Passive acoustic monitoring as a tool for offshore wind farm biodiversity assessments: a pilot study

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Passive acoustic monitoring as a tool for offshore wind farm biodiversity assessments: a pilot study

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1. Abstract

Passive Acoustic Monitoring (PAM) has been used to monitor marine mammal species in Scottish waters over the past 10 years. A question remains over whether recordings collected within the scope of marine mammal monitoring can be used to monitor the presence and changes in the communities of species, such as benthic invertebrates and fish. This study aimed to investigate whether bio-and eco-acoustical measurements can be used to assess changes in benthic biodiversity through unlocking PAM data from eight locations along the east coast of Scotland (UK). The focus of this study was to assess fish's and crustacean's active (i.e. intentionally produced sounds for communication) and passive (i.e. un-intentionally non-communicative produced sounds) sounds. As part of this study, data around each study location were extracted from the National Biodiversity Network (NBN) atlas, indicating the potential presence of at least 32 species at our sites that can produce either passive or active sounds. However, invertebrates in particular are understudied in the field of bioacoustics, therefore other soniferous species may be present at the study sites. A total of four 10-minute recordings at dusk, midnight, dawn and mid-day were analysed in Raven, R and Matlab. The phonic richness (PR) was measured as the total number of types of sounds, while the acoustic communities are an aggregation of species which interact acoustically in the same acoustic space. Here, active and passive sounds were grouped together to investigate if differences between the phonic richness and acoustic communities can be related to differences in benthic faunal communities and richness. In addition, seven acoustic indices were measured as part of the soundscape analysis approach at the low (50-1000 Hz), higher (1000-2000 Hz) and total (50-2000 Hz) frequency bands. Benthic biodiversity and

environmental variables were extracted using QGIS from a variety of open-source platforms, such as EmodNET, the OneBenthic Portal and the essential fish habitat report.

A total of 16 different types of sounds were identified. Redundancy analysis (RDA) showed that the suitability of the area for spawning for a larger number of fish, the current velocity and the modelled benthic richness are the most important drivers of differences in the acoustic community. Kruskall Wallis test showed that the phonic richness of hard substrate habitat types is higher, compared to sandy habitat types. Pearson's correlation tests were conducted to establish if any of the seven acoustic indices could be used as a proxy for benthic richness, habitat type (i.e. hard or sandy) or phonic richness. Three indices (ACI, AEI and M) were correlated with benthic richness, and five (BI, H, TE, SE, M) with habitat type and phonic richness. Greater benthic richness was associated with an increased acoustic complexity index, reduced unevenness across frequency bands, and quieter recordings. Harder substrates were associated with more uniform signals overall, but not with increased evenness across time bands within recordings. They were also associated with louder recordings but exhibited lower variability across frequency bands. Given that phonic richness correlates with harder substrates, the acoustic indices showed a similar pattern.

Our results indicate that spatial differences in the acoustic communities associated with different habitat types and levels of benthic richness are present, suggesting that PAM data collected for marine mammal monitoring could be 'unlocked' to reveal long-term temporal and spatial changes in the biodiversity associated with benthic habitats and serve as a cost-effective tool to understand future impacts of human and climate-driven changes. Although our results indicated that acoustic indices are a promising tool, more data need to be analysed before they could reliably be used as a proxy for phonic or benthic richness or habitat type. If the goal is to analyse variations in species-specific vocalisations or the overall acoustic community, as well as to determine which acoustic properties are relevant to management (such as richness or abundance), then manual annotations or the development of automated sound detectors are essential.

2. Introduction

2.1 The importance of monitoring

Marine biodiversity is rapidly changing due to the direct and indirect impacts of climate change and ocean sprawl, which is the proliferation of human-made structures in the ocean and coastal areas (Duarte 2014).The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Service (IPBES) declared a global biodiversity emergency (IPBES, 2019), and it is therefore essential that effective long-term monitoring programmes are established to ensure sustainable development (Borja and Elliott 2021). This is particularly important in an offshore marine environment, which can be difficult and expensive to access and where impacts are not always clearly visible (Nathanael et al. 2024). Due to the dynamic nature of marine ecosystems, it can be challenging to obtain a clear signal to connect human activities (and the associated pressures) with an ecosystem response. On the other hand, some interventions, if done correctly, can potentially enhance biodiversity and improve ecosystem outcomes (Strain et al. 2018). Therefore, monitoring methods should be able to detect when biodiversity increases as well as potential decreases as a route to demonstrating environmental gains, which is especially important in light of recent discussions around Marine Net Gain (Hooper et al. 2021).

Traditional monitoring methods for monitoring the biodiversity associated with benthic habitats include grab sampling, box cores, benthic trawls and visual surveys (remotely operated vehicles, autonomous underwater vehicles and time-lapse images/videos) (Scottish Government report, 2023). Except for time-lapse cameras attached to benthic observation stations and landers (Kutti et al. 2014; Osterloff et al. 2016; De Clippele et al. 2023; Clark et al. 2024), these approaches only provide a snapshot of information at one point in time. Some of these tools can introduce sampling biases and cause damage to sensitive features (Beisiegel et al. 2017). There is a need, therefore, to improve monitoring regimes and investigate the effectiveness of non-invasive cost-effective tools, such as Passive Acoustic Monitoring (PAM).

2.2 Passive Acoustic Monitoring

Passive Acoustic Monitoring is emerging as a tool to assess and monitor changes in aquatic benthic biological communities (Minello et al. 2021; Havlik et al. 2022). Traditionally, in marine ecosystems, PAM has been used to monitor the presence and abundance of marine mammals. However, in recent years, PAM has been proposed and used for the monitoring of benthic habitats at a high temporal resolution and for long periods (months to years) with global efforts rapidly increasing (Mooney et al. 2020; Van Hoeck et al. 2021; Di Iorio et al. 2021; Havlik et al. 2022; Looby et al. 2023; Darras et al. 2024). Sounds produced by vertebrates and invertebrates such as fish, and crustaceans, worms and bivalves contribute to the biophonical component of the acoustic landscape or soundscape, while currents and wind contributes to the geophonical component, and boat noise and other man-made noise contribute to the anthroponical component (Duarte et al. 2021). Characterising the biological component of underwater soundscapes and monitoring changes in acoustic communities composition, diversity and abundance can provide information on animal presence and behaviour (i.e. mating, aggression), as well as on species diversity (Ladich 1997; Fudge and Rose 2009; Desiderà et al. 2019a; Mooney et al. 2020; Di Iorio et al. 2021).

2.3 Benthic soundscapes

Both fish and crustaceans can produce either active or passive sounds (Rountree et al. 2018; Caiger et al. 2020; Raick et al. 2021). Active sounds are here defined as sounds which animals intentionally produce for communication purposes, i.e. all those sounds emitted by a sender which influence the behaviour of a receiver in a fashion that provides fitness-related advantages at least to the sender. For example, cod can vibrate their sonic muscles around their swim bladder, which produces "grunt" sounds used to attract mates during spawning events (Brawn 1961) and spiny lobsters can make "rasp" stridulation sounds to fend off predators (Buscaino et al. 2011). Other sounds, which are here referred to as passive sounds, are non-intentional and can be a by-product of certain behaviours, such as air movement, jaw movement, swimming or food consumption (Rountree et al. 2018; Parsons et al. 2022; Looby et al. 2023). These sounds typically have more variable acoustic characteristics (Rountree et al. 2018). For example scallops (*Pecten maximus*) produce a "cough" sound while moving their valves (Di Iorio et al. 2012).

Some of these sounds may be more abundant during certain times of the day and year. The circadian cycles (i.e. the daily cycle) of acoustic activity are regulated by changes in light levels generated by the sun or the moon cycles. Times when acoustic activity of benthic species may be increased depend on the species. For examples. The European spiny lobster (*Palinurus elephas*), is most active at night (Buscaino et al. 2011), while the tropical domino damsel fish (*Dascylus albisella*) produces more sound during the day (Lammers et al. 2008). Increased acoustic activity can sometimes be observed at dusk and dawn, as well as during new moon periods (e.g., Lammers et al., 2008; Radford et al., 2008). Seasonal patterns are usually associated with fish's spawning (Lobel 1992, Luczkovich et al 1999, Bolgan et al. 2017, Hawkins and Amorim 2000), and breeding periods (Mann et al 1997). Therefore, analysing the sounds present in offshore marine environments could be a valuable tool for monitoring specific biological processes and identifying both natural and shifting patterns of biological activity across various locations.

2.3.1 Acoustic Community and Phonic Richness

The acoustic community can be defined as the aggregation of soniferous species, and the phonic richness is a measure of the total number of types of sounds made by soniferous species. These acoustic metrics have been used as a proxy for biodiversity and habitat condition (Mooney et al. 2020), with alterations to their spatial or temporal patterns potentially being indicative of changes in community composition or ecological state (Rabin et al. 2022, Sueur et al. 2019, Lamont et al. 2022). For example, differences in acoustic community composition have been found related to variations in water depth and the percentage cover of structure-forming benthic habitats, such as coralligenous reefs, in the north-western Mediterranean (Di Iorio et al., 2021). Habitats that are regarded to be healthy or in better condition tend to have a higher phonic richness, although significant differences are not always found (Lamont et al., 2020, Di Iorio et al., 2021). Visually and aurally analysing the presence and abundance of the different types of sounds is, therefore, a useful approach to providing an understanding of patterns in biodiversity, which is otherwise difficult to monitor.

2.5 Acoustic Indices

Since manually annotating the different types of sounds present in a recording is very time-consuming, the application of computational acoustic indices, initially developed for terrestrial habitats, is increasingly being applied in marine habitats. Rather than investigating patterns of species-specific calls, acoustic indices target diversity assessment at the community level or use spatio-temporal changes of sounds to estimate alterations in ecosystem functionality (Sueur et al., 2018, Pieretti and Danovaro 2020) (Table 1).

Soundscape indices can be used separately or in combination with each other to quantify the complexity of the soundscape in one or more "simple" values (Lillis et al. 2014, Williams et al. 2022). The list of indices used in this study, along with a summary description and the R packages used is provided in Table 1. The acoustic complexity index (ACI) is the most commonly used index and appears to be the most reliable metric for assessing fish diversity, habitat quality and certain key ecosystem functions (Harris et al. 2015, Elise et al. 2019, Minello et al. 2025). The total-, spectral-, and temporal entropy indices are also commonly used in marine habitats (Sueur et al. 2008, Villanueva-Rivera et al. 2011, Depraetere et al. 2012, Minello et al. 2025), with the total entropy appearing to work well for temperate reefs (Harris et al. 2015). The bioacoustics index has been shown to detect fish chorusing to some extent and was found to be important when using a multi-metric approach (Siddagangaiah et al. 2019, Williams et al., 2022). Changes in the amplitude of recordings over time, have been used to indicate the presence of fish choruses (Siddagangaiah et al. 2021) or discriminate between different habitats or habitat states (Elise et al. 2019, Lamont et al. 2021).

Although multiple reviews highlighted the potential of using acoustic indices in monitoring, they also pointed out the need for further studies due to sometimes a lack of a clear relationship between more traditional biodiversity indices, including phonic richness and values generated by acoustic indices (Mooney et al. 2020; Pieretti and Danovaro 2020; Minello et al. 2021). In addition, noise pollution, equipment self-noise fish chorusing, and even geophysical sounds can disrupt the reliability and interpretability of the indices (Parks et al. 2014, Rice et al. 2017, Minello et al. 2021, Nguyen Hong Duc et al., 2021). For example, equipment self-noise can artificially increase ACI values, while fish chorusing can reduce it (Nguyen Hong Duc et al., 2021).

