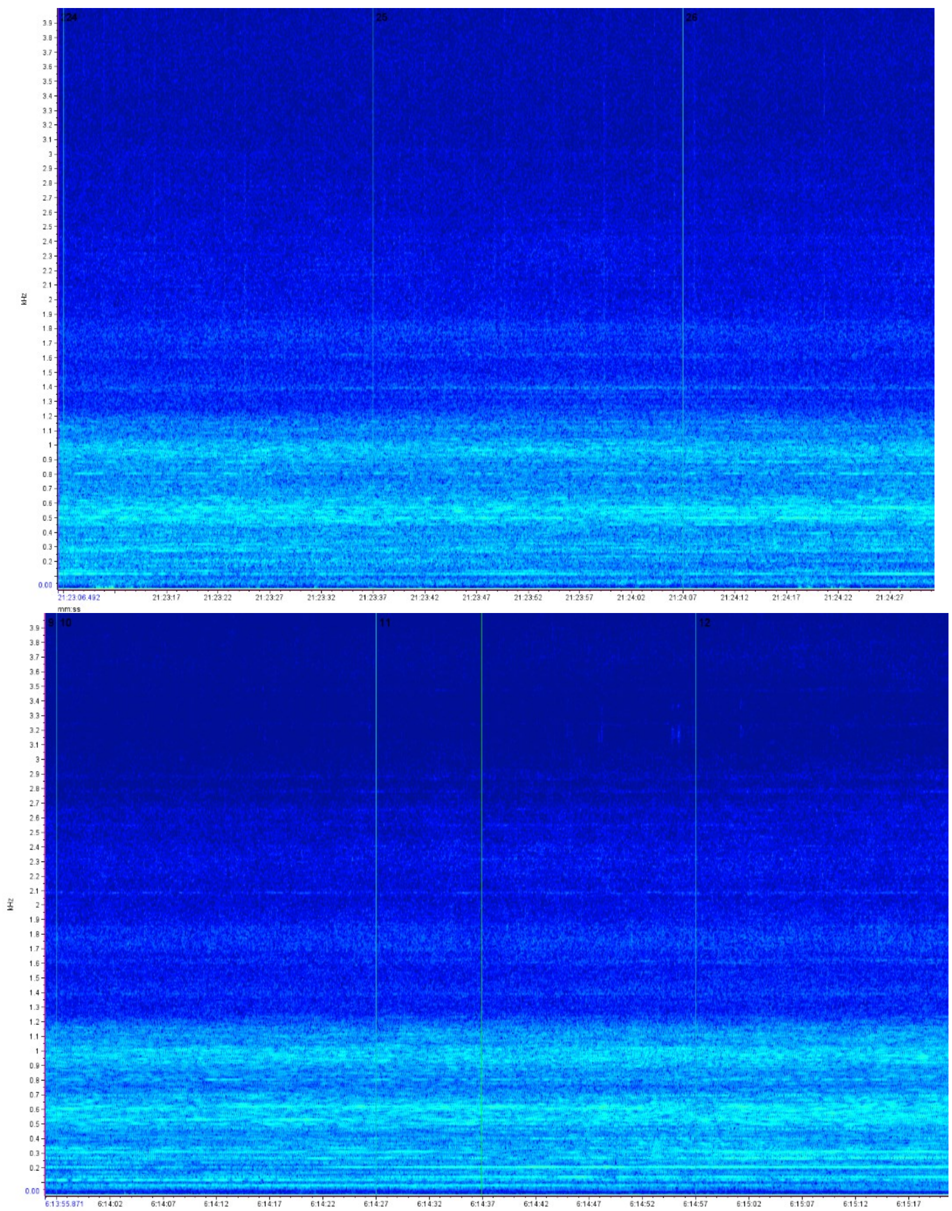


Figure C.10. Cluster 7 samples with frequency range 0 – 4 KHz. Three 30 s samples from the RI station (date: 2019/07/12; time: 21:23:06) (top); three 30 s samples from the RI station (date: 2019/08/08; time: 06:13:56) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Cluster 8 – Vessel noise 6

Number of samples

BU: 0 RI: 466

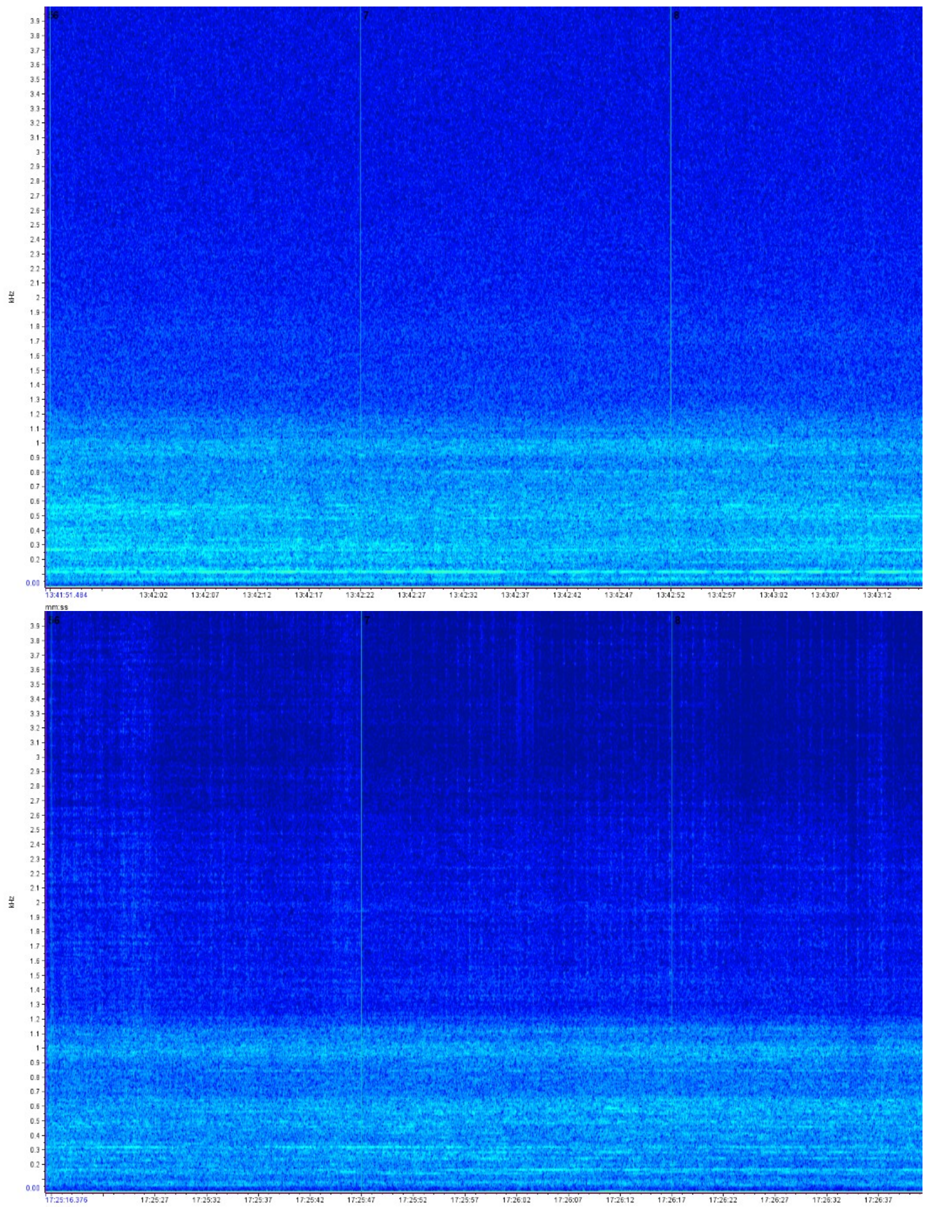


Figure C.11. Cluster 8 samples with frequency range 0 – 4 KHz. Three 30 s samples from the RI station (date: 2019/07/07; time: 13:41:51) (top); three 30 s samples from the RI station (date: 2019/10/12; time: 17:25:16) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Cluster 9 – Background

