MAJOR SOUNDSCAPE DIFFERENCES IN THE WEST COAST OF SCOTLAND ARE REFLECTED IN ACOUSTIC INDICES

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1 INTRODUCTION

Passive Acoustic Monitoring (PAM) is increasingly used to monitor marine soundscapes, which are often characterised using anthrophony (human-related sounds), biophony (biotic events) and geophony (abiotic events) categories. The soundscape is especially complex in shallow marine habitats, and has been shown to vary on small temporal-spatial scales[1]. Processing PAM data sets with high sample rates remains a challenge in signal extraction, efficiency of data processing and balancing the requirement of long-term data visualisation or statistical summaries with often short duration soundscape drivers such as delphinid clicks.

The study of all components of a soundscape, alongside individual sources or species, is vital in the context of rapidly changing habitats and increasing evidence of the impact of anthrophony on marine ecosystems[2,3,4]. Soundscape Ecology considers an entire soundscape, allowing questions around the inter-relation between soundscape components and their spatial-temporal patterns to be considered[5]. Understanding and efficiently quantifying soundscapes which may differ over small regions is vital if marine management and protection is to utalise PAM data effectively[1,6].

Soundscape analysis predominantly relies on Sound Pressure Levels (SPLs) and Power Spectral Densities (PSDs) either to establish summary statistics over long temporal periods, or to visualise data through methods such as Long Term Spectral Averages (LTSA's)[7]. Known characteristics of signals and the use of ground-truth data such as wind speeds, tidal cycles and lunar phases may then be used to establish statistically significant correlations between noise levels and sound sources[1,8,9]. Ambient noise levels have been quantified using root mean square (rms) broadband SPLs over a specified frequency range[10]. The relative levels of rms SPL's to the 90th and 95th percentiles in Spectral Probability Density (SPD) plots can be used to infer the impact of impulsive noise sources on the soundscape as the rms SPL is more strongly influenced by the highest sound levels[11].

Acoustic indices (henceforth referred to as indices) are summary statistics of acoustic data which reflect features of the waveform or spectrum and may be used to provide further understanding to soundscape analysis. The field of indices is relatively new and their utility contested in part due to varying methodologies, research questions and data processing parameters[12]. Whilst numerous studies have found promising correlations between individual indices and ecological parameters when ground-truthed[13], these correlations were often specific to a habitat or location and not general[14]. Indices are yet to be extensively used in marine habitats, but early studies have shown similarly inconsistent correlations between ecological parameters and indices[15,16,17,18].

The application of a single index as a measure of one noise source (such as an animal call) assumes that the source of interest has unique spectral-temporal features in the specified frequency range. This assumption is not valid across entire marine soundscapes. The use of numerous indices can increase their discriminatory power between sound sources as different features of are measured by each index[15,19]. A simple example is to consider the spectral entropy (**Hs**) which may return a high value when there is an even spectrogram such as during overlapping chorus's or periods of ambient noise. The application of a second index, such as the Acoustic Complexity Index (**ACI**) which measures SPL changes between adjacent temporal widows within frequency bands, can be applied to distinguish between these two acoustic regimes. The application of numerous indices alongside machine learning techniques has been successfully applied to discriminating marine habitat type[15] and health[20].

Work to establish the response of indices to known marine sound sources is ongoing[21] but questions around the validity of applying indices in marine habitats remains. Without standardised methodologies regarding the application of indices and in the absence of a rigorous understanding of acoustic index behaviour in marine environments, demonstrating the utility of indices which may not have simple correlations to well-established metrics such as SPL's is not straightforward. A-priori predictions of index changes are further complicated as the influence of a changing ambient soundscape on index values is also unknown.