Standardisation of the data collection, while accounting for geophysical drivers and removing or reducing anthropogenic noises have been suggested to improve the reliability of the indices (Minello et al. 2021). Increasing the spatial and temporal sample sizes, along with habitat-specific testing can improve their effectiveness (Minello et al. 2021). Furthermore, it is essential to recognise that acoustic indices do not enable the discrimination of fish community properties, which are crucial for management, such as abundance and diversity (Bolgan et al., 2018; Raick et al., 2023a).

Table 1. Overview of the acoustic indices calculated, with details on the R package used to calculate them, and a brief description of how each is calculated (adapted from Williams et al. 2022).

Acoustic Index	Abbreviation	R package	Description
Acoustic Complexity Index	ACI	Seewave	Measures variability in intensity of frequencies across time. Designed to give high values where variable biophony is present, low values in systems with constant sounds.
Acoustic Evenness Index	AEI	soundecology	Measures diversity across frequency bands. High values indicate greater unevenness between frequency bands. As diversity of sound increases, scores will decrease.
Bioacoustic Index	BI	soundecology	Measures cumulative intensity across frequency bands. Higher values indicate higher variability – intended to give proxies for avian species abundance
Total Entropy	H	Seewave	Measures randomness across temporal and spectral domains. The calculation is adapted from Shannon's diversity index. Higher values indicate more even signals (amplitude equally spaced across frequency and time). It is the product of TE and SE.
Temporal Entropy	TE	Seewave	Measures randomness across the temporal domain. Higher values indicate amplitude even across time bands within the recording.
Spectral Entropy	SE	Seewave	Measures randomness across the frequency domain. Higher values indicate amplitude even across frequency bands within the recording.
Amplitude index	M	Seewave	Measures median of the amplitude envelope. This is a relative measure of sound amplitude. Higher values indicate louder recordings.

2.6 Offshore wind

Coastal habitats with structure-forming benthic animals and plants, such as coral reefs, kelp and seagrass, have been the primary focus of marine benthic soundscape studies (Havlik et al. 2022). Sedimentary habitats that are characterised by sandy, muddy and coarse sediments are mostly only being used as a control rather than being the focus of previous studies (Ceraulo et al. 2018). Offshore developments typically affect the latter. Using PAM as a monitoring tool could be particularly relevant for the planned global offshore wind farm developments, as these have the potential to change benthic biodiversity at a local and regional scale through the introduction of hard substrates and changes in sediment deposition, food supply and local hydrodynamics (Mangi 2013; Clark et al. 2014; Dannheim et al. 2020). The application of PAM could provide long-term, remote and scalable information on aquatic biodiversity which are not achievable by other monitoring techniques (Mooney et al. 2020; Ross et al. 2023).

The Scottish Government has set a range of targets to cut greenhouse gas emissions and to generate more energy from renewable sources. The Climate Change (Scotland) Act 2019 commits the Scottish Government to reach net zero emissions of all greenhouse gases by 2045. Offshore wind will play a vital part in meeting these targets and is set to expand substantially in Scotland over the next decade and beyond, as evident by the recent ScotWind seabed leasing round by the Crown Estate Scotland. In January 2021 and through its clearing process in August 2022, Crown Estate Scotland offered Option Agreements for 20 offshore wind projects around Scotland, totalling 27.6 Giga Watts (GW) of potential new offshore wind developments. The related offshore wind Innovation and Targeted Oil and Gas (INTOG) decarbonisation planning and leasing process outlined a further 5.4 GW of projects that have been offered exclusivity agreements.

This pilot study set out to demonstrate the usefulness of PAM recordings as a tool to detect spatial changes in offshore benthic biodiversity associated with sedimentary European Nature Information System (EUNIS) classified sandy to muddy and coarse habitat types. It will do this by first assessing which soniferous species could be present in the study sites by extracting data from open source platforms such as the OneBenthic and National Biodiversity Network (NBN), then by establishing if there are differences in benthic acoustic communities associated with the different habitat types, and finally by establishing if passive acoustic biodiversity metrics such as phonic richness and acoustic indices can be used as a proxy for benthic biodiversity using both raw data and data cleaned from noise pollution. This pilot study is a first step towards determining the value of this tool in monitoring programmes and survey requirements for marine renewable energy devices (MREDs) in Scottish waters. The Marine Directorate has been using PAM to monitor cetacean species in Scottish waters over the past 10 years, with click detectors and broadband acoustic recorders. There is therefore the potential to 'unlock' data from the comprehensive PAM network to add value to Scottish marine monitoring programmes.

3. Methods

3.1 Study sites

Passive acoustic monitoring metadata from 332 moorings provided by the Marine Directorate were screened for the presence of calibration information and broadband acoustic data. From the latter, 200 moorings were identified as having broadband and calibration data originating from 20 different locations. For the purpose of this pilot study, and to maximise the amount of data from contrasting habitat types while minimising the effect of seasons and interannual changes on the soundscape, the available datasets were searched for the year in which most sites had data collected in April. April was chosen as this is when key fish species are likely to spawn in Scottish waters (FishBase, 2024) and the effect of wind on the ambient noise would be reduced (De Clippele and Risch 2021).

The centre frequency 1/3 Octave Band Sound Pressure Level (SPLrms) were then calculated using PAMGuide (Merchant et al. 2015) to determine which day in April was the least affected by wind and anthropogenic noise pollution. The PAM data collected in April 2021 included most sites (datasets), 18 in total. The 100 Hz (SPLrms) data was plotted using ggplot in R version 4.0.0 and revealed that 23rd of April was the most suitable day for further analysis, as it had the least amount of ambient noise at the 100 Hz frequency band (Supplementary Materials, SM1). However, one of the locations, Arbroath site, only had data available until the 12th of April. To avoid reducing the number of sites for analysis, the 10th of April was identified as the second most suitable day. Visual inspection of historical weather data on Visual Crossing (Visual Crossing, 2024) revealed that the noise levels were predominantly driven by wind gust strength at the sites. Inspection of the acoustic data from the Latheron site, confirmed that the peak in SPL (up to ~130 dB re 1 μPa of the 1/3 Octave band) was related to ship activity very near the site (SM1). Of the 18 moorings sites reviewed, nine were used for further analysis as sharing permissions were in place during the duration of the project (Figure 1). One of the locations, Duncansby Head (Deployment no 558), was heavily polluted with artificial mooring noise and was therefore also excluded, leaving eight sites in total (Table 2).

Table 2 Overview of the passive acoustic monitoring (PAM) datasets used in this study. The table provides the mooring's ID number, deployment number, location name, and coordinates.

ID	Deployment no.	Location & buoy number	Latitude (decimal degrees)	Longitude (decimal degrees)
1	554	Latheron 5	58.27	-3.23
11	549	Spey Bay 10	57.74	-3.05
13	530	Fraserburgh 5	57.71	-2.13
26	543	St Andrews 10	56.26	-2.5
28	536	St Abbs 5	55.93	-2.18
6	523	Helmsdale 15	57.98	-3.54
16	533	Cruden Bay 5	57.38	-1.83
23	546	Arbroath 10	56.5	-2.38

3.2 Environmental data

To understand what biological and environmental variables contribute to explaining spatial differences in the soundscape, Geographic Information System (GIS) layers were downloaded from open-source platforms and imported into QGIS (version 3.4.13, QGIS, 2024). An overview of the data and their web links are provided in the supplementary materials (SM2), and include, depth, the EUNIS (European Nature Information System) habitat type (Figure 1), temperature, current speed, primary productivity, and dissolved organic carbon. The QGIS spatial analyst tool (Extract Multi Values to Point tool) was used to extract the environmental information from the sites for statistical analysis.

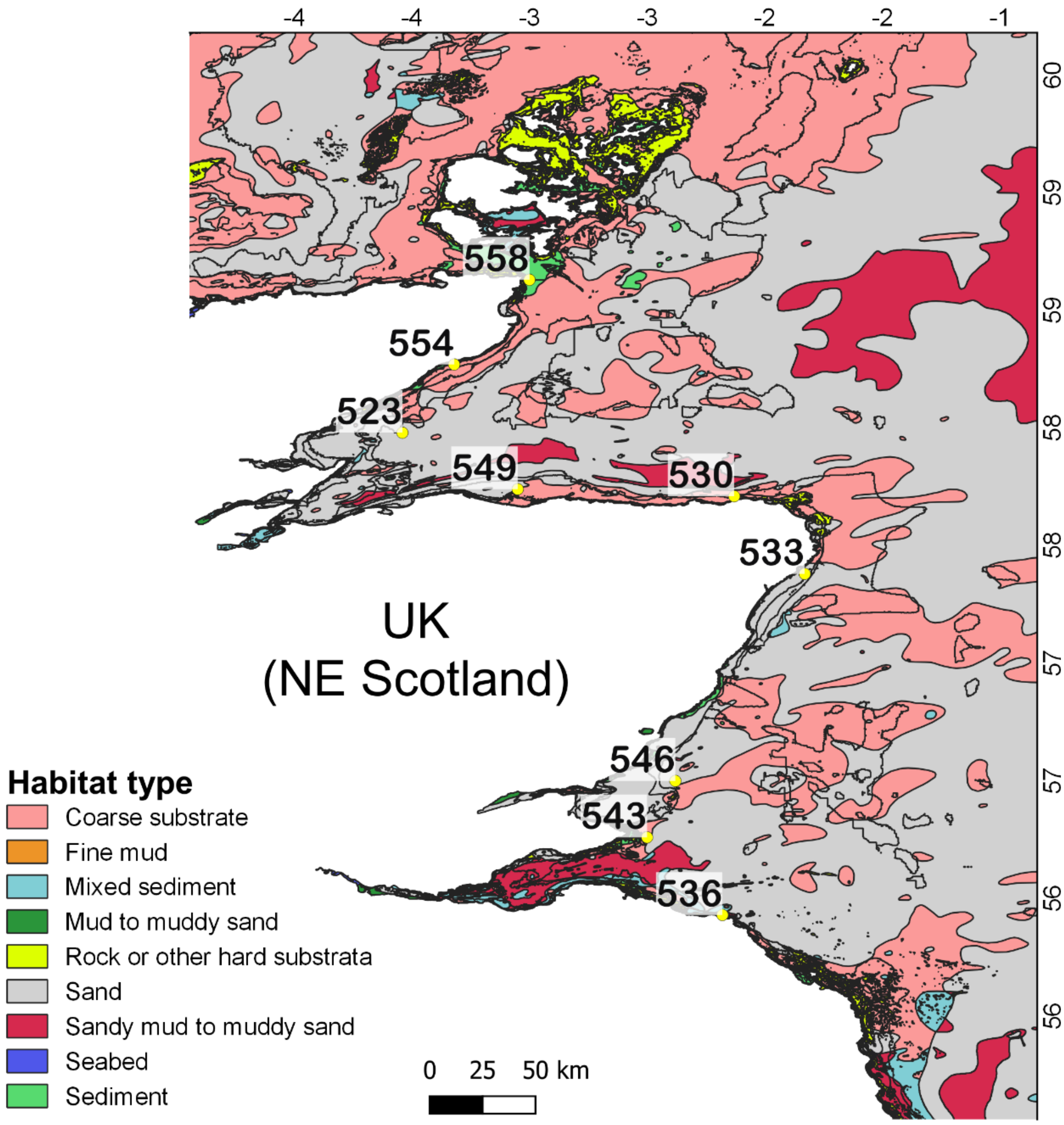

Figure 1. Map of the northeast (NE) of Scotland (United Kingdom) showing the locations of the passive acoustic mooring sites and associated EUNIS habitat types. Site 554 is Latheron, 523 is Helmsdale, 549 is Spey bay, 530 is Fraserburgh, 533 is Cruden Bay, 546 is Arbroath, 543 is St Andrews and 536 is St Abbs. Site 558 is Duncansby Head which was excluded from the analysis.