Number of samples

BU: 21 RI: 1702

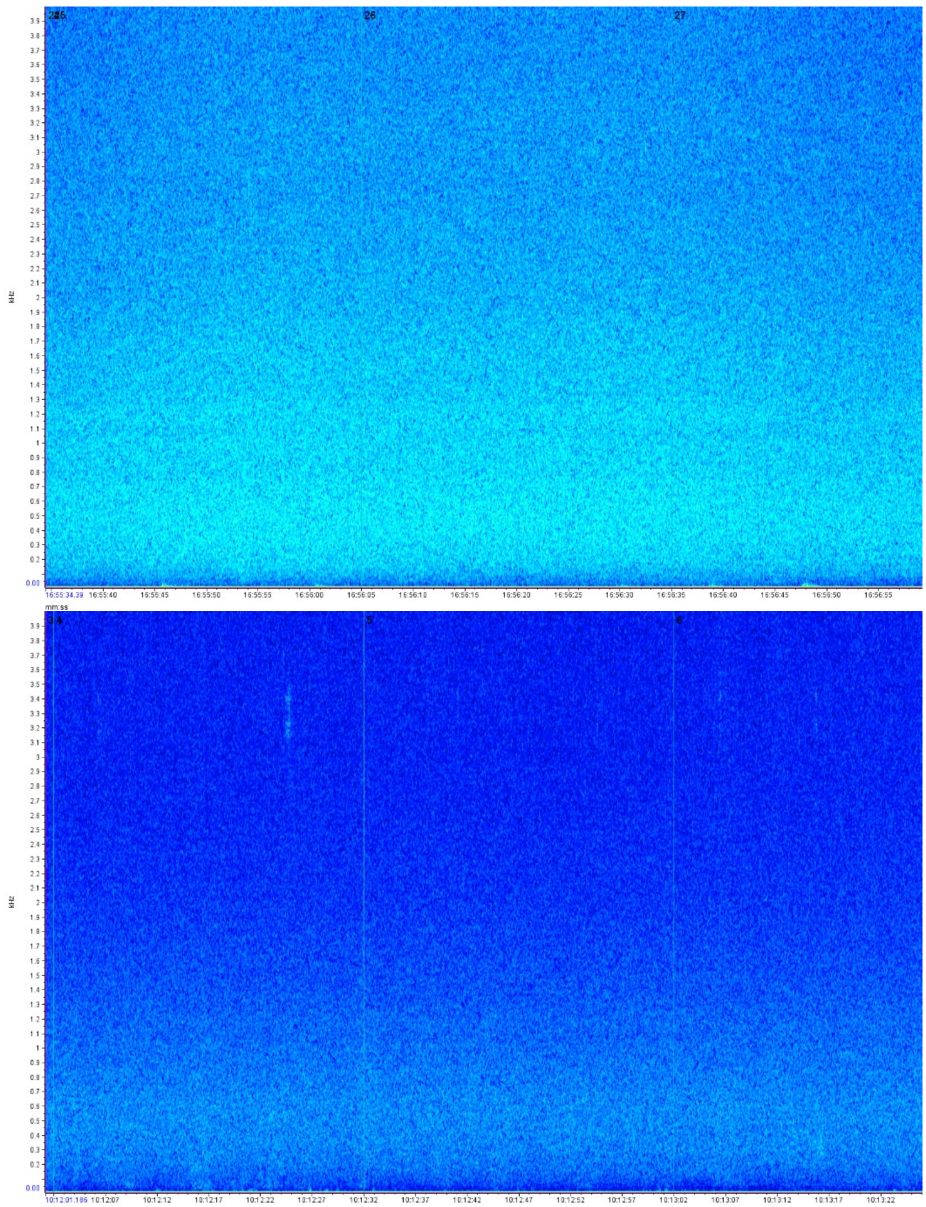


Figure C. 12. Cluster 9 samples with frequency range 0 – 4 KHz. Three 30 s samples from the BU station (date: 2019/09/16; time: 17:12:49) (top); three 30 s samples from the RI station (date: 2019/07/07; time: 10:12:01) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Cluster 10 – Odontocete whistles and clicks

Number of samples

BU: 218

RI: 653

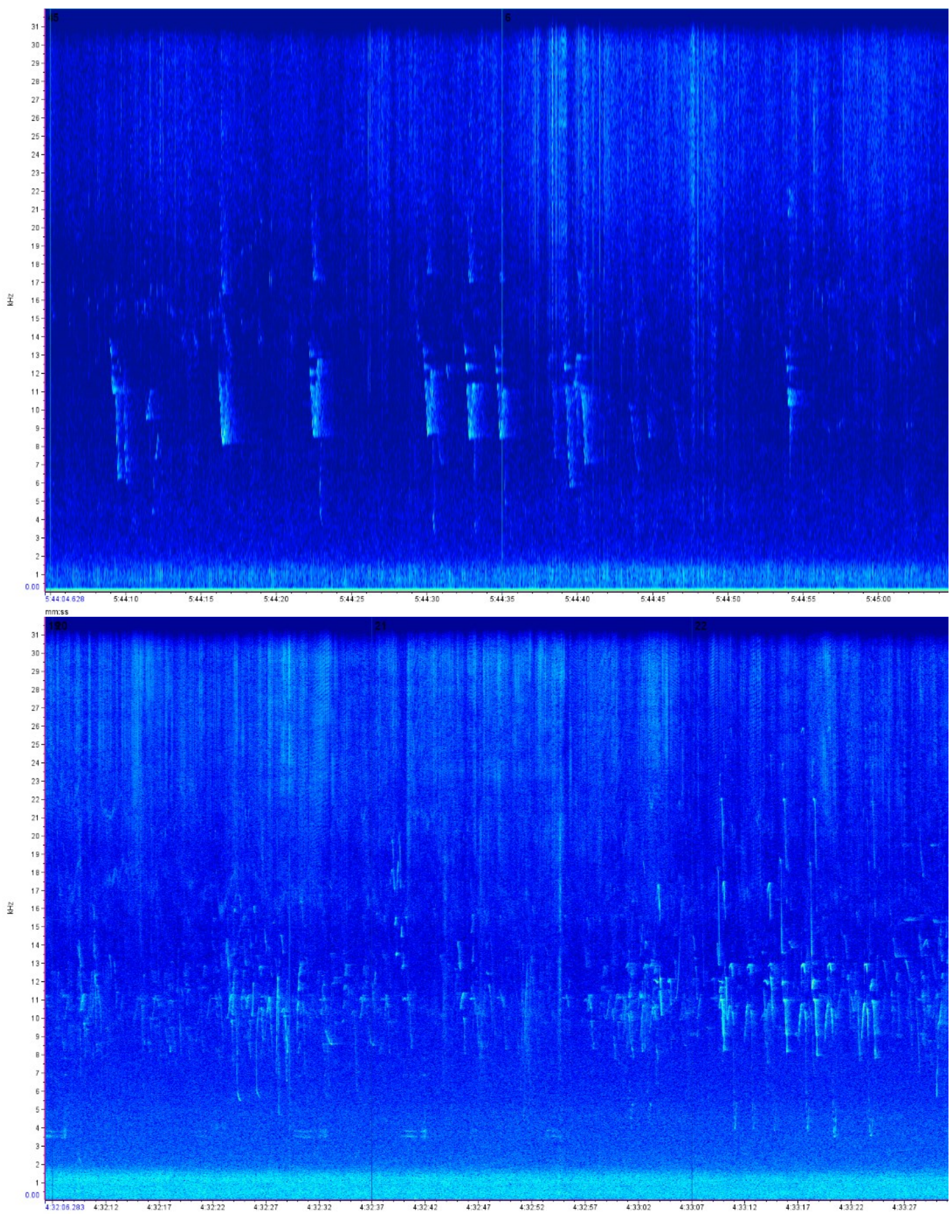


Figure C.13. Cluster 10 samples with frequency range 0 – 32 KHz. Two 30 s samples from the BU station (date: 2019/06/16; time: 16:19:26) (top); three 30 s samples from the RI station (date: 2019/09/09; time: 04:32:06) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 512.