In this paper we consider two 'case studies' to investigate the response of four commonly used indices in similar ambient soundscapes with the presence of a known soundscape driver. Case studies were chosen from the COMPASS network across numerous sites in 2019 by finding weeks in which two classes of hierarchically labelled data were dominant. Subsampling the data to periods of each class provided two datasets with the same ambient soundscape in which one class was present. SPD's were used to establish differences in the soundscape of the classes, before changes in index distributions between the classes were considered. LTSA's were used to visualise the whole data period, as the labelling process did not consider all sound sources.

2 MATERIALS AND METHODS

2.1 Data

Data was used from the network of hydrophone moorings in Western Scotland and Northern Ireland, Fig. 1, which was operational between 2017 and 2022 as part of the EU INTERREG 'COMPASS' project[22]. Hydrophones sites were located across numerous shallow habitats, with mooring depths ranging from 50 m to 110 m. Soundtrap ST300 broadband recorders were moored 3-5 m above the seabed, sampling at 96 kHz on a 20/40 minute on/off duty cycle[22]. For this study, 2019 data from Tolsta, Hyskier and Stoer Head were considered. One week of data was available for each site in January, March, July, September and November, with the exception of September in Tolsta due to instrument failure.

3 second windows were assigned a single label following a hierarchical order of Whistle, Click, Vessel

and Ambient. A whistle label could include all other labels, click labels excluded whistles, vessel labels excluded clicks and whistles, and ambient labels excluded the other three. The labelling processes was designed for a CNN model[23], with 3 second labelling windows chosen as a compromise between the time periods of milliseconds for clicks, seconds for whistles and minutes for a vessel passage. Data were labelled both visually using spectrograms, and aurally using Audacity Software (Audacity version 3.0.02, 2021). Data were labelled chronologically allowing for the context of subsequent windows to aid the labelling of a current window, such as when a whistle occurred over 2 windows, and meaning signals could occur at any point in the window. Data was labelled between the hours of 18:00 and 09:00 for each day to maximise the detection of delphinid activity. Mean error rate in the labelling was estimated to be 3.3%, with the greatest error occurring between Ambient (6.3%) and Vessel (3.7%) classes (see[23] for full details).

As soundscapes can change significantly over small temporal-spatial scales an approach was designed to ensure similar ambient soundscapes with the known presence of a given class. Case studies were chosen by identifying two weeks in which two classes were dominant within the soundscape: Hyskier in June had 43% Ambient labels and 41% Vessel; Tolsta in November had 45% Whistle labels and 40% Vessel. 5 days of data were available in Tolsta in November, corresponding to 36,262 labels, and 7 days were available in Hyskier in July, corresponding to 44,683 labels.

2.2 Acoustic Analysis

To ensure consistency across the analysis methods considered, the signal processing parameters were kept constant for the calculation of the indices, LTSA's and SPD's. This required a compromise between temporal and spectral resolution as SPD's are commonly calculated at a 1 Hz resolution, whilst indices are not. SPD's were examined using increasing Fourier Transform window lengths to find the frequency resolution beyond which no new major changes were observed. All acoustic analysis was subsequently carried out on data calibrated using the low gain values provided by Ocean Instruments, with a hann window length of 8192 samples (frequency resolution of 11.7 Hz), 50% overlap and a low pass filter of 100 Hz to exclude self noise. LTSA's were calculated using the Welch method and applying a median

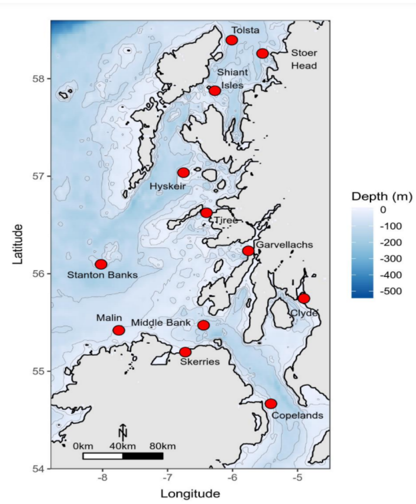

Figure 1: Location of the PAM moorings which make up the COMPASS network. Data was used from Hyskier, Tolsta and StoerHead in 2019. Reproduced from[22].

average to the periodograms. Custom python code was used for all data analysis.