3.3 Biodiversity data from open-source platforms

Benthic biodiversity data were downloaded from the OneBenthic portal (Cooper and Barry 2017, 2020). The OneBenthic data is a map of 12 different faunal clusters, based on classifications from random forest models of environmental data and seabed core and sediment samples (Cooper and Barry 2017, 2020). Each faunal cluster is associated with an assemblage of likely taxa that would be found in each area. At each mooring location, the OneBenthic faunal cluster species richness and faunal cluster category, alongside the area (km^2) of the faunal cluster occupied at the mooring location were extracted and used as additional variables for statistical analysis.

The area that an animal will use to feed, i.e. their home range, is species dependent. While some species, such as the European Lobster, have a home range smaller than 5 km (Smith et al. 2001), fish such as cod may travel a distance of 15 km to find food (Neat et al. 2006). The number of faunal clusters present within an intermediate home range area of 10 km radius, was therefore extracted, as a higher diversity of habitats present in an area may affect species presence. This variable is here referred as “Habitat complexity”. This radius was chosen based on the assumption that species of interest may travel in these areas, but it is important to note that their vocalisations may not. For example, sounds produced by cod may travel around 400 m (Seri et al. 2023). The OneBenthic faunal cluster categories are also solely based on invertebrates, for which soniferous behaviour is largely unknown or unlikely (Parsons et al. 2022; Looby et al. 2023). The number of species which use our sites as essential spawning or nursery fish habitats were extracted from essential fish habitat (Franco et al. 2022) and fisheries sensitivity maps (Marine Scotland 2022). As part of these maps, areas are categorised as “absent”, “low”, and “high” for certain fish species. Since numerical data was needed for analysis, here the sum of the species, which were categorised as “high”, were counted.

To determine if and which soniferous species may be present in the area surrounding the study sites, species available per a location’s 10 km^2 radius (see above’s justification) were downloaded from the National Biodiversity Network (NBN) Atlas (NBN Trust 2024). The NBN Atlas contains species occurrence data submitted by trusted organisations and recorders and collated, integrated and standardised by the NBN Trust (2024). The extracted NBN data was screened to ensure only relevant marine species were included. Records from museums, historical surveys, non-animal and non-marine were excluded. Due to shifting species ranges, as a result of changing sea temperatures, only records from 2014 onwards were kept.

This list was compared against a recently published global inventory of species confirmed or expected to produce sound underwater as part of a collaboration between the Global Library of Underwater Biological Sounds (GLUBS) with the World Register of Marine Species (WoRMS) (Looby et al. 2023) and fishsounds.net. The GLUBS database uses species lists from WoRMS and assigns species to one of six categories denoting knowledge of sonifery. A further literature search was then conducted to detail any available acoustic characteristics of sounds made by soniferous species. If open-access sounds were available, available information on sound type, peak frequency and duration of the sound were recorded.

3.4 Passive Acoustic Data

All recordings had a sampling rate of 96 kHz. All acoustic files were visually and auditorily screened in the software Raven Pro (version 1.6). The noise produced by vessels, the moorings, or pile driving were categorised as anthropogenic. Distinct anthropogenic noises such as pile driving, self or vessel noise were annotated in Raven with bounding boxes. These selections were then removed using the delete tool within Raven Pro, to further test if noise pollution affects acoustic index values (Zhang et al. 2024). Any biological sounds which may have been masked by this anthropogenic noise would also have been removed. Four subsamples of ten-minute continuous recordings were selected per site, around sunset, midnight, sunrise and midday. Based on historical data, sunrise happened at 06:16 and sunset happened at 20:08 on 10/04/2021; with the exception of St Abbs at dawn, these times appeared clear of shipping noise pollution. Due to slight differences in the timings of recordings at each site, the four selected were the first after sunrise, the last before sunset, and the closest to both solar midday and midnight (SM3).

3.4.1 Acoustic Community, Phonic Richness and abundance

Biologically produced sounds were manually annotated in Raven Pro version 1.6. For the purpose of this study, both active and passive sounds were considered, which resulted in the acoustic community and phonic richness data. Due to the typical low frequency content of fish sounds, the Raven Pro spectrogram was explored up to 4 kHz. Sounds which had a frequency range higher than 4 kHz were also annotated when they were visible in the lower frequency ranges (< 4kHz), as some benthic invertebrate sounds can extend to around 10 kHz. The x-axis was zoomed to ~12 seconds, to give enough detail to clearly label the start and end of specific acoustic events. Sounds were labelled and counted and a datasheet was created containing information on the number of different type of sounds per subsample. The phonic richness was calculated as the total number of types of sounds per 10 minute sample. To determine if the sounds were active or passive sounds, the envelope of the sounds were investigated by a fish bioacoustic expert. Detailed characterisation of the different sounds types is out of the scope of this report.

3.4.2 Acoustic indices

A total of seven acoustic indices (Table 1) were calculated (Sueur et al. 2014). To calculate the acoustic indices, each selected recording was filtered using a short-term Fourier transform band-pass filter into different frequency bands at the low-frequency band (50 – 1,000 Hz), a relatively higher frequency band (1,000 – 2,000 Hz) and this frequency band as a whole (20 – 2,000 Hz). The chosen range of the different frequency bands was based on the frequency bounds of the annotated types of sounds and to avoid impacts of marine mammal sounds. While peak frequency bands of some invertebrate sounds may not be included in this range, their sounds usually extend to the lower frequency ranges as well. As mentioned above, only sounds extending below 4 kHz were annotated. The indices were calculated in R using the packages seewave (Sueur et al. 2008) and soundecology

(Villanueva-Rivera and Pijanowski 2018). Acoustic indices were calculated for both the raw and cleaned audio files, i.e. after mooring and anthropogenic noise were removed.

3.5 Statistical analysis

To determine what drives the differences between the acoustic communities, first, the acoustic community data were Hellinger transformed using the decostand function in the vegan package (Oksanen et al. 2017). A Hellinger transformation was used to convert sound type abundance values to relative values, to address absences of certain types of sounds across multiple samples. Then, the Bray–Curtis dissimilarity measure was computed with the vegdist function. This measure calculates the dissimilarity between two samples based on the relative abundances of species present in those samples (Oksanen et al. 2017). To test if the acoustic communities significantly differ in relation to the OneBenthic faunal cluster type and the habitat type groups an analysis of similarity (ANOSIM) was conducted using the Bray-Curtis dissimilarity matrix. ANOSIM compares the mean of ranked dissimilarities between groups to the mean of ranked dissimilarities within groups. This was followed by a permutational analysis of variance (PERMANOVA) to test the magnitude of the dissimilarities, using the adonis2 function. This allowed to test if the patterns of variation in composition and in abundance of types of sounds in relation to faunal cluster and habitat type were different. If differences were found using ANOSIM, then similarity percentages (SIMPER) analysis was used to identify which types of sounds primarily accounted for observed differences in soundscape assemblages between faunal clusters and habitat types. This method does this by calculating the average percentage contribution of each variable to the overall Bray-Curtis dissimilarity between the chosen groups.

This was followed by the development of multivariate redundancy analysis (RDA) models to establish which variables contributed to explaining differences in the acoustic communities. The explanatory variables (i.e. depth, temperature, current speed, primary productivity, dissolved organic carbon, substrate, OneBenthic richness, Area of the OneBenthic class, and the number of species that use the area as a nursery or for spawning) were normalised using the decostand function in the vegan package. This function makes the margin sum of squares equal to one (default margin is 1) (Oksanen et al. 2017). To determine which explanatory variables were statistically important, forward selection was conducted using the ordistep function. The selected variables were then used in a partial RDA model, constraining the variables that are not metrics representative of the benthic biodiversity.

Correlation and Kruskal-Wallis tests were furthermore used to test correlations between metrics and differences between habitat types and faunal clusters. To test correlations between the habitat types and the acoustic indices, the habitat types were categorised, with “2” indicating hard substrates and “1” indicating sandy substrates.

4. Results

4.1 Benthic biodiversity

The data extracted from the NBN database resulted in a total of 5,615 records belonging to 482 different species, extracted from the 10 km^2 buffer area around the location of the mooring sites. The species list from NBN Atlas across all eight sites was combined with the publicly available sonifery information from the GLUBS database. Of the 482 species recorded in the NBN data, 49 species had been assessed in the GLUBS database (Parsons et al. 2022; Looby et al. 2023). Details of the soniferous categories and numbers of species in different taxonomic groups are presented in Table 3, Figure 2 (see Data Availability). Of the 433 species not featured in the database, 417 were invertebrates, which are understudied in terms of the sounds they produce, so should be treated as "unknown or undetermined". Other species that were not assessed were two *Elasmobrachii* (shark) species and 14 *Actinopterygii* (ray-finned fish) species. The full list of species found in the buffer area includes invertebrate and vertebrate species, as well as all species included in Marine Scotland's Essential Fish Habitat reports (Franco et al. 2022), some of which were not recorded in the NBN records. Because the NBN records are not collected in a standardised manner, this data is not used in the analysis but is used as contextual information.

Table 3. Overview of the types of sounds (i.e. active, passive, unconfirmed or unlikely) the 49 species make according to GLUBS database. The number of species in each category within higher taxonomic groups is provided, along with the names of highlighted species in each category also provided.

Group	Type of sound	Highlighted species
Mammals	**Active sound** = 10 species	Both native seal species and eight cetaceans
Fish	**Do not or unlikely** = 4 species	Angler, dragonets, common sole, lemon sole, plaice
	Likely but unconfirmed = 15 species	Atlantic mackerel, others
	Passive sound = 6 species	Conger eel, pollock, others
	Active sound = 5 species	John dory, Atlantic cod, others
	Active and passive sound = 1 species	Corkwing wrasse
Invertebrates	**Unknown or undetermined** = 3 species	Brittlestars, spiny starfish
	Passive sound = 3 species	Urchins, scallops
	Active sound = 2 species	Lobsters

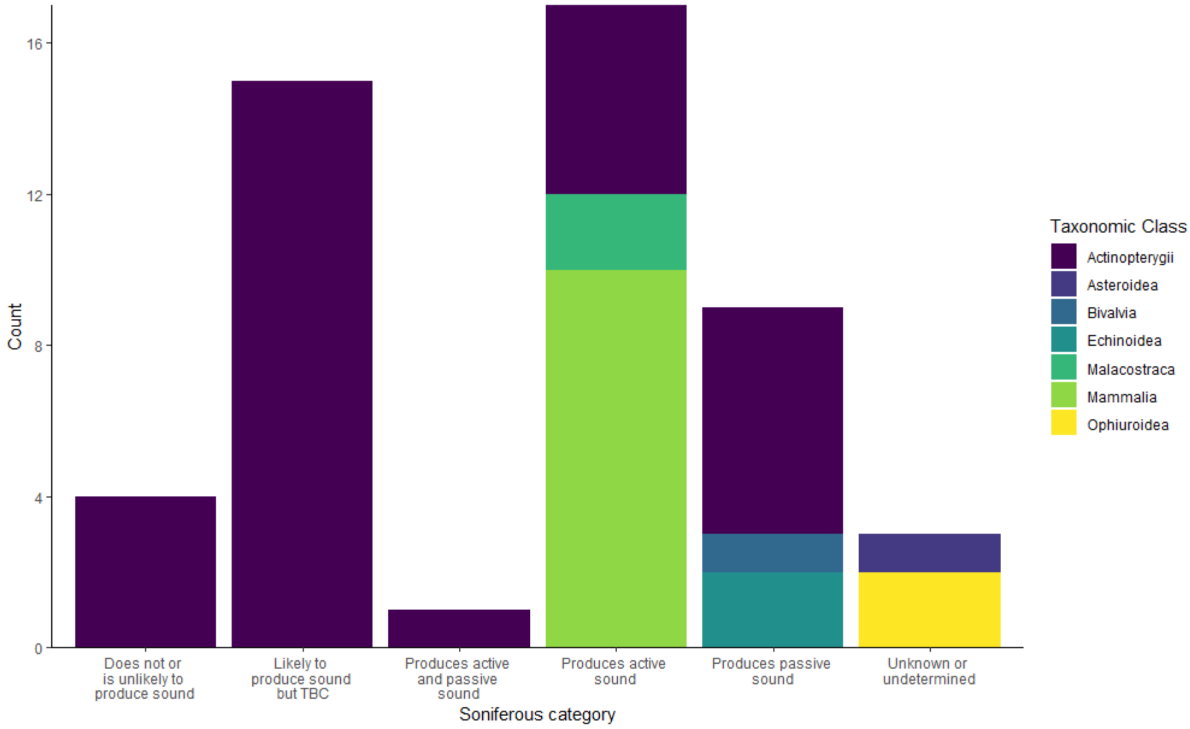

Figure 2. Bar chart denoting the number of species from NBN data in each of the GLUBS categories. Bars are coloured according to the Class of each animal species.