Cluster 11 – Mooring noise 4

Number of samples

BU: 336 RI: 0

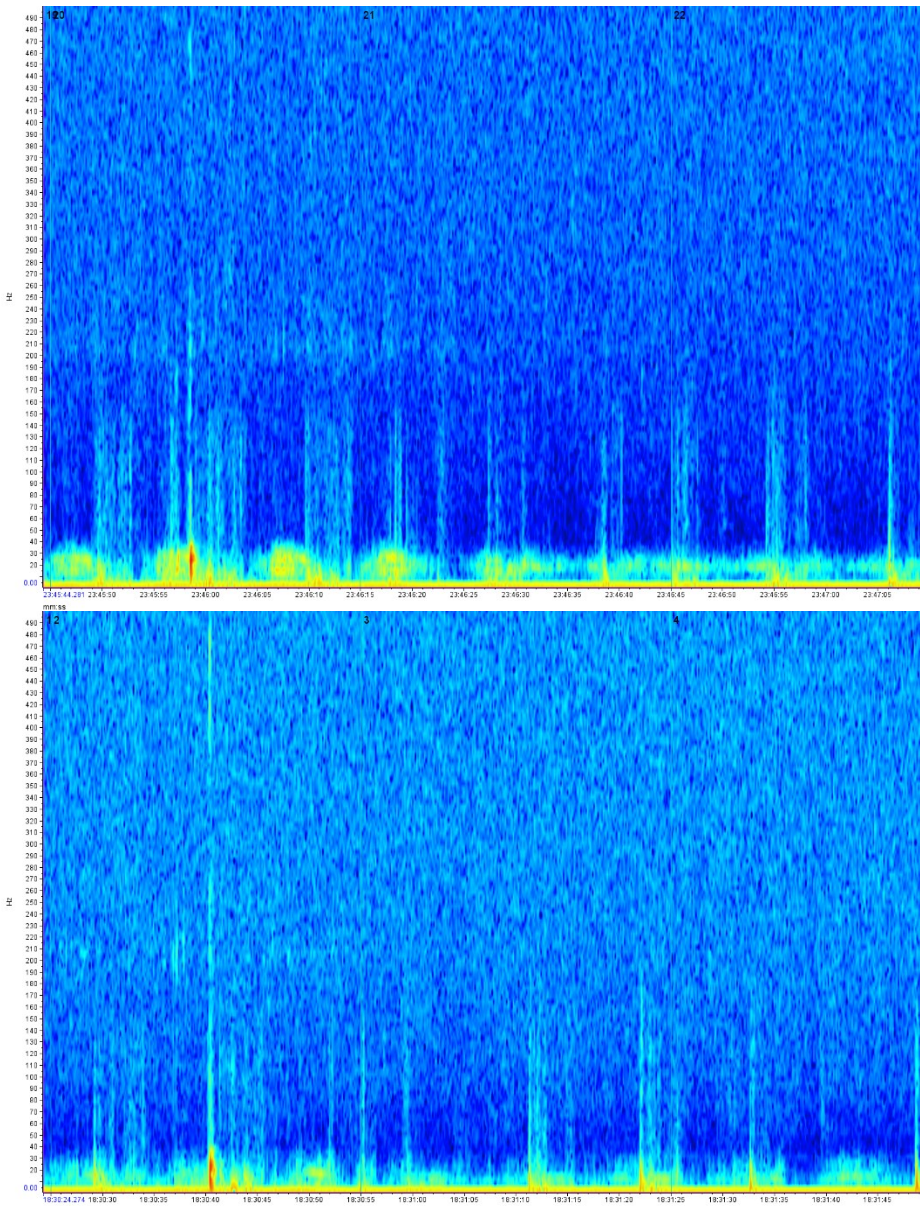


Figure C.14 Cluster 11 samples with frequency range 0 – 500 Hz. Three 30 s samples from the BU station (date: 2019/07/12; time: 05:37:09) (top); three 30 s samples from the BU station (date: 2019/10/19; time: 18:30:24) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 12 – Mooring noise 5

Number of samples

BU: 2

RI: 327

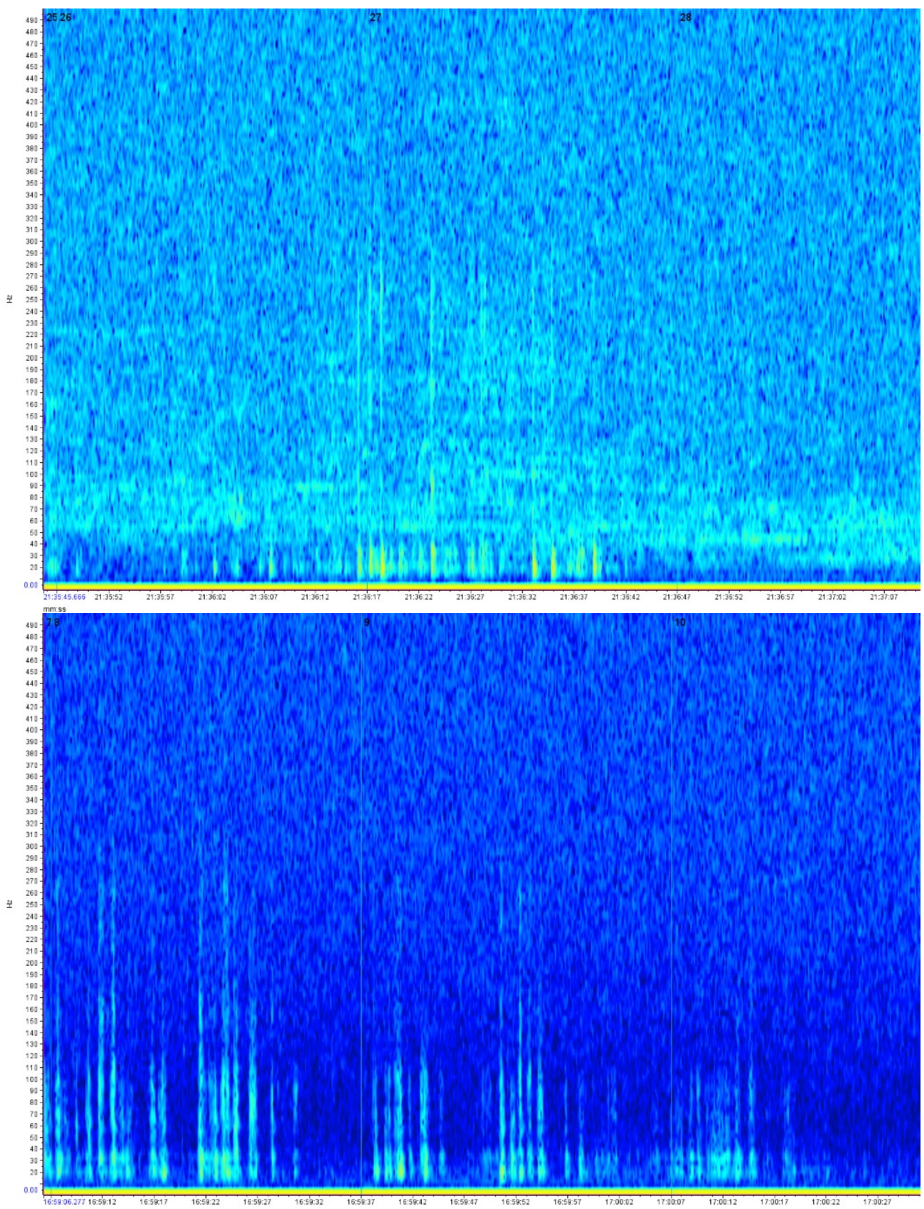


Figure C.15. Cluster 12 samples with frequency range 0 – 500 Hz. Three 30 s samples from the RI station (date: 2019/07/18; time: 21:35:45) (top); three 30 s samples from the RI station (date: 2019/08/13; time: 16:59:06) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 13 – Vessel noise 7
Number of samples

BU: 250

RI: 77

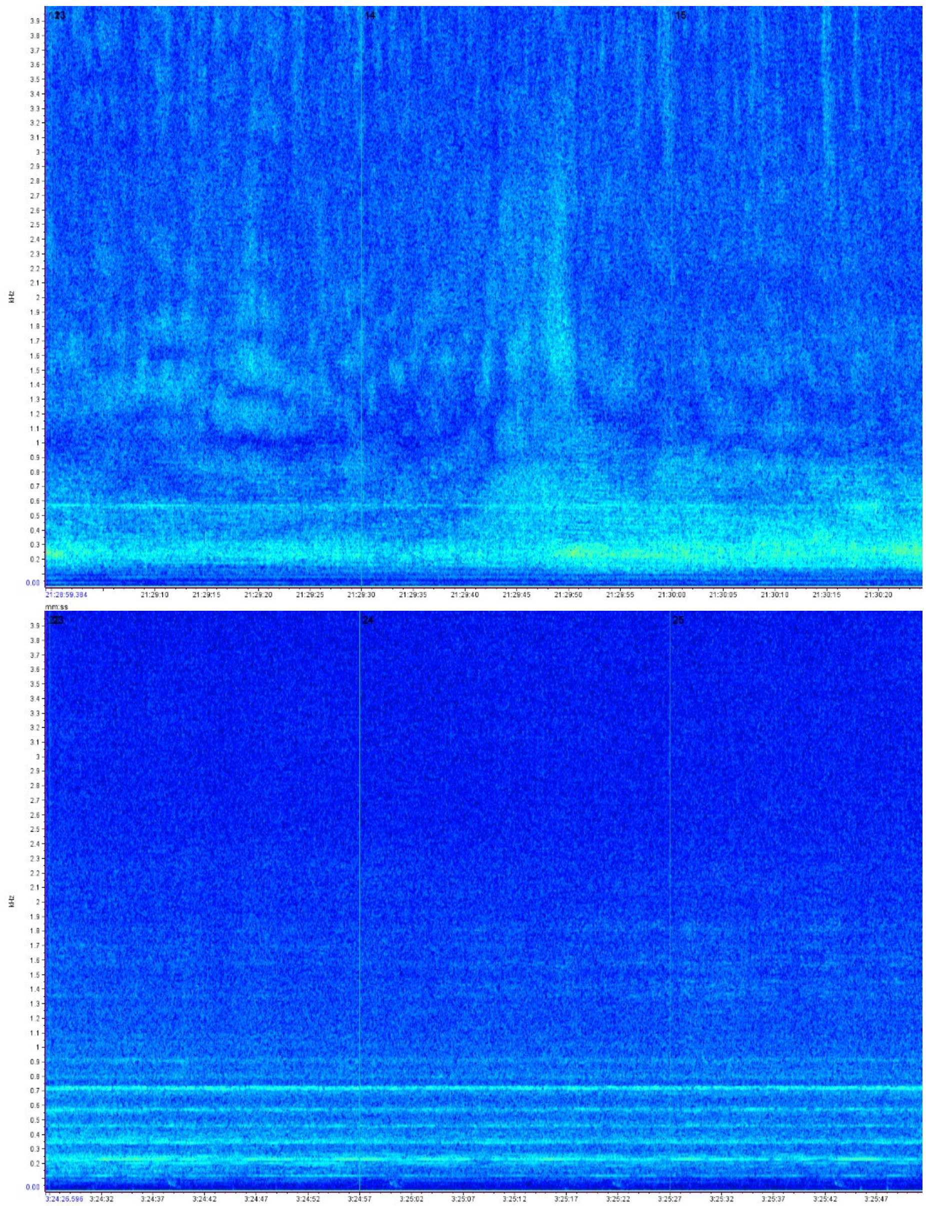


Figure C.16. Cluster 13 samples with frequency range 0 – 4 KHz. Three 30 s samples from the BU station (date: 2019/06/28; time: 21:28:59) (top); three 30 s samples from the RI station (date: 2019/08/30; time: 03:24:26) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 8192.