2.3 Acoustic Indices

Four commonly used indices were chosen which reflect different spectro-temporal features of soundscapes. **Hs** considers the mean of non-overlapping spectrogram windows as a probability mass function of random variables and calculates the Shannon Index across an input frequency range[24]. It is normalised by definition to [0,1] with high values indicating an even soundscape. The Bioacoustic Index (**BIO**) estimates the area under the mean SPL spectrum, minus the minimum mean SPL within an input frequency range[25]. A higher value indicates greater SPL difference relative to the quietest frequency band. The **ACI** calculates the mean absolute fractional change in spectral amplitude between adjacent temporal windows within each frequency band, summed over a given temporal step and frequency range[26]. SPL changes in adjacent bins, caused by a signal which rapidly changes in frequency, increase the **ACI**. The Normalised Difference Soundscape Index (**NDSI**) calculates the PSD in 1 kHz bins and 2 frequency ranges referred to as 'anthro' and 'bio' bands. It calculates $\frac{(\beta-\alpha)}{\alpha+\beta}$, where β is the maximum binned value in the 'bio' band and α is the maximum value in the 'anthro' band.

Indices were calculated across three second windows to match the labelled data. Four frequency ranges were considered, 0.1-48 kHz, 0.1-1.1 kHz, 2-10 kHz and 10-48 kHz, chosen to correspond to the frequency ranges of different classes. Vessel noise is mostly constrained to 0.1-1 kHz, delphinid whistles between 5-20 kHz and delphinid clicks between 10-48 kHz. The frequency ranges chosen for the **NDSI** were 'low' (anthro band 0.1-1.1 kHz and bio band 2-48 kHz), 'med' (anthro band 1-2 kHz and bio band 2-10 kHz), and 'high' (anthro band 2-10 kHz and bio band 10-48 kHz).

BIO and **ACI** values were normalised using $\frac{x-L_{25}}{\sigma}$, where L_{25} is the 25^{th} exceedance level or 75^{th} percentile level and σ the standard deviation of indices calculated across the entire data set, meaning indices from each class were normalised using the same values. Ridgeplots were used to compare index distributions between classes, calculated using Gaussian Kernel's evaluated at 2500 points, a number chosen through visual inspections of the ridgeplots whilst varying the number of evaluation points.

Index values were calculated using custom Python code. Values were checked against 'Soundecology' (ver 1.3.3; Villanueva-Rivera and Pijanowski, 2018) and 'seewave' (ver 2.1.0; Sueur et al., 2008) packages in R using 1000 random 3 second windows, resulting in a mean percentage difference between the R and Python values of 1.8%, 2.1%, 1.4% and 0.5% for **ACI**, **Hs**, **NDSI** and **BIO** respectively. The **NDSI** was tested following the implementation in seewave, in which a sum of the binned PSD is taken for the alpha band[19]. The original definition of the **NDSI** uses the largest PSD bin in each band[27], and this implementation of the **NDSI** was used in this paper.

3 RESULTS

3.1 Tolsta, November

Fig. 2 shows SPD's from Tolsta in November for 14,536 vessel labels (a) and 16,317 whistle labels (b). The shape of the plots is similar, with elevated noise in frequencies below 10 kHz and convergence of the 1^{st} and 50^{th} percentiles in the higher frequencies. The rate at which the PSD values decrease up to 10 kHz is higher in the Whistle class, as is the distance between the 95^{th} and 1^{st} percentiles across all frequencies. This indicates a less stable soundscape. Impulsive noises are only evident above 20 kHz in the Vessel class as seen in the elevated rms and 99^{th} percentile levels. All percentiles increase below

5 kHz in both SPD's likely caused by vessel noise – this is expected as whistle labels allow for vessel noise to be present. Significant peaks are observed in the rms and 99th percentile levels in the Whistle class from 5-20 kHz, which corresponds to the frequency range of delphinid whistles. Increases in the rms, 90th, 95th and 99th percentile levels above 20 kHz are likely caused by clicks and burst pulses which were commonly observed alongside whistles during labelling. This is supported by clear periods of high density clicks in the LTSA shown in Fig. 3, though individual clicks are not visible due to the temporal averaging. Vessel noise is clear in Fig. 3 as are high density whistles.