A total of four PAM moorings were located within “coarse” sediment habitat types (i.e. Spey Bay, Latheron, Fraserburgh, St Andrews), one in “rock or hard” substrate (i.e. St Abbs) and three within “sandy” habitat types (i.e. Cruden Bay, Arbroath, Helmsdale) (Table 4, SM4). The coarse and hard substrate categories were merged as “hard substrates” for further analysis. The depth of the moorings ranged from 21-48 m depth, with Arbroath (47 m) and Helmsdale (48 m) being the deepest sites, and Spey Bay (23 m) and Cruden Bay (21 m) being the shallowest sites. Only three benthic faunal clusters were found to be associated with the study locations, i.e. D2a, D2b and D2c. According to Cooper and Barry (2017) the D2a assemblages are found in areas with more mixed sediments, while assemblages associated with D2b and D2c are found associated with deeper water and are assumed to be largely stable through time. The D2b assemblage is found in areas of high mud content with weaker currents and D2c dominates in areas of higher sand content. Polychaetes were the dominant faunal group across the assemblages, with bivalve molluscs being a feature of group D2b. D2c has the lowest mean number of taxa and abundances associated with faunal groups (Table 4).

Table 4 Dominant benthic faunal groups per cluster, along with the dominant families according to the model produced by Cooper and Barry (2017).

Faunal cluster type	**Sites**	**Taxa**	**Family**
D2a	Latheron	five polychaeta (P) and one nemertea (N) taxa	Spionidae (P), Glyceridae (P), Nemertea (N), Terebellidae (P), Capitellidae (P), Phyllodocidae (P)
D2b	Fraserburgh, St Andrews, Arbroath, Helmsdale	seven polychaetes (P), one echinoderm (E), one nemertea (N) and one bivalve mollusc (BM) taxa	Spionidae (P), Amphiuridae (E), Nephtyidae (P), Lumbrineridae (P), Oweniidae (P), Cirratulidae (P), Capitellidae (P), Nemertea (N), Semelidae (BM), Ampharetidae (P)
D2c	Spey Bay, St Abbs, Cruden bay	three polychaete (P) taxa	Nephtyidae (P), Spionidae (P), Opheliidae (P)

The faunal cluster's habitat size underneath the moorings located at Helmsdale, St Andrews and Cruden Bay were the largest. The "complexity", i.e. the number of different classes found per mooring site, within a 10 km^2 radius is shown in the Supplementary Materials (SM4). The most complex site was St Andrews, with 6 faunal cluster classes ranging from 1.25 km^2 to 154.45 km^2 in patch size. The least complex sites were Latheron and Fraserburgh, each only having 3 benthic classes present, although both of these sites were in the bottom four for sea surface area within the 10 km^2 buffer. This is because they were located close to land, meaning that some of the 10 km^2 overlapped with land rather than the sea. All other sites had 5 classes present, though many had less than 0.5 km^2 of some classes. It is noteworthy that all sites, except Helmsdale were located within 10 km from land meaning that part of their 10 km^2 buffer zone did not contain any benthic classes.

Some of the locations were categorised as potential spawning grounds for cod, plaice, sandeel and whiting, and nursery areas for cod, spurdog, Blue Whiting, Tope Shark, herring, Hake, ling, mackerel, anglerfish, plaice, sandeel and Spotted Ray (Franco et al. 2022). An overview of which species were listed to use each of our study locations as a spawning or nursery habitat can be provided upon request (See Data Availability).

4.2 Acoustic Community

In total, 2,592 individual sounds were labelled across the 310 minutes of audio examined. These sounds were labelled as 16 different types of sounds, likely including both passive and active sounds (Table 5). Spey Bay and St Andrews have the highest abundance of sounds across the four 10-minute samples. Two types of sounds were characterised by acoustic features similar to those previously reported for communicative fish sounds (Desiderà et al. 2019; Bolgan et al. 2022; Raick et al. 2023b); these were labelled "thump" and "drum". Thump was recorded in Arbroath, Spey Bay, St Abbs and St Andrews, while Drum was only recorded Spey Bay (Table 5). "Thump" can be described as a complex sound made of two components; a pulsed component followed by a frequency-modulated component. Its total abundance was highest at St Andrews. "Drum" can be described as a pulse series and was present only at Spey Bay. The types of sounds "whoop", "tap", "sneeze", "whew", and "plop" were either fish or invertebrate active or passive sounds, while the others, such as "tick", "grunt", "scrape", "crackle", "click", "squeak", "snap" and "chirp" were either invertebrate or passive fish sounds (Table 5). More information on their acoustic characteristics can be found in the supplementary materials (SM5).

The acoustic community data exhibited distinct clusters depending on the habitat type (i.e. hard vs sandy habitats) (ANOSIM: R: 0.1426, p-value < 0.02) and faunal cluster type (i.e. D2a,b,c) (ANOSIM: R = 0.12, p-value = 0.05). There was a significant interaction of faunal cluster and habitat type (PERMANOVA; F= 3.1173, p-value = 0.002). The cumulative contribution of the most influential types of sounds between hard and sandy substrates were "thump" (73%), "tick" (63%) and "grunt" (52%) with "thump" and "grunt" being higher in hard substrates, and grunt being higher in sandy habitats. "Thump" and "crackle" explain the majority of the dissimilarity between D2b and D2a (ST1: 74.85% and ST7: 67.76%) and, "grunt" and "thump" between D2b and D2c (ST3: 79.61% and ST1: 68.00%). "Whoop" (74.34%) and "thump" (68.22%) are the other two types of sounds which are most different between D2b and D2a. "Thump" and "tick" were on average highest in D2c, "grunt" was on average highest in D2a, although only one site was associated with this faunal cluster. "Whoop" was only present in D2a (Table 5). 23

Table 5. Overview of the EUNIS habitat type, OneBenthic faunal cluster number, the total number of occurrences per sound type (ST) and the average ± standard deviation of the phonic richness per site.

	Latheron	**Fraserburgh**	**St Andrews**	**Spey Bay**	**St Abbs**	**Helmsdale**	**Arbroath**	**Cruden Bay**
Habitat Type	Coarse	Coarse	Coarse	Coarse	Rock or hard	Sandy	Sandy	Sandy
Faunal Class	D2a	D2b	D2b	D2c	D2c	D2b	D2b	D2c
ST1 - Thump	3	0	66	50	19	0	5	0
ST2 - Tick	5	4	11	21	2	0	2	4
ST3 - Grunt	3	0	0	7	1	10	1	0
ST4 - Scrape	16	0	0	5	0	1	31	0
ST5 - Whoop	4	0	0	0	0	0	0	0
ST6 - Tap	15	5	224	499	108	3	23	47
ST7 - Crackle	9	0	0	0	25	0	0	0
ST8 - Squeak	3	0	0	0	0	0	0	0
ST9 - Sneeze	1	0	0	0	0	0	0	0
ST10 - Snap	1	0	0	2	0	0	0	0
ST11 - Chrip	1	0	4	11	1	0	1	0
ST12 - Whew	1	0	0	2	0	1	0	1
ST13 - Plop	1	0	3	9	0	0	5	0
ST14 - Whoosh	0	0	0	1	0	0	1	0
ST15 - Hard grunt	0	0	0	1	1	0	0	0
ST16 - Drum	0	0	0	15	0	0	0	0
Total number of sounds	**63**	**9**	**308**	**623**	**157**	**15**	**69**	**52**
Phonic Richness	**3.00 ± 0.76**	**1.00 ± 0.00**	**2.50 ± 0.53**	**5.25 ± 1.16**	**2.33 ± 0.52**	**1.00 ± 0.76**	**2.50 ± 1.60**	**1.25 ± 0.46**

An RDA was conducted to establish which environmental and biodiversity variables drive differences in the acoustic communities (i.e. based on abundance data of the different types of sounds) associated with each of the samples (Figure 3). Collinearity was reduced by removing variables with strong correlations (>0.8), while keeping the variables that explain the most variability in the data. Benthic richness, velocity, and the number of spawning species were kept in the final model. The model explained 27% of the variation in the acoustic communities. A partial RDA, constraining velocity, showed that the benthic biodiversity variables (i.e. NBN benthic richness and number of spawning species) accounted for 17% of the variation, while velocity accounted for 9%. A total of 73% of the variability remains unexplained. ST6 “tap”, ST1 “thump”, ST7 “crackle”, ST4 “scrape” and ST3 “grunt” were the top five sounds driving differences between the different communities.

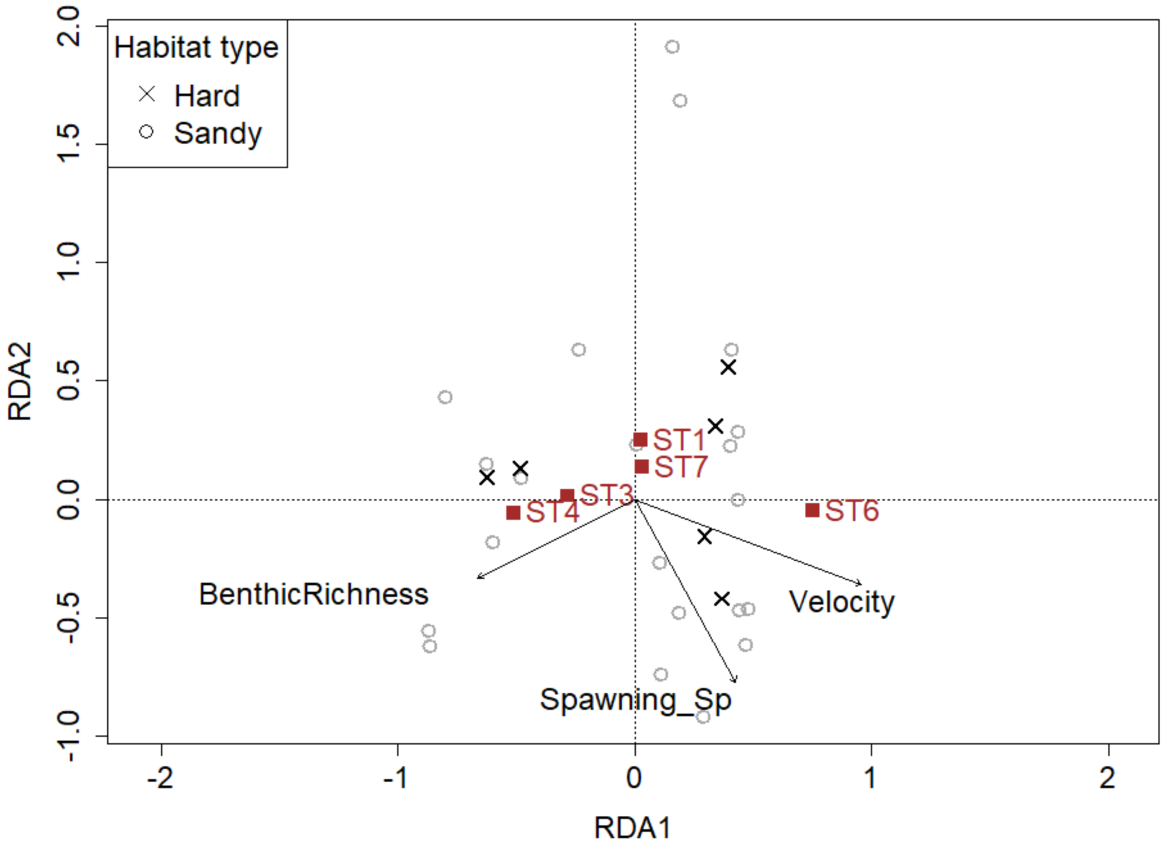

Figure 3. RDA plot showing the relationship between the acoustic communities and biodiversity and environmental variables, highlighting patterns of variation and key drivers of differentiation. ST1 is "Thump", ST3 is "Grunt", ST4 is "Scrape", ST6 is "Tap" and ST7 is "Crackle".