Cluster 14 – Mooring noise 6

Number of samples

BU: 50497 RI: 1639

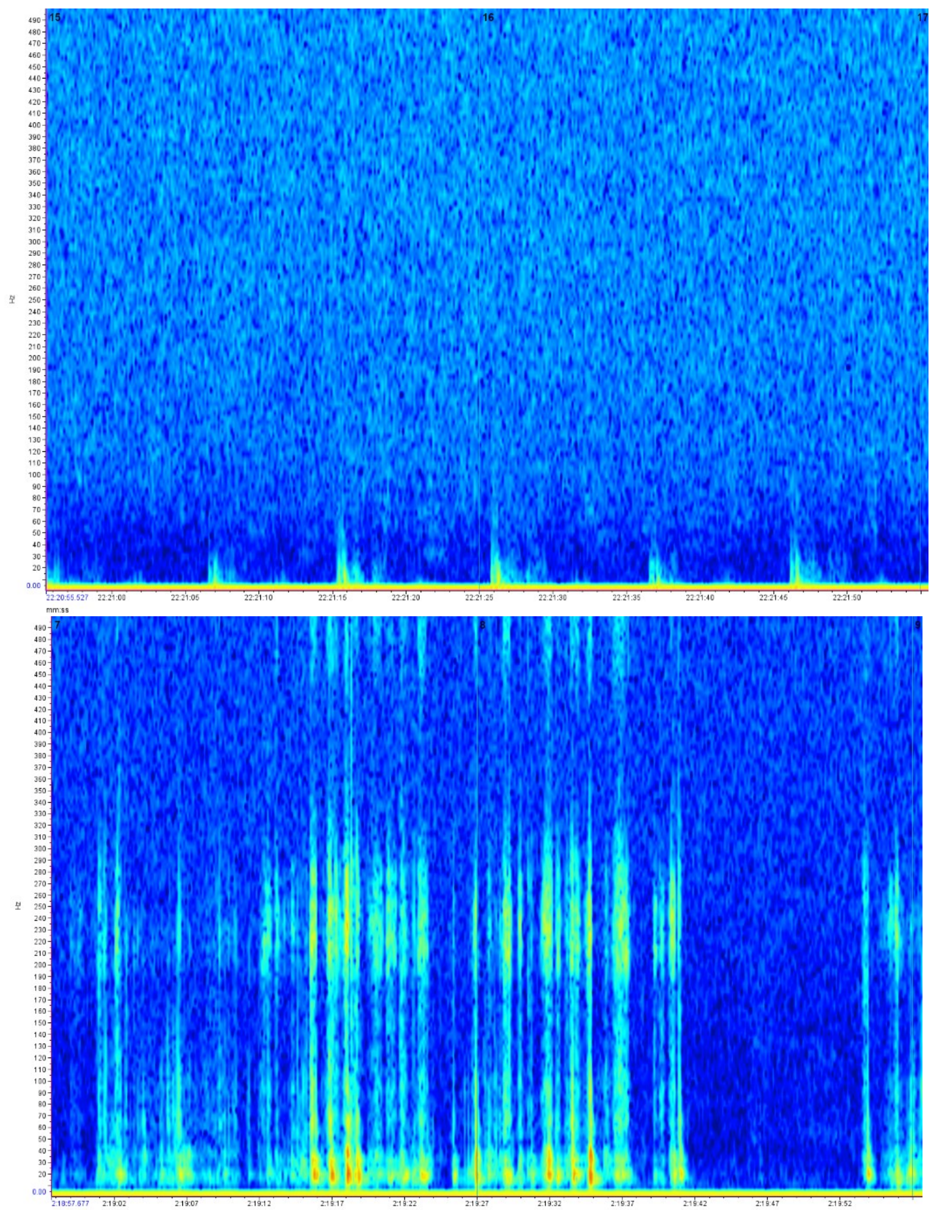


Figure C.17. Cluster 14 samples with frequency range 0 – 500 Hz. Two 30 s samples from the BU station (date: 2019/09/21; time: 22:50:56) (top); three 30 s samples from the BU station (date: 2019/08/26; time: 02:18:57) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 15 – Mooring noise 7

Number of samples

BU: 38 RI: 779

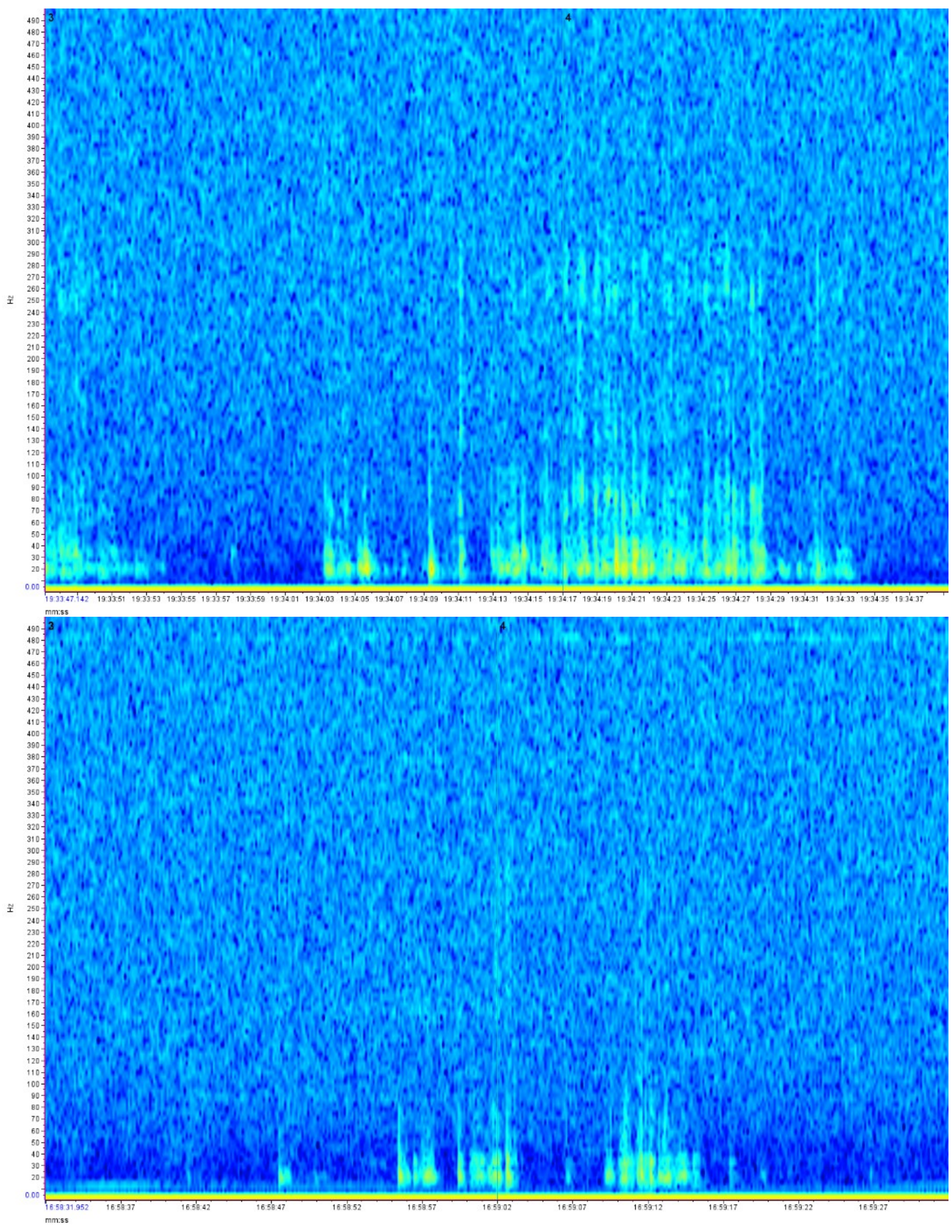


Figure C.18. Cluster 15 samples with frequency range 0 – 500 Hz. Three 30 s samples from the RI station (date: 2019/08/12; time: 19:33:47) (top); two 30 s samples from the RI station (date: 2019/09/06; time: 16:58:31) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 16 – Mooring noise 8
Number of samples