Indices were additionally calculated from 5-20 kHz corresponding to the peak in the SPD of the Whistle class. Fig. 4 shows ridgeline plots for each index and each frequency range. All indices and frequencies show changes in distributions between the Vessel and Whistle classes. Values in the 2-10 kHz and 5-20 kHz frequency bands increase most significantly in the ACI (a). The distributions of three frequency bands in the BIO index (b) broaden and values decrease in the Whistle class. The 0.1-1.1 kHz frequency band is the exception to this, with an increase in values in the Whistle class. Changes between classes are also seen in each of the NDSI bands (c), with an increase of 0.14 in the standard deviation of the high band (anthro band 2-10 kHz and bio band 10-48 kHz) in the Whistle class. In the low band (anthro band 0.1-1.1 kHz, bio band 2-48 kHz) for the Vessel class two peaks in the probability density are seen for values greater than the main distribution, which are not seen in the Whistle class. The med band (anthro band 1-2 kHz, bio band 2-10 kHz) shows a general decrease in NDSI values in the Whistle class. Of all the indices, the Hs (d) distributions are most similar across the two classes. A small increase of values is seen in the Whistle class, with the exception of the 0.1-1.1 kHz frequency band in which calculated means and percentiles all increased on the order of 0.5% in the Vessel class.

3.2 Hyskier, July

Fig. 5 shows SPD's for 18,426 ambient labels (a) and 19,316 vessel labels (b) in Hyskier in July. The SPD's are highly similar above 20 kHz, which is consistent with a soundscape in which only 15% of labels were not ambient or vessel. The rms and 99thpercentiles levels of the Vessel class increase above 24 kHz. Below 20 kHz, the distance between the 90th and 10th percentiles increases in the Vessel class relative to the Ambient class, with the most significant difference between the two SPD's below 5 kHz where all percentile levels are elevated in the Vessel class. The LTSA of Hyskier showed these vessel

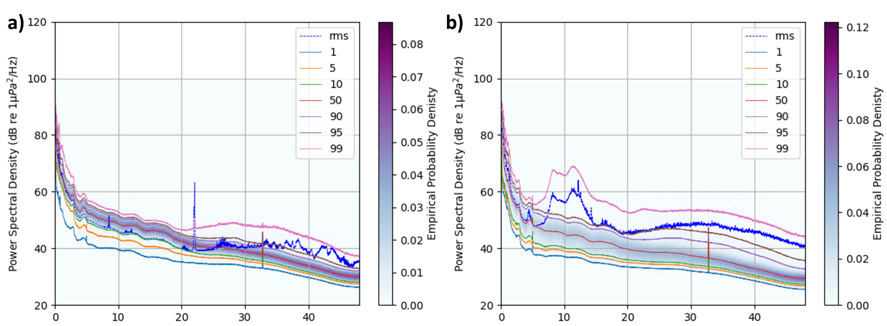

Figure 2: Spectral Probability Densities from Tolsta in November, using only whistle labels (a) and only vessel labels (b). Vessel noise below 5 kHz is present in both. The rms and 99th PSD percentile increase between 5-20 kHz in (b) coinciding with the frequency range of delphinid whistles. Elevated levels above 20 kHz are likely caused by burst pulses and delphinid clicks.