Removing noise pollution from recordings resulted in files of different lengths (SM3). Latheron, Arbroath and Fraserburgh had the highest occurrence of anthropogenic noise, based on the removal of distinct anthropogenic noise events. Helmsdale was the least noise-polluted site, with only one second being removed on average. The dawn recording from St Abbs was listened to, however no sounds were labelled due to loud boat noise masking all other audio in this recording.

4.3 Phonic Richness

Spey Bay, Latheron and St Andrews had the highest richness of types of sounds (Table 5). Overall, the phonic richness (PR) was significantly higher in areas with coarse/hard EUNIS habitat types, compared to sandy EUNIS habitat types (Kruskall-Wallis test, p-value = 0.03; Figure 4). When comparing the PR between the benthic faunal clusters, no significant differences were found (Figure 5). PR at sunrise and sunset tended to be higher compared to midday and midnight, although no significant differences between time of the day could be found, likely due to the lack of temporal replicates per site (Figure 6). A negative relation (p-value <0.05) between phonic and benthic richness was found (correlation: -0.30), although this was not significant.

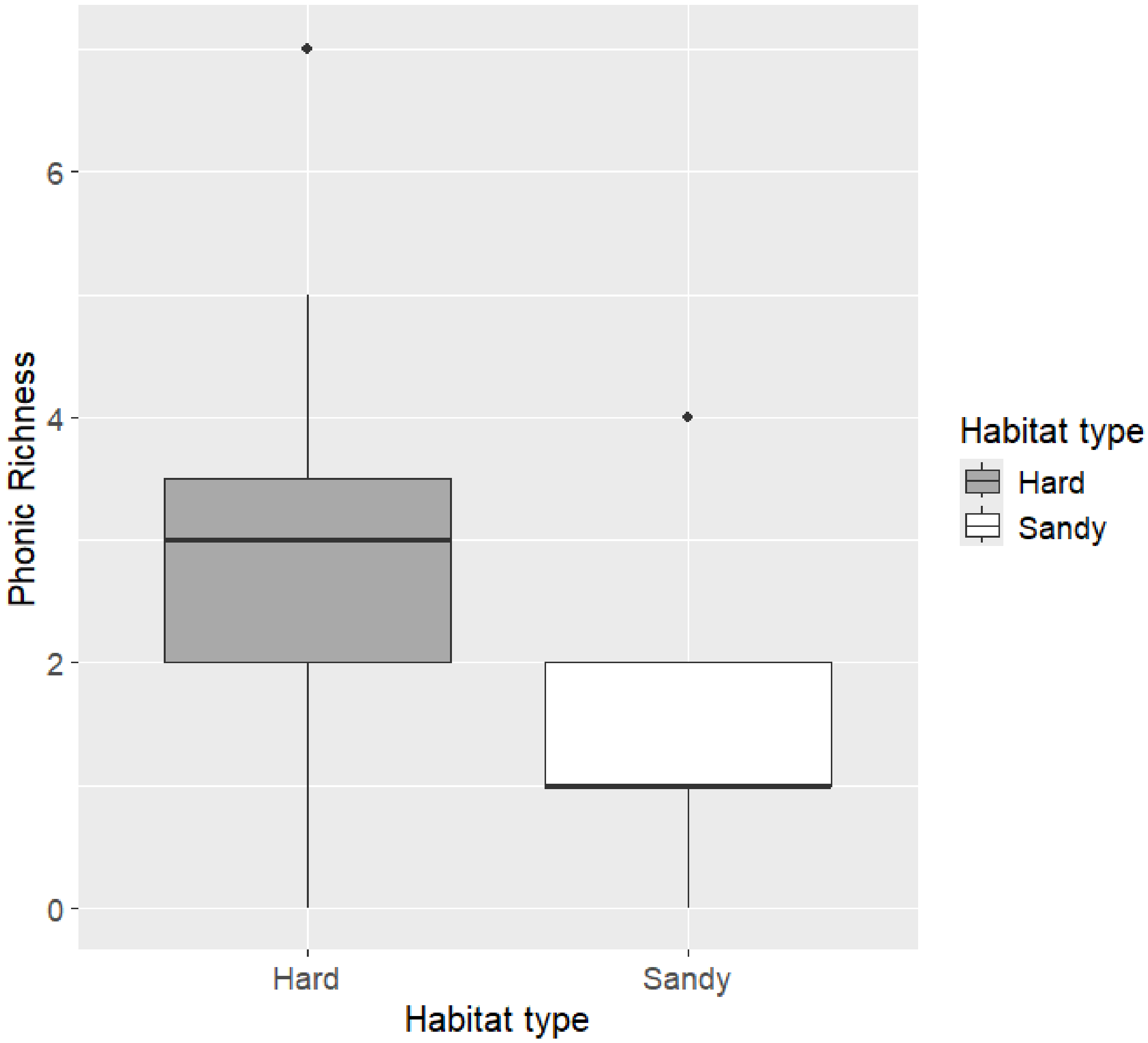

Figure 4. Boxplot, with phonic richness on the y-axis and EUNIS habitat type on the x-axis.

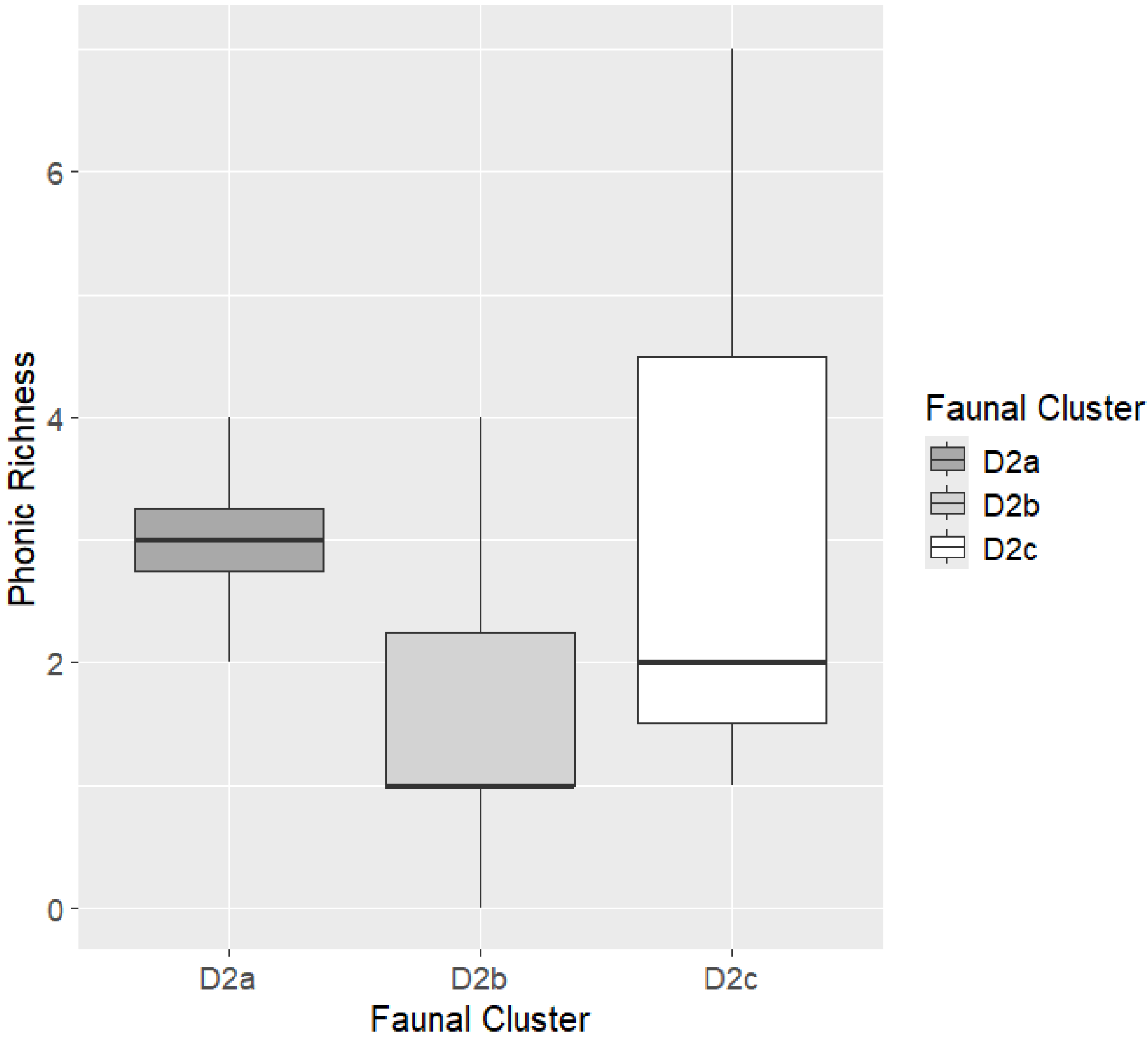

Figure 5. Boxplot, with phonic richness on the y-axis and OneBenthic faunal cluster on the x-axis.