BU: 19

RI: 284

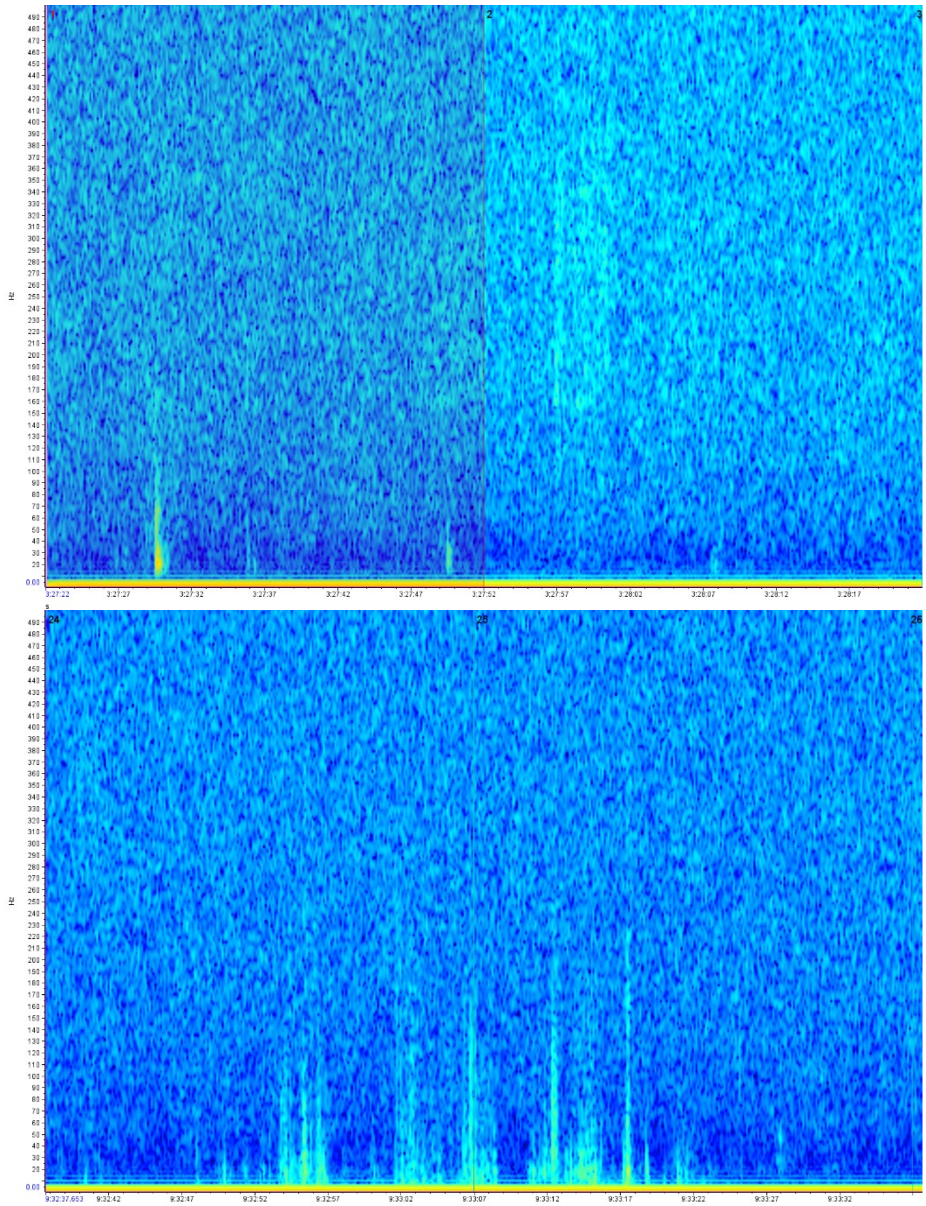


Figure C.19. Cluster 16 samples with frequency range 0 – 500 Hz. Two 30 s samples from the RI station (date: 2019/06/24; time: 03:27:22) (top); two 30 s samples from the RI station (date: 2019/10/20; time: 09:32:37) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 17 – Vessel noise 8

Number of samples

BU: 8107 RI: 64342

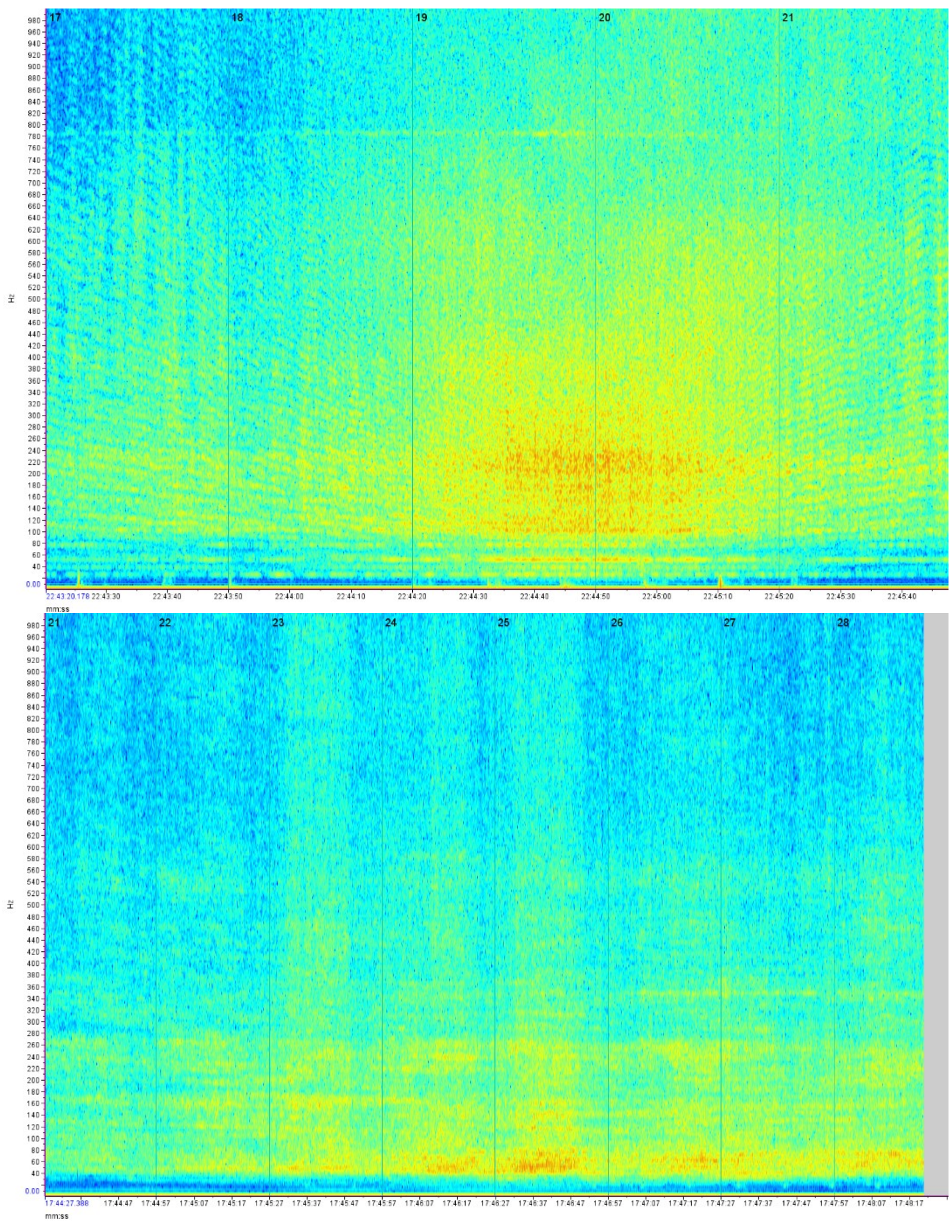


Figure C.20. Cluster 17 samples with frequency range 0 – 1000 Hz. Five consecutive 30 s samples recorded at the BU station (date: 2019/09/09; time: 22:43:20) (top). Eight consecutive 30 s samples recorded at the RI station (date: 2019/10/18; time: 17:44:27) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 18 – Mooring noise 9