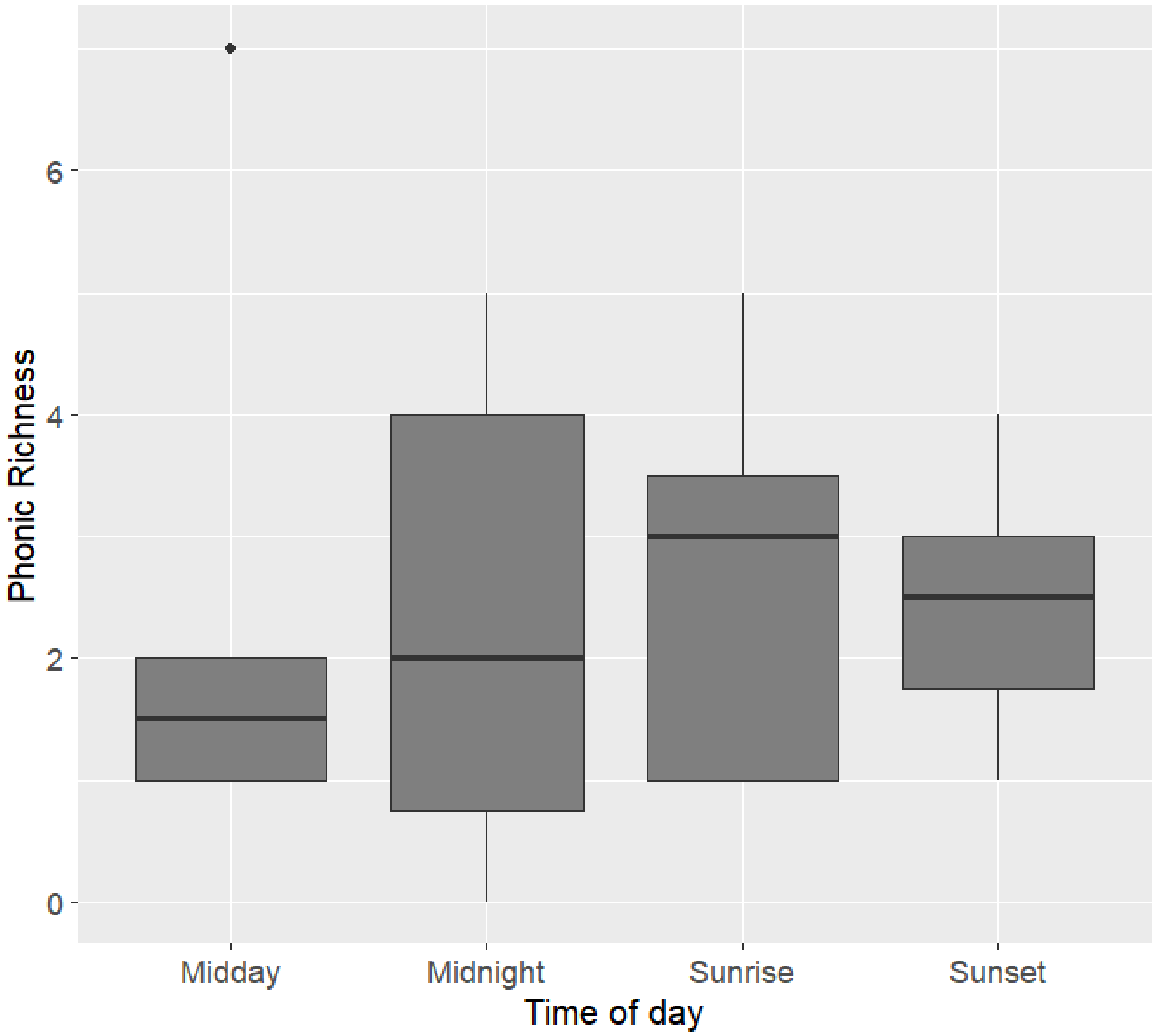

Figure 6. Boxplot, with phonic richness on the y-axis and time of day on the x-axis.

4.4 Acoustic Indices

Three of the acoustic indices (definitions and acronyms are explained in Table 1) were correlated with benthic richness, i.e. ACI, AEI and M (Table 6). Higher benthic richness values were correlated to a higher acoustic complexity index, a lower unevenness between frequency bands and to quieter recordings (Table 6).

A total of five acoustic indices were correlated to habitat type and phonic richness, i.e. BI, H, TE, SE, and M. Harder substrates were correlated to more even signals as a whole, but not across time bands within the recordings. Harder substrates are also related to louder recordings, but a lower variability across frequency bands. Since phonic richness is correlated to harder substrates, the acoustic indices follow a similar pattern (Table 6)

Table 6. Overview of the relationships between the traditional metrics of benthic habitats and the computational acoustic metrics.

OneBenthic Richness

Acoustic index	Significant Pearson's correlation numbers
ACI low	+0.38
ACI high	+0.37
ACI broad	+0.38
AEI broad	-0.36
M high	-0.40

Habitat type (i.e. hard vs soft sediments)

Acoustic index	Significant Pearson's correlation numbers
BI low	-0.56
H low	+0.53
H broad	+0.50
TE low	-0.38
TE broad	-0.36
SE low	+0.54
SE broad	+0.51
M high	+0.54

Phonic Richness

Acoustic index	Significant Pearson's correlation numbers
BI low	-0.56
H low	+0.53
H broad	+0.51
TE low	-0.38
TE broad	-0.37
SE low	+0.54
SE broad	+0.51
M high	+0.54

The above-mentioned indices, calculated from the cleaned data, were compared with those calculated from the raw data to test if they produced different results. No overall significant differences were found when comparing the index values with each other. However, this doesn’t rule out that the acoustic index values can be drastically different for a file which has anthropogenic noise removed. For example, in Figure 7 it can be observed that the ACI for the D2a faunal cluster is much higher in the cleaned (ACI: ~30) vs the uncleaned data (ACO: ~20), while in Figure 8 no difference was observed for the BI values related to hard and sandy habitat types.

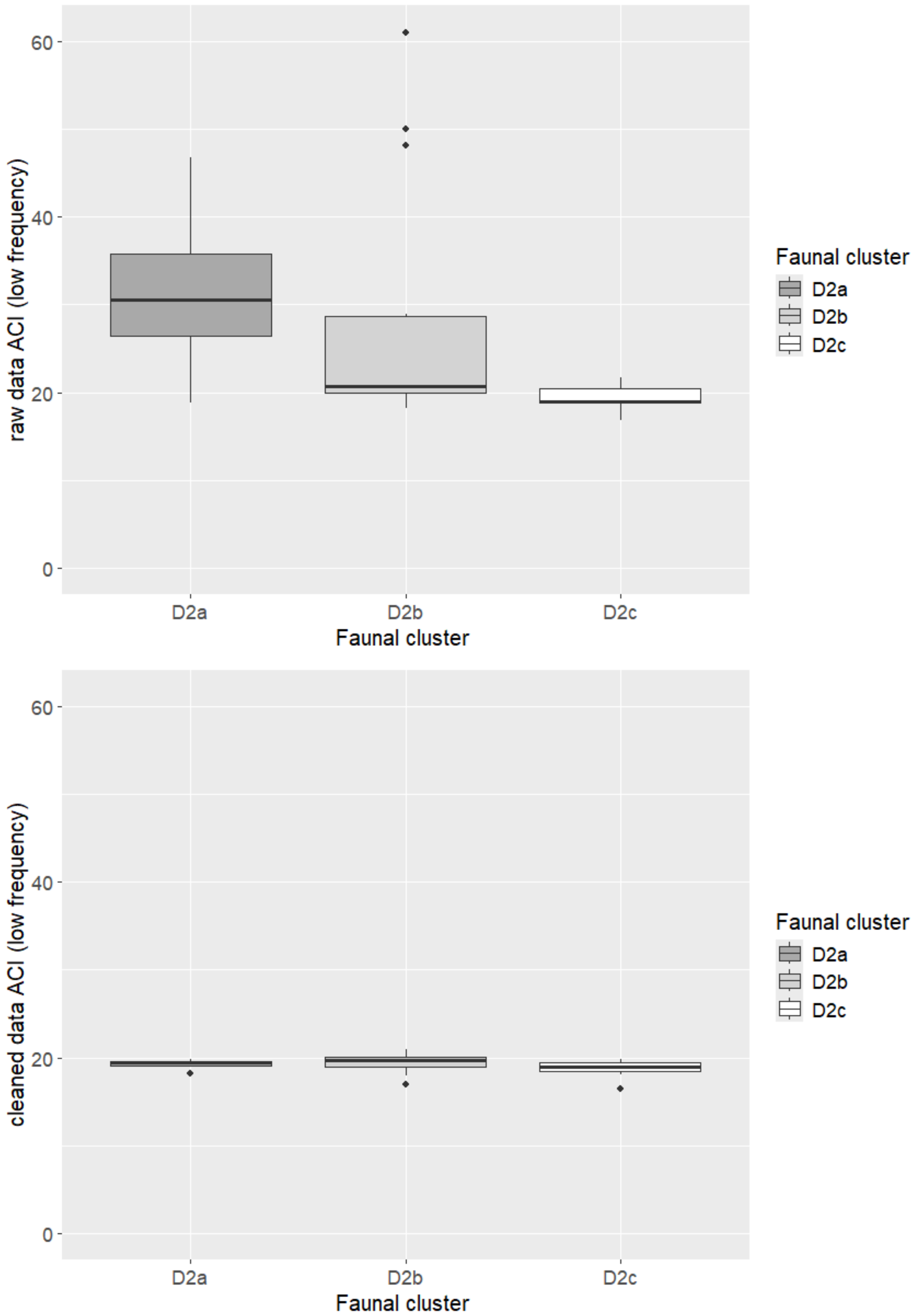

Figure 7. The Acoustic Complexity Index (ACI) calculated for the low-frequency band on the y-axis against the faunal cluster classes on the x-axis, calculated for the uncleaned raw recordings on the top, and for the recordings which had noise pollution removed on the bottom.

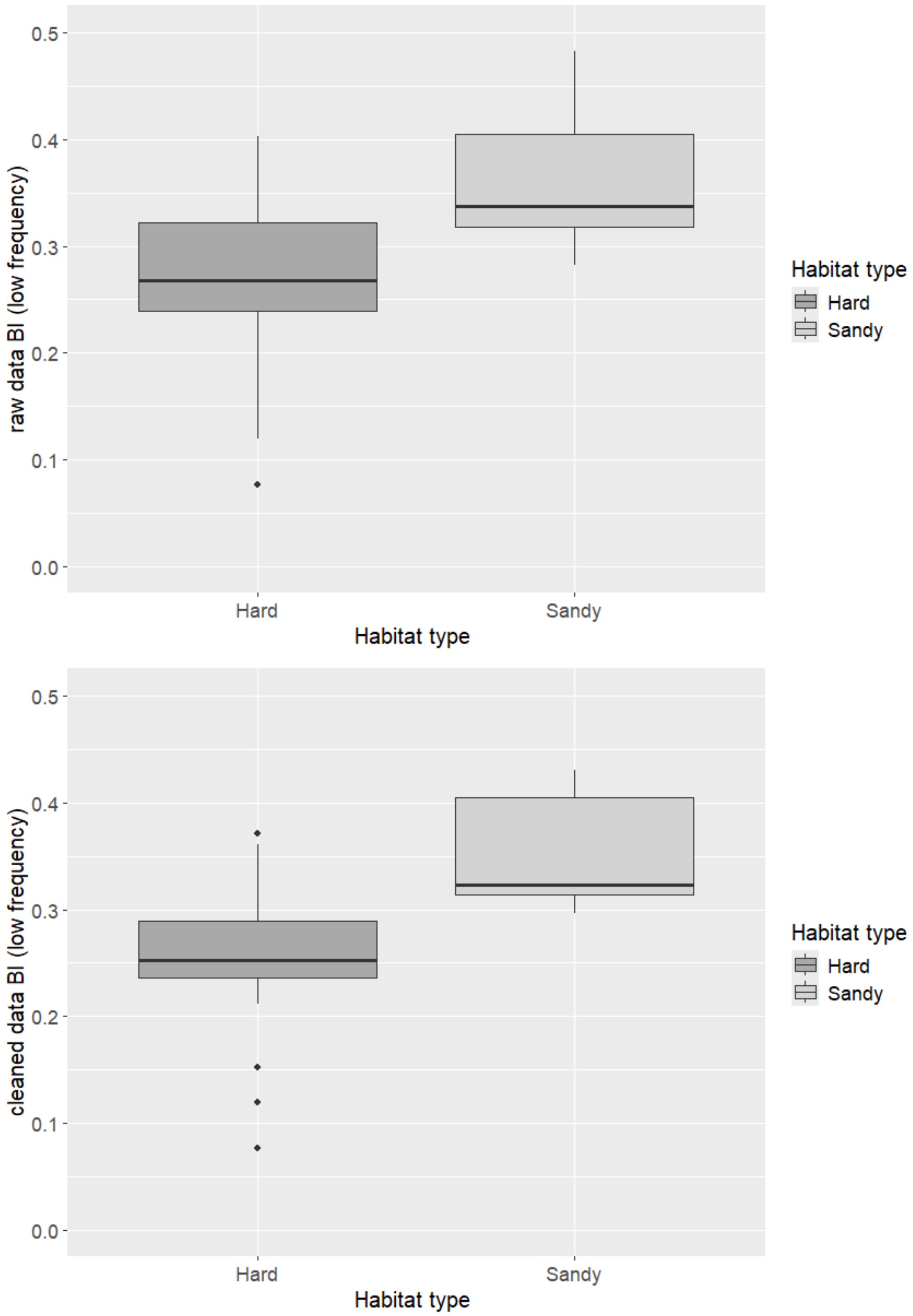

Figure 8. The BioAcoustic Index (BI) was calculated for the low-frequency band on the y-axis against the EUNIS habitat types on the x-axis, calculated for the uncleaned raw recordings on the top, and for the recordings which had noise pollution removed on the bottom.