Number of samples

BU: 0 RI: 1027

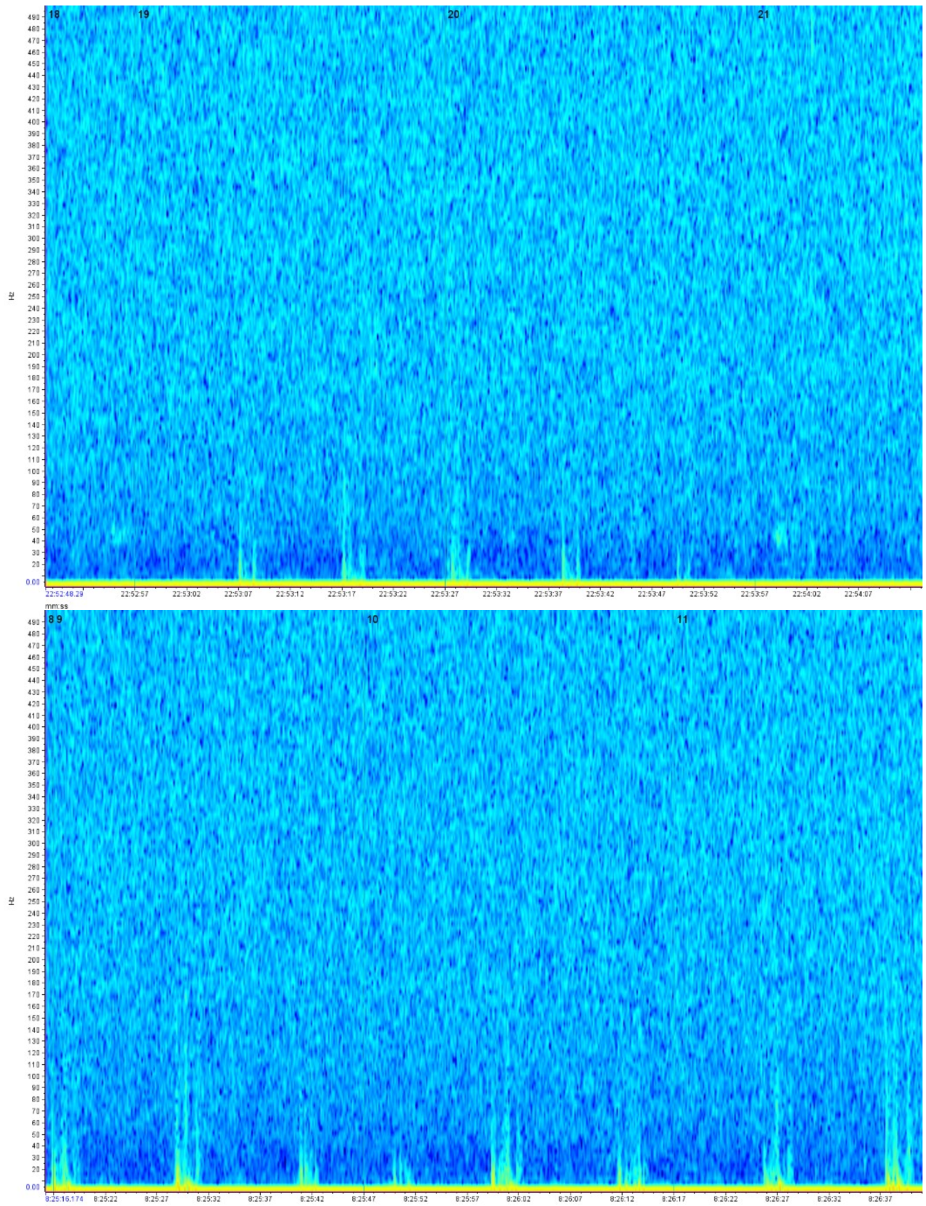


Figure C.21. Cluster 18 samples with frequency range 0 – 500 Hz. Three consecutive 30 s samples recorded at the RI station (date: 2019/06/23; time: 22:52:57) (top). Three consecutive 30 s samples recorded at the RI station (date: 2019/09/09; time: 08:25:16) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Cluster 19 – Mooring noise 10

Number of samples

BU: 3 RI: 3196

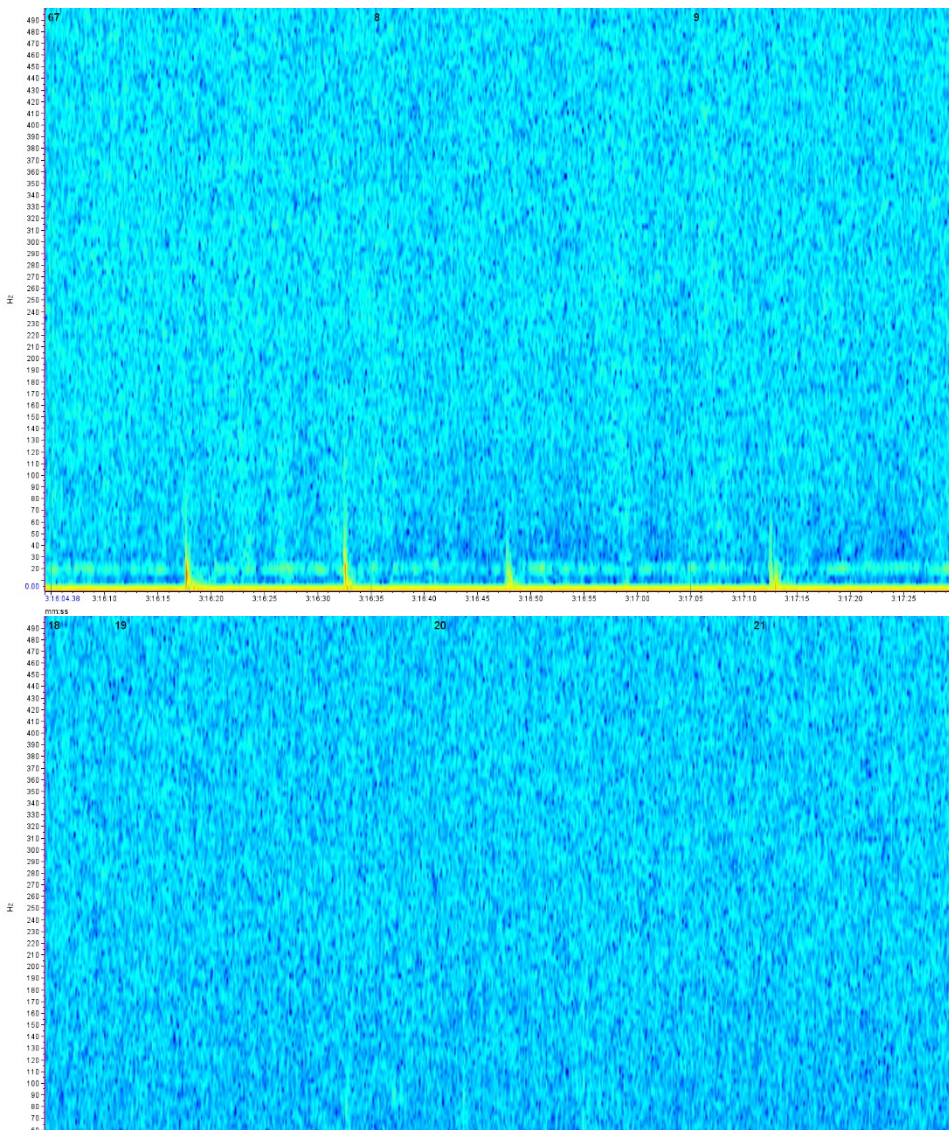


Figure C.22. Cluster 19 samples with frequency range 0 – 500 Hz. Three consecutive 30 s samples recorded at the BU station (date: 2019/10/18; time: 03:16:04) (top). Three consecutive 30 s samples recorded at the RI station (date: 2019/09/09; time: 06:45:51) (bottom). Spectrograms produced using Raven Lite software (Version 2.0.5) with brightness 50, contrast 50, and window size 16384.

Appendix D - QGAM Models Details

This appendix contains additional information regarding the QGAM models described in Chapter Three of this dissertation. In particular, the appendix provides details on model diagnostics (proportion of negative residuals, model bias, calibration loss curves) (Table B1, Figures B2-5) and includes tables summarizing the QGAM models outputs (Tables B2-5).

QGAM MODEL DIAGNOSTICS

D.1 Proportion of negative residuals and model bias.

Table D. 1. Proportion of negative residuals and model bias.

QGAM model	Quantile	Exceedance level	Proportion of negative residuals	Integrated absolute bias
Model 1 - Broadband (10 - 1000 Hz)	0.05	L95	0.0402072	0.0106386
	0.5	L50	0.4982543	0.0211914
	0.95	L5	0.9594549	0.0109083
Model 2 - 63 Hz band SPL	0.05	L95	0.0406577	0.0103862
	0.5	L50	0.5028719	0.0056133
	0.95	L5	0.9543868	0.0063972
Model 3 - 125 Hz band SPL	0.05	L95	0.0426850	0.0087268
	0.5	L50	0.4989301	0.0155751
	0.95	L5	0.9565266	0.0077166
Model 4 - 500 Hz band SPL	0.05	L95	0.0416714	0.0090131
	0.5	L50	0.4928483	0.0208572
	0.95	L5	0.9594549	0.0113575

D.2 Calibration loss plots

The following four plots report the QGAM models calibration process, where each dot corresponds to a loss evaluation run. Ideally, the QGAM's internal calibration procedure should return a calibration loss curve with a clear single minimum and without the presence of irregularities (Fasiolo et al., 2021, 2021a).

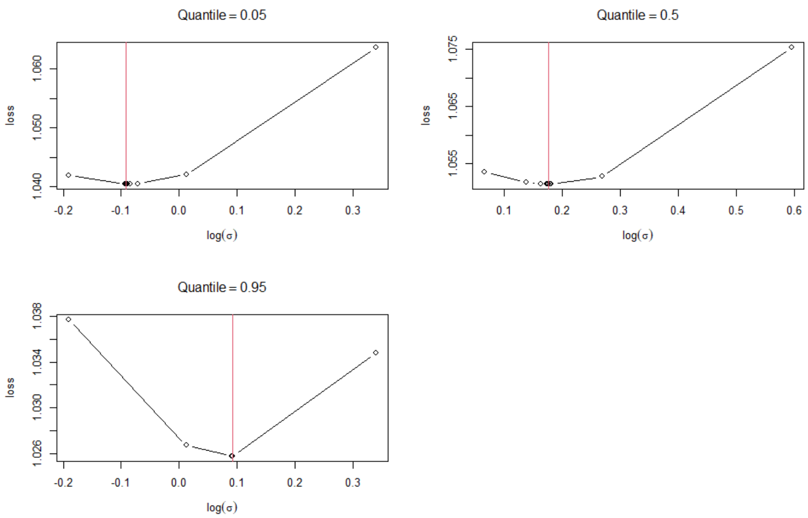


Figure D.1. Calibration loss curves for QGAM Model 1, fitted on the broadband (50-1000 Hz) SPL expressed as dB re 1 µPa. The figure includes a curve for all three quantiles tested: 0.05 (L95); 0.5 (L50); 0.95 (L5).