5. Discussion

This study demonstrates that spatial differences in the habitat type and benthic richness associated with offshore benthic habitats can be associated with acoustic metrics calculated from passive acoustic monitoring datasets, which were originally collected for marine mammal monitoring purposes. Significant differences in the acoustic community composition, the phonic richness and the acoustic indices were found in relation to the benthic faunal cluster classes and their habitat types, with benthic richness and the number of spawning species being an important driver in explaining differences between the communities. This indicates that PAM can be used as a cost-effective tool for measuring spatial and temporal changes in the benthic richness and substate composition of offshore benthic habitats. However, we show that depending on the monitoring goal, different acoustic-based metrics or approaches should be considered. This study suggests that efficient computational acoustic metrics could be a powerful tool to monitor and pinpoint if and when changes in benthic richness and habitat type might occur. However, to understand changes in species-specific sounds or the acoustic community as a whole, and to understand which acoustic community properties are relevant for management (richness or abundance), manual or automatic sound detectors are required.

5.1 Acoustic community

This study shows that in sedimentary habitats, acoustic communities are broadly associated with differences in benthic richness and habitat types The acoustic community and richness of the two EUNIS habitat types studied (coarse/hard and sandy habitats) were different. Two diversity variables and one environmental variable explained the differences in the acoustic community composition best. Of the diversity variables, benthic richness and the suitability of the area for spawning for a larger number of fish were found to be the most important. The environmental driver that was important in explaining differences between the acoustic community was the current velocity. Local differences in current speed could indeed impact the soundscape indirectly through their known impacts on benthic biodiversity and substrate composition (Kregting et al. 2016; Cooper and Barry 2017, 2020). Although collecting acoustic community data is time-consuming, it can allow for an in-depth understanding of which types of sounds are more or less common in different habitats or can be used as an indication of habitat condition. Understanding which acoustic communities are associated with certain habitats can be useful to monitor the impacts of degradation or restoration over time (Lamont et al. 2022).

5.2 Phonic richness

Here we demonstrate that phonic richness, based on the inclusion of communicative and non-communicative sounds, can be used as a proxy for sedimentary habitat types, which could be a useful metric considering habitat composition may change as a consequence of activities such as those associated with offshore windfarms and other marine renewable energy developments (MREDs).

Overall, the phonic richness was higher for coarse/hard EUNIS modelled habitat types, which is in agreement with studies conducted in the Mediterranean (Ceraulo et al. 2018; Di Iorio et al. 2021). Unless reef-forming tube worms or bivalves are present within a soft-bottom habitat, coarse and hard sediments are generally found to be associated with higher biodiversity compared to sandy-soft bottoms (Lillis et al. 2014; Coolen et al. 2015; Cooper and Barry 2017, 2020), which is also reflected in this study's phonic richness values. Ceraulo et al. (2018) compared the acoustic communities associated with a seagrass meadow and sandy bottom habitats, and found that the acoustic richness was higher in seagrass habitats. Hard/coarse habitats provide surface areas for sessile epifauna to attach to and have a higher availability of microhabitats, which in turn increase the niches available for species, with the data in Figure 4 being in line with this assumption. While not enough spatial replicates were available to test if all faunal clusters were significantly different, the cluster (D2b) characterised by muddy sediments had the lowest phonic richness. The cluster represented by mixed sediments (D2a) had the highest phonic richness, while those with sandy habitats (D2c) were the most variable and had an intermediate average phonic richness (Figure 5).

Sandy habitats are dynamic and mobile environments which allow animals to burrow to ambush prey or escape predators (Kenyonax et al. 1995; Steendam et al. 2020), which could affect their acoustic detectability. In addition, certain species, such as sandeels, which could contribute to the production of passive sounds when burrowing or foraging, exhibit high fidelity to their burrows and specific sand banks and, therefore, could affect local and regional scale spatial variability in the soundscape (Tien et al. 2017). This could potentially explain why a higher variability in the phonic richness associated with the D2c habitat was observed, although this would need to be confirmed with visual surveys.

Although the faunal assemblages have discrepancies in their composition, they, in fact, involve three very closely related cluster groups (Cooper and Barry 2017) and are all characterised by relatively low numbers of taxa, as opposed to the other nine assemblages identified in UK waters. In addition, the substrate types (mixed, muddy, sandy) which are described to be generally associated with each faunal cluster groups (Cooper and Barry 2017), do not align with the habitat types classified by the EUNIS habitat map (coarse/hard and sandy). Our results indicate that a distinction can be made both at the coarser resolution EUNIS classifications and, to a lesser extent, at the finer resolution faunal cluster level. While no significant differences were found between the phonic richness associated with the faunal clusters, this can be explained by a lack of replication for cluster D2a and the high variability for samples collected in D2c. Ground truth sediment samples, rather than modelled results, may also help unravel further differences between the acoustic biodiversity associated with benthic habitats.

Although this study didn't aim to describe temporal patterns, a higher phonic richness at dusk and dawn suggest a higher soniferous activity at this time. Similar patterns have previously been detected in marine soundscapes (Siddagangaiah et al. 2021; Lamont et al. 2022). Further studies could reveal when, where and why these temporal patterns occur in offshore waters, which could, for example, also reveal information on the presence and duration of spawning events (Fudge and Rose 2009; Caiger et al. 2020).

5.3 Acoustic indices

Correlations between specific acoustic indices, the benthic richness, habitat type and phonic richness were found, which is in contrast with some previous studies (Mooney et al. 2020; Pieretti and Danovaro 2020; Minello et al. 2021). Higher benthic richness was linked to a greater acoustic complexity index, more even frequency bands, and quieter recordings. Harder substrates and a higher phonic richness were associated with more even signals overall, although this was more random across time bands in the recordings. They also corresponded to louder recordings but displayed less variation across frequency bands compared to sandy substrates. Fish sounds typically cover the low-frequency bands, while invertebrate snapping and scraping sounds typically cover a broadband spectrum. The sounds recorded in our samples had both low and higher peak frequencies, which explains a correlation across all frequency bands. Although not enough replicates were present to test for the presence of significant differences, the indices suggest that the soundscapes associated with the D2a and D2b faunal assemblages, which also have a relatively high benthic richness, are driven by the presence of both low-frequency fish sounds and higher invertebrate sounds. A higher variability in the ACI was found for the D2c faunal cluster, which could be indicative of these habitats being more dynamic, with distinct sandbanks having been found associated with distinct fish and epifaunal assemblages (Kaiser et al. 2004). While our results indicate that amplitude is correlated with the richness and habitat type metrics, these values will be influenced by both the amount of sound produced and the distance of the sound from the recorder. Since information on the distance of the sound from the recorder is missing, it is not possible to know if the amplitude is a reliable indicator of richness. Although our results suggest that benthic richness could be monitored with computationally efficient acoustic indices such as the ACI, AEI, and M could be used (and indices such as BI, H, TE, SE, and M could be used to monitor changes in habitat type and phonic richness) a larger dataset needs to be analysed before any conclusions can be drawn.

5.4 Noise pollution

Noise pollution, largely caused by self-noise (i.e. mooring noise), but also as a consequence of pile driving and shipping, affected the length of the recordings that were usable for the analysis of types of sounds and acoustic indices. Arbroath was the most heavily affected site, followed by Latheron and Fraserburgh. Only ~10% of the recording length of the samples from the other locations were affected. Noise pollution could mask the presence of sounds and could, therefore, negatively affect the number of sounds detected in the file and alter the performance of the acoustic indices. When comparing the acoustic indices calculated on the raw and cleaned files, no significant differences were found. However, since the values still differed, and location- or habitat-specific differences exist, it is not advisable to draw conclusions when comparing metrics from cleaned datasets with those that are uncleaned. Also, it is not advisable to compare the values of different indexes between locations or timelines, as the influence of different levels of noise pollution can not be detangled in their response. The best practice would be to minimise mooring noise during installation, and quality check the data for high amounts of mooring or pile driving noise, in addition to removing them where possible.

5.5 PAM as a benthic biodiversity monitoring tool

To fully establish the use of PAM as a tool to monitor benthic biodiversity we recommend the following three key steps. First, to overcome the time-consuming task of annotating and removing noise pollution from samples to calculate soundscape metrics, machine learning models could be developed to automatically annotate their presence in large acoustic datasets (Haver et al. 2023). Second, this study only characterised the soundscapes associated with three faunal classes, and included only a very small subset of the existing PAM data. The next step would be to characterise the soundscapes associated with all twelve clusters as identified by Cooper and Barry (2017), ideally while collecting additional visual or physical survey data to categorise the habitats and local diversity. Third, to distinguish natural from human- and climate change-driven changes, a before-and-after impact (BACI) study and a long-term study of the benthic soundscapes would be required.

Our literature review indicated that at least 32 species which are likely or potentially present at our sites can make either passive or active sounds. The large majority of those potentially present, i.e. 417 species, are invertebrates, which are notoriously understudied for sonifery (Looby et al., 2023). While phonic richness does not provide an exact count of individuals or species, it serves as an indicator of the presence or absence of certain sound-producing animals, offering an indirect measure of overall community diversity (Desiderà et al. 2019; Lamont et al. 2022). It's important to note that each unique sound type does not always correspond to a single species, as some fish can produce multiple types of sounds for activities such as mating, aggression, or hunting (Colleye and Parmentier 2012; Parmentier et al. 2017). However, the richness, abundance and diversity of the fish acoustic community, when measured on active sounds and by calculating traditional ecology indexes based on types of sounds (e.g. Shannon and Simpson index), have been shown to reflect fish taxonomic diversity, thus providing relevant information for managers (Desidera' et al. 2019). This is true also when the acoustic community composition is unknown or partially unknown.

Being able to identify and develop machine learning classifiers for species-specific sounds would allow the use of PAM for species-based as well as ecosystem-biodiversity-based monitoring (Fudge and Rose 2009; Caiger et al. 2020; Pieretti and Danovaro 2020). Furthermore, PAM can be used to reveal changes in environmental conditions as it has been linked to changes in wind, waves and current speed conditions as well as anthropogenic activity measures such as noise pollution (Merchant et al. 2016; Duarte et al. 2021; De Clippele and Risch 2021).

To understand how offshore benthic habitats are changing a variety of benthic tools and technologies are being used, each of which have pros and cons (Scottish Government Report, Oct 2024). In addition to established tools, this pilot study demonstrates that PAM has the potential to be used as a generic benthic biodiversity indicator in sedimentary habitats, typically found around offshore wind farms. However, to monitor specific species, more data would need to be analysed and species-specific sounds would need to be identified and characterised. To increase our knowledge of which species makes which sound, audio-video arrays can be deployed, which allows one to associate sounds with specific species and behaviours (Mouy et al., 2022). An in-depth understanding of the different species-specific types of sounds has the potential to reveal changes in the functional use and behaviour of species associated with a specific location.

Through passive acoustic recorders' ability to collect data over long periods of time, at a high temporal resolution, without negatively impacting the environment, this cost-effective tool could be used to fill in gaps in our understanding regarding how benthic diversity and habitat use changes over diel, seasonal and inter-annual patterns across local and regional spatial scales. Future research could involve the refinement of fish detectors (Mouy et al. 2024) or species-specific machine learning classifiers (Caiger et al. 2020) to automatically analyse large datasets. Since certain sounds are linked to behaviour such as spawning or aggression, they could reveal more information on habitat use by fish and crustaceans (Caiger et al. 2020). However, it may be more challenging to use PAM data to reveal information on their age and growth rate which is also needed for fish stock assessments.