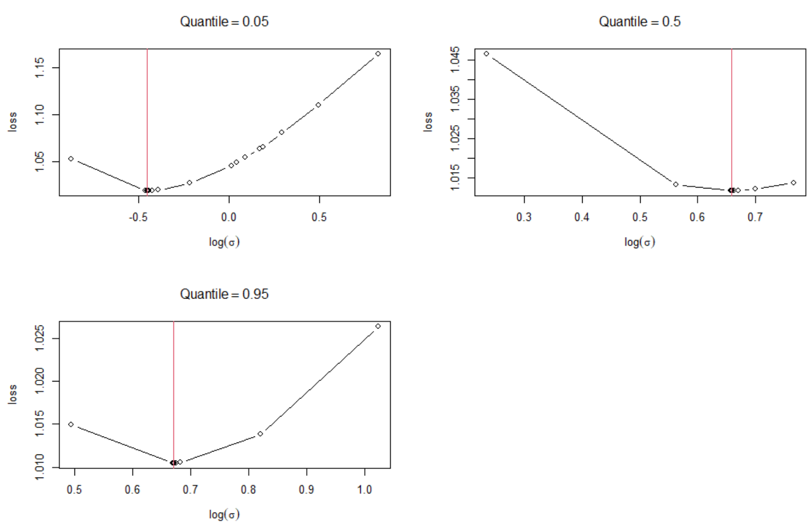


Figure D.2. Calibration loss curves for QGAM Model 2, fitted on the 63 Hz 1/3 octave band SPL expressed as dB re 1 µPa. The figure includes a curve for all three quantiles tested: 0.05 (L95); 0.5 (L50); 0.95 (L5).

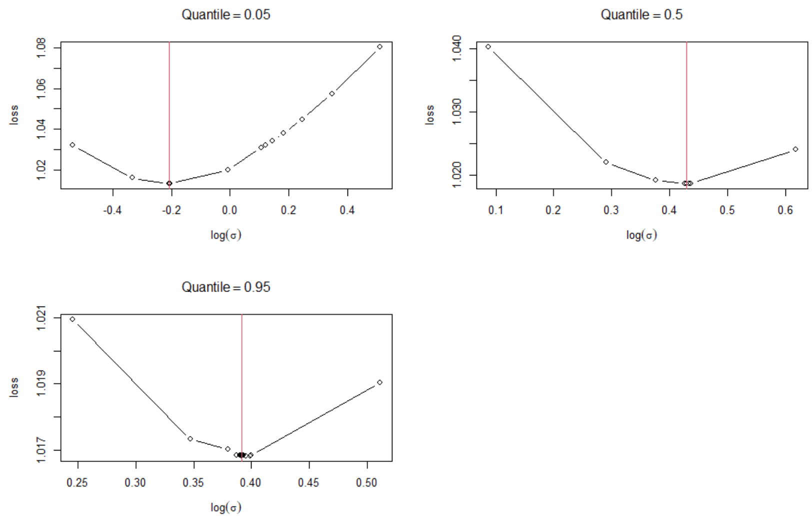


Figure D.3. Calibration loss curves for QGAM Model 3, fitted on the 125 Hz 1/3 octave band SPL expressed as dB re 1 μPa. The figure includes a curve for all three quantiles tested: 0.05 (L95); 0.5 (L50); 0.95 (L5).

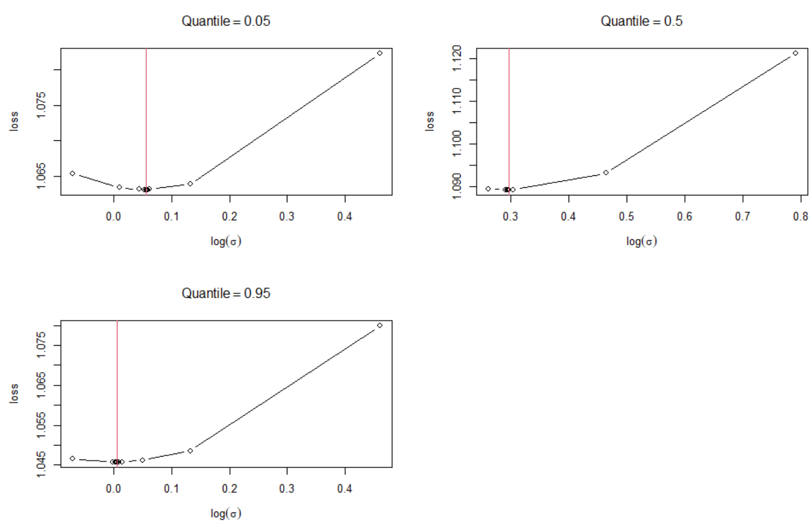


Figure D.4. Calibration loss curves for QGAM Model 4, fitted on the 500 Hz 1/3 octave band SPL expressed as dB re 1 μPa. The figure includes a curve for all three quantiles tested: 0.05 (L95); 0.5 (L50); 0.95 (L5).

QGAM MODELS RESULTS

D.3 QGAM Model Summary Tables

The following tables report estimates, standard errors, z values and relative p-values for the QGAM parametric coefficients, as well as estimated degrees of freedom (edf), reference degrees of freedom (Ref.df), and Chi-square statistics for the models' smooth terms.

Table D. 1. Summary of QGAM Model 1.

QGAM Model 1 - Broadband SPL (50-1000 Hz)	L95					L50					L5				
Parametric coefficients	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**
(Intercept)	98.6447	0.1019	968.03	<2e-16	***	106.32009	0.07022	1514.05	<2e-16	***	113.6525	0.1128	1007.602	< 2e-16	***
StationRed_Island	3.7973	0.1273	29.83	<2e-16	***	1.3636	0.0855	15.95	<2e-16	***	-0.4252	0.1448	-2.935	0.00333	**
Approximate significance of smooth terms:	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**
s(Date)	*0.02523*	9	0.023	7.18E-05	***	7.66186	9	170.505	< 2e-16	***	0.01855	9	0.013	1.09E-02	*
s(Date):StationBurin	8.20976	9	144.734	< 2e-16	***	0.0174	9	0.02	0.0000514	***	3.098	9	9.858	0.00343	**
s(Date):StationRed_Island	5.90051	9	30.765	< 2e-16	***	5.020071	9	101.458	< 2e-16	***	4.672	9	29.18	< 2e-16	***
s(Hours)	*0.03836*	8	0.029	0.02005	*	2.639873	8	10.26	0.00353	**	3.122	8	11.213	0.00258	**
s(Hours):StationBurin	3.49508	8	21.018	2.04E-05	***	5.266827	8	46.604	< 2e-16	***	1.707	8	5.024	2.50E-02	*
s(Hours):StationRed_Island	3.35153	8	15.267	0.000268	***	0.021865	8	0.02	0.01565	*	0.01405	8	0.008	0.17748	
s(wind_spd_avg)	2.93014	9	26.524	< 2e-16	***	3.478202	9	21.273	< 2e-16	***	0.0003156	9	0	0.538	
s(wind_spd_avg):StationBurin	*0.08434*	9	0.101	0.000573	***	0.013063	9	0.009	0.02734	*	0.002611	9	0.001	0.54154	
s(wind_spd_avg):StationRed_Island	6.40054	9	35.56	< 2e-16	***	7.36987	9	64.413	< 2e-16	***	7.548	9	36.796	< 2e-16	***
s(ship_label)	2.36885	9	43.894	< 2e-16	***	3.147164	9	470.88	< 2e-16	***	2.06	9	90.345	< 2e-16	***
s(ship_label):StationBurin	*0.01875*	9	0.009	0.166482		0.006251	9	0.004	0.26013		0.004475	9	0.004	0.14315	
s(ship_label):StationRed_Island	*0.54305*	9	1.21	0.02198	*	0.003473	9	0.001	0.35721		0.002276	9	0.001	0.33848	
s(wind_spd_avg,ship_label)	10.69886	27	19.981	< 2e-16	***	21.201397	27	606.513	< 2e-16	***	8.35	27	13.486	< 2e-16	***
s(wind_spd_avg,ship_label):StationBurin	11.92965	27	30.167	< 2e-16	***	0.072532	27	0.072	< 2e-16	***	16.79	27	60.519	< 2e-16	***
s(wind_spd_avg,ship_label):StationRed_Island	15.19036	27	43.463	< 2e-16	***	15.049524	27	127.968	< 2e-16	***	13.28	27	32.073	< 2e-16	***

Table D. 2. Summary of QGAM Model 2.

QGAM Model 2 - 63 Hz band SPL	L95					L50					L5				
Parametric coefficients	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**
(Intercept)	69.10864	0.06525	1059.15	<2e-16	***	74.36148	0.07965	933.6	<2e-16	***	83.1518	0.182	456.75	<2e-16	***
StationRed_Island	2.40272	0.08925	26.92	<2e-16	***	2.82683	0.10789	26.2	<2e-16	***	3.3371	0.2506	13.32	<2e-16	***
Approximate significance of smooth terms:	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**
s(Date)	1.68112	9	2.022	< 2e-16	***	0.003136	9	0.003	8.14E-06	***	0.161733	9	0.163	< 2e-16	***
s(Date):StationBurin	6.68386	9	23.792	< 2e-16	***	8.395	9	151.893	< 2e-16	***	7.837098	9	61.897	< 2e-16	***
s(Date):StationRed_Island	7.68224	9	35.217	< 2e-16	***	7.465	9	94.263	< 2e-16	***	6.061648	9	39.652	< 2e-16	***
s(Hours)	4.97204	8	32.51	< 2e-16	***	3.783	8	11.808	0.00218	**	0.66796	8	0.837	0.002214	**
s(Hours):StationBurin	0.93612	8	1.361	1.88E-03	**	0.04029	8	0.04	4.55E-03	**	1.957797	8	4.889	3.07E-04	***
s(Hours):StationRed_Island	1.57463	8	2.654	0.00562	**	5.113	8	24.674	1.65E-06	***	5.89871	8	24.12	3.33E-06	***
s(wind_spd_avg)	3.37963	9	6.57	< 2e-16	***	3.927	9	27.659	< 2e-16	***	0.004513	9	0.002	0.40225	
s(wind_spd_avg):StationBurin	2.28217	9	3.318	0.000273	***	0.04575	9	0.04	0.00359	**	1.829688	9	9.544	0.000114	***
s(wind_spd_avg):StationRed_Island	3.54893	9	6.195	0.000169	***	7.42	9	38.523	< 2e-16	***	0.007956	9	0.007	0.208164	
s(ship_label)	2.91418	9	46.19	< 2e-16	***	2.361	9	65.564	< 2e-16	***	1.479109	9	9.956	7.43E-06	***
s(ship_label):StationBurin	0.09912	9	0.025	0.032085	*	0.0003383	9	0	0.59634		0.010196	9	0.001	0.715254	
s(ship_label):StationRed_Island	1.1834	9	4.479	0.000426	***	0.0005153	9	0	0.83874		0.002566	9	0.001	0.308851	
s(wind_spd_avg,ship_label)	0.02865	27	0.028	4.84E-06	***	10.23	27	19.664	< 2e-16	***	13.412787	27	44.119	< 2e-16	***
s(wind_spd_avg,ship_label):StationBurin	8.53473	27	24.214	0.0000102	***	4.189	27	5.63	< 2e-16	***	0.012477	27	0.013	0.000363	***
s(wind_spd_avg,ship_label):StationRed_Island	17.74039	27	238.195	< 2e-16	***	17.23	27	93.43	< 2e-16	***	7.67804	27	38.458	< 2e-16	***

Table D.3. Summary of QGAM Model 3.

QGAM Model 3 - 125 Hz band SPL	L95					L50					L5				
Parametric coefficients	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**
(Intercept)	73.20387	0.08536	857.62	<2e-16	***	80.17328	0.07598	1055.2	<2e-16	***	88.2158	0.1382	638.434	< 2e-16	***
StationRed_Island	2.52617	0.11105	22.75	<2e-16	***	1.7079	0.10017	17.05	<2e-16	***	1.4603	0.192	7.606	2.83E-14	***
Approximate significance of smooth terms:	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**
s(Date)	7.662393	9	34.374	< 2e-16	***	4.565	9	101.469	< 2e-16	***	1.192321	9	1.537	3.86E-04	***
s(Date):StationBurin	6.595992	9	157.22	< 2e-16	***	0.01886	9	0.016	0.001963	**	7.189475	9	42.666	< 2e-16	***
s(Date):StationRed_Island	0.01873	9	0.012	0.000768	***	7.585	9	104.052	< 2e-16	***	2.530435	9	4.936	0.000186	***
s(Hours)	3.23244	8	15.05	0.000233	***	0.6659	8	0.748	0.000426	***	0.313538	8	0.326	0.302991	
s(Hours):StationBurin	0.010313	8	0.009	1.72E-02	*	4.242	8	13.106	1.20E-04	***	0.148458	8	0.13	3.56E-01	
s(Hours):StationRed_Island	3.724362	8	7.859	0.029253	*	3.89	8	11.156	0.0000768	***	4.803991	8	36.754	< 2e-16	***
s(wind_spd_avg)	0.002592	9	0.003	0.0000917	***	3.523	9	38.499	< 2e-16	***	3.691604	9	8.037	0.002257	**
s(wind_spd_avg):StationBurin	4.20315	9	41.895	< 2e-16	***	0.0006878	9	0.001	0.003593	**	1.035049	9	3.1	0.005724	**
s(wind_spd_avg):StationRed_Island	6.597781	9	57.191	< 2e-16	***	7.58	9	69.753	< 2e-16	***	0.016612	9	0.021	0.004777	**
s(ship_label)	3.304481	9	71.452	< 2e-16	***	2.972	9	170.495	< 2e-16	***	2.044705	9	20.709	< 2e-16	***
s(ship_label):StationBurin	0.008536	9	0.006	0.220228		0.002531	9	0	0.618133		0.007693	9	0.007	0.076009	.
s(ship_label):StationRed_Island	0.064199	9	0.078	0.10528		0.004448	9	0	0.83607		0.097933	9	0.181	0.021016	*
s(wind_spd_avg,ship_label)	4.343337	27	5.742	< 2e-16	***	14.98	27	166.029	< 2e-16	***	11.620536	27	40.577	< 2e-16	***
s(wind_spd_avg,ship_label):StationBurin	11.876691	27	33.436	< 2e-16	***	0.0004256	27	0	0.0000118	***	0.053099	27	0.057	0.0000218	***
s(wind_spd_avg,ship_label):StationRed_Island	17.860793	27	91.327	< 2e-16	***	20.03	27	308.817	< 2e-16	***	12.887644	27	43.461	< 2e-16	***

Table D.4. Summary of QGAM Model 4.

QGAM Model 4 - 500 Hz band SPL	L95					L50					L5				
Parametric coefficients	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Sig.**
(Intercept)	77.6143	0.1353	573.74	<2e-16	***	87.81667	0.08714	1007.766	<2e-16	***	96.3592	0.1148	839.7	<2e-16	***
StationRed_Island	5.4249	0.1587	34.19	<2e-16	***	0.94525	0.10094	9.365	<2e-16	***	-2.0231	0.1435	-14.1	<2e-16	***
Approximate significance of smooth terms:	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**	**edf**	**Ref.df**	**Chi.sq**	**p-value**	**Sig.**
s(Date)	1.875301	9	2.631	< 2e-16	***	8.018011	9	101.394	< 2e-16	***	5.930099	9	34.475	< 2e-16	***
s(Date):StationBurin	2.961848	9	6.169	0.0000277	***	7.161066	9	136.315	< 2e-16	***	0.008157	9	0.002	0.692	
s(Date):StationRed_Island	6.252355	9	26.638	< 2e-16	***	0.007282	9	0.004	0.000605	***	0.007412	9	0.002	0.686	
s(Hours)	0.013967	8	0.014	0.01421	*	1.757874	8	4.364	0.055969	.	0.002996	8	0.001	0.746	
s(Hours):StationBurin	4.722467	8	45.291	< 2e-16	***	5.54306	8	62.639	< 2e-16	***	2.747614	8	18.774	4.34E-05	***
s(Hours):StationRed_Island	2.121173	8	7.412	0.01179	*	0.007784	8	0.008	0.044701	*	0.004277	8	0.001	0.769	
s(wind_spd_avg)	3.075415	9	47.752	< 2e-16	***	4.724951	9	37.984	< 2e-16	***	0.019561	9	0.015	0.259	
s(wind_spd_avg):StationBurin	0.049079	9	0.05	0.00166	**	0.006148	9	0.003	0.05327	.	0.08554	9	0.072	0.259	
s(wind_spd_avg):StationRed_Island	7.396436	9	63.713	< 2e-16	***	7.247712	9	65.565	< 2e-16	***	7.714269	9	67.311	< 2e-16	***
s(ship_label)	2.45426	9	58.948	< 2e-16	***	3.310753	9	623.578	< 2e-16	***	1.869136	9	106.527	< 2e-16	***
s(ship_label):StationBurin	0.007048	9	0.002	0.44769		0.027438	9	0.025	0.156006		0.003071	9	0	0.8	
s(ship_label):StationRed_Island	0.264513	9	0.28	0.15513		0.010853	9	0.008	0.216656		0.004613	9	0.001	0.646	**
s(wind_spd_avg,ship_label)	7.748652	27	12.14	< 2e-16	***	21.546638	27	268.471	< 2e-16	***	10.173566	27	18.293	< 2e-16	***
s(wind_spd_avg,ship_label):StationBurin	17.95833	27	76.254	< 2e-16	***	3.288665	27	3.974	< 2e-16	***	16.291675	27	50.536	< 2e-16	***
s(wind_spd_avg,ship_label):StationRed_Island	15.581594	27	45.769	< 2e-16	***	11.616307	27	26.6	< 2e-16	***	15.15943	27	34.083	< 2e-16	***