Long-term marine monitoring is needed to inform management decisions addressed to reduce the impacts of human activities and pressures (Borja and Elliott 2021). This is especially relevant to Scotland, investing in a total of 27.6 GW for potential new offshore wind developments. The introduction of hard substrates, changing hydrodynamics, local primary productivity and activities such as dredging and pile driving have the potential to impact benthic and benthopelagic communities at a local and regional scale (Wilhelmsson et al. 2006; Clark et al. 2014; Scott et al. 2018; Degraer et al. 2020; De Borger et al. 2021; Buyse et al. 2023a, b; Knorrn et al. 2024). Existing PAM data, which has been collected for marine mammal monitoring could be used to reveal how benthic biodiversity has changed over the last ten years, and could act as a baseline to understand future change as a consequence of offshore wind developments and climate change. In addition, the use of PAM would also reduce our reliance on ships, which would contribute to the UK net zero goal to reduce carbon emissions (Liu et al. 2024). In light of recent discussions regarding Marine Net Gain (Hooper et al. 2021), PAM could also potentially be used as a tool to provide the metrics needed to measure biodiversity and functioning in areas associated with recovery or restoration activities.

6. Data availability

An overview of the list of soniferous species, along with their acoustic characteristics and the data used in the statistical analysis along with the acoustic data can be made available on request.

7. References

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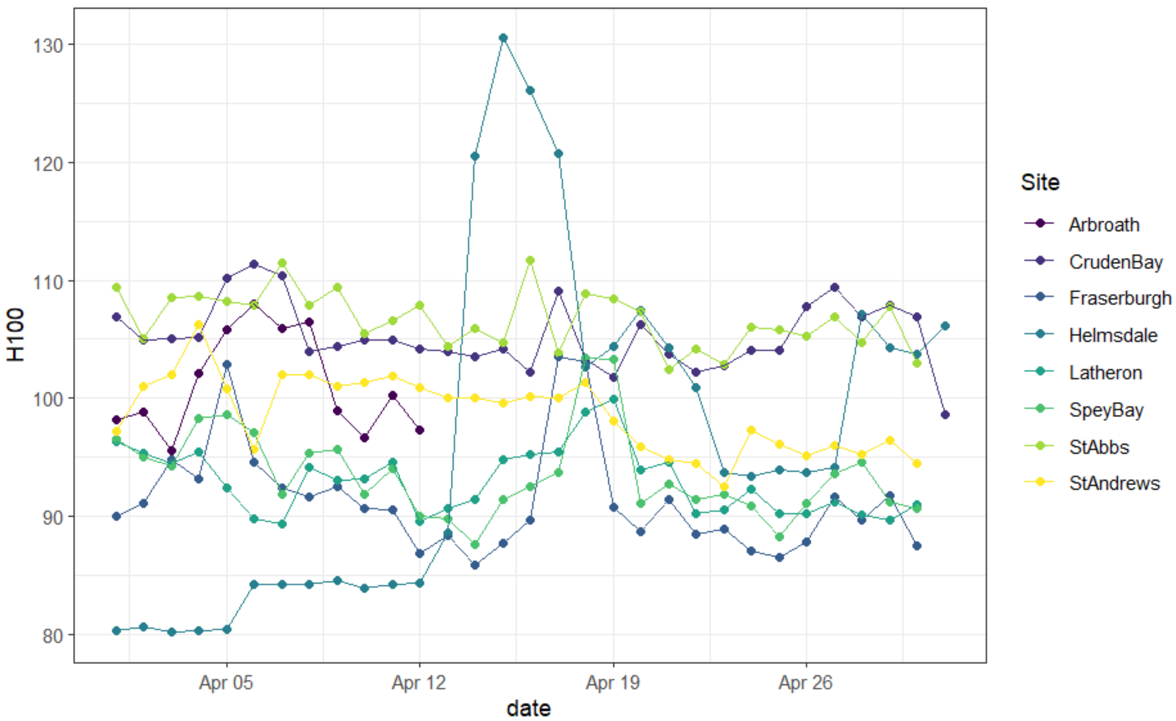
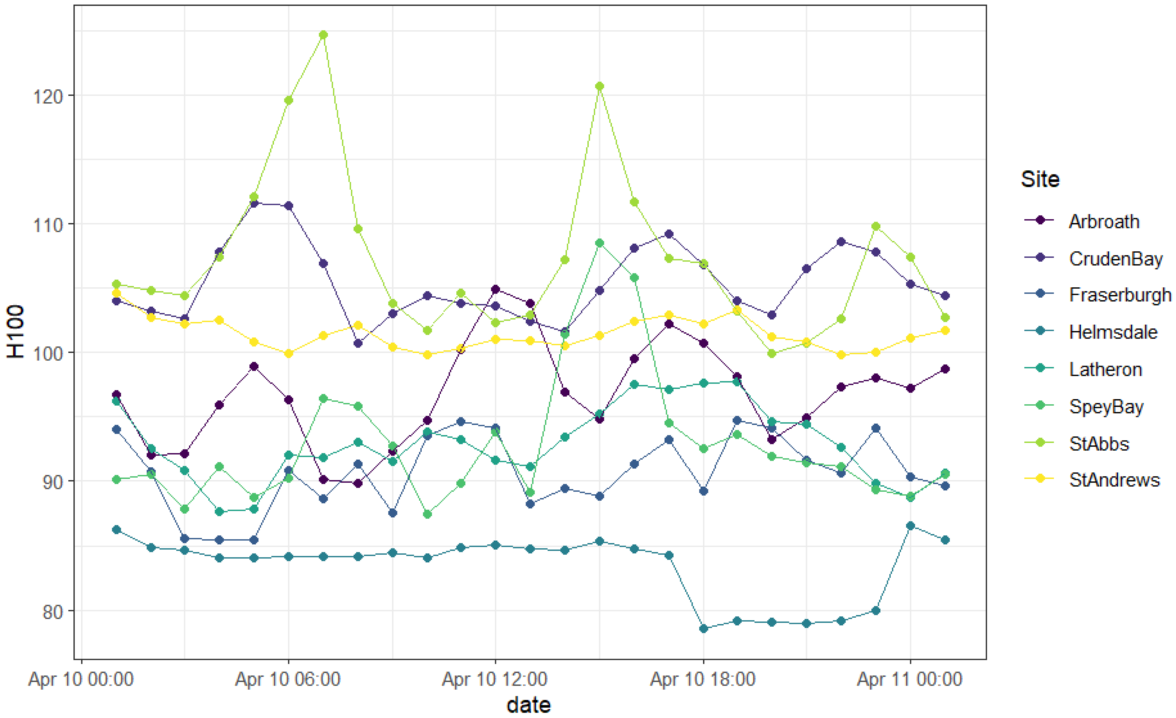
8. Supplementary materials

S1 Sound Pressure Levels

Sound Pressure Levels were calculated using PAMGuide in MATLAB (Merchant et al. 2015). Third-Octave Level (TOL) SPLs were calculated at 60-second resolution from 1-2000Hz, in order to characterise both benthic biodiversity and noise pollution from shipping noise (Merchant et al. 2016). TOL data was calculated based on the raw sound files. While some shipping activity is present at the St Abbs location (SPL peaks at 130 dB and 120 dB), the 10th of April is mostly absent of ship noise.



Daily average SPL data for the 100Hz third-octave level across all 8 moorings. April 10th is the best date for covering all sites, without high levels of shipping noise.



Hourly average SPL for 100Hz third-octave level on April 10th 2021.

S2 Biological and environmental data sets

Overview of the contextual and environmental data layers, which were downloaded from open-source websites.

Layer	Source
Depth (m)	General Bathymetric Chart of the Oceans
Habitat map (EUNIS classification)	UK Sea Map 2018
Temperature, Currents, Light, DOC, Phytoplankton, Primary Productivity, Chlorophyll	Bio Oracle
Faunal cluster class, benthic biodiversity	OneBenthic Portal
NBN atlas	NBN atlas
Spawning and nursery ground layers	Spawning and Nursery Grounds Layers for Selected Fish in UK Waters in 2010 - Cefas Developing essential fish habitat maps - Scottish Government 2023

S3 Start time and length of the recordings

The timings which are highlighted in bold indicate the files that had the largest amount of noise pollution and were therefore drastically reduced in file length.

Site	Phase	Start time	Cleaned file length (mm:ss)
Arbroath	Midnight	01:20:00	**04:12**
Arbroath	Sunrise	06:20:00	**03:16**
Arbroath	Midday	13:20:00	**02:43**
Arbroath	Sunset	19:50:00	**04:02**
CrudenBay	Midnight	01:25:00	09:50
CrudenBay	Sunrise	06:25:00	09:56
CrudenBay	Midday	12:55:00	09:46
CrudenBay	Sunset	19:55:00	09:40
Fraserburgh	Midnight	01:05:00	**05:31**
Fraserburgh	Sunrise	06:35:00	09:17
Fraserburgh	Midday	13:05:00	**06:02**
Fraserburgh	Sunset	20:05:00	09:40
Helmsdale	Midnight	01:25:00	09:59
Helmsdale	Sunrise	06:25:00	09:59
Helmsdale	Midday	13:25:00	09:59
Helmsdale	Sunset	19:55:00	09:59
Latheron	Midnight	01:15:00	**06:27**
Latheron	Sunrise	06:15:00	09:38
Latheron	Midday	13:15:00	**04:29**
Latheron	Sunset	19:45:00	06:50
SpeyBay	Midnight	01:15:00	09:58
SpeyBay	Sunrise	06:15:00	09:59
SpeyBay	Midday	13:15:00	09:40
SpeyBay	Sunset	19:45:00	10:00
StAbbs	Midnight	01:00:00	09:27
StAbbs	Sunrise	06:30:00	10:00
StAbbs	Midday	13:00:00	09:18
StAbbs	Sunset	20:00:00	09:09
StAndrews	Midnight	01:00:00	09:58
StAndrews	Sunrise	06:30:00	09:53
StAndrews	Midday	13:00:00	10:00
StAndrews	Sunset	20:00:00	09:52

S4 Biological variables associated with each site

Location	Predicted Habitat type	Depth (m)	Taxa Richness	Faunal Class	Area Class (km^2)	No. Taxonomic Classes
Spey Bay	Coarse	23	8±5	D2c	136.66	5
Latheron	Coarse	26	24±8	D2a	30.69	3
Fraserburgh	Coarse	38	27±8	D2b	147.57	3
St Andrews	Coarse	41	27±8	D2b	152.59	6
St Abbs	Hard	34	8±5	D2c	17.86	5
Cruden Bay	Sandy	21	8±5	D2c	152.72	5
Arbroath	Sandy	47	24±8	D2b	65.13	5
Helmsdale	Sandy	48	24±8	D2b	295.15	5

S5 Summary data for the types of sounds used to calculate phonic richness

Presented are the mean duration, frequencies and power of each sound type.

Row Labels	Count of Sound Type	Average Duration (s)	Low frequency (Hz)	High frequency (Hz)	Peak frequency (Hz)
ST1	143	0.44	25.56	572.6	82.28
ST2	49	0.19	5682.49	26705	7875
ST3	22	0.35	193.75	1037.16	421.88
ST4	53	0.83	197.53	2610.7	397.11
ST5	4	0.2	145.84	745.78	410.16
ST6	931	0.3	260.8	2386.31	547.7
ST7	27	2.58	1786.84	12053.26	3168.4
ST8	3	0.67	1996.22	20478.08	2828.13
ST9	1	0.24	0	5714.31	46.88
ST10	3	0.44	2067.21	5885.98	3015.63
ST11	18	0.23	856.82	1956.79	1200.52
ST12	5	0.36	650.29	1978.17	937.5
ST13	18	0.25	32.04	642.29	85.94
ST14	2	0.27	0	2373.23	46.88
ST15	2	0.88	129.27	1246.28	164.06
ST16	15	0.78	40.22	1634.3	115.63

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