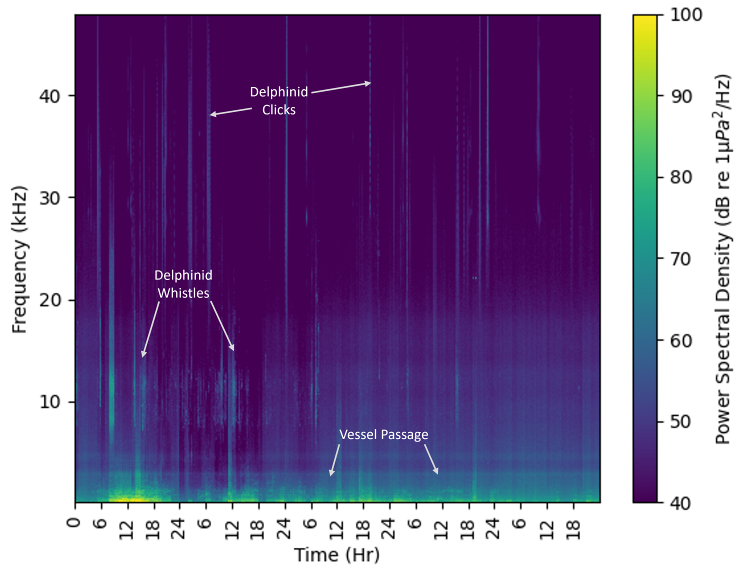

Figure 3: LTSA of data from Tolsta in November. High density clicks and burst pulses are visible above 20 kHz. Vessel periods are clear, as are high density delphinid whistles. Less dense clicks and whistles are not visible due to the time averaging requirement of the LTSA.

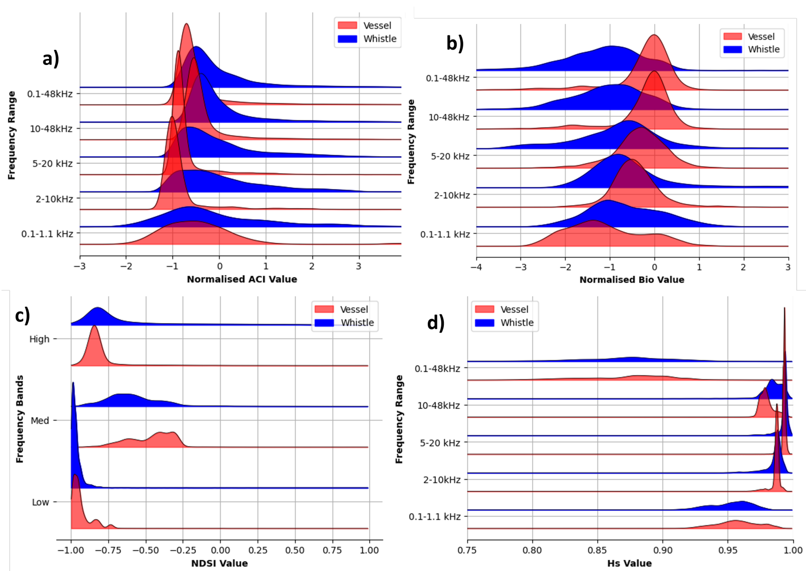

Figure 4: Ridgeline plots showing index distributions from the Whistle and Vessel classes in Tolsta in November. In frequency ranges in which whistles are present, ACI (a) distributions increase and BIO index distributions decrease in the whistle class - whilst the 0.1-1.1 kHz band shows little change. NDSI (c) bands differ between the classes. The standard deviation of the Whistle class increases in the high band, and values decrease in the med and low bands. Hs (d) distributions increase across all frequencies in the Whistle class, but are similar between classes.

transisits, but provided no other information on the soundscape so is not presented.

Fig. 6 shows ridgeline plots for each index and each frequency range. All frequency bands for the ACI (a) increase in the Ambient class. The reverse relation is seen in the BIO index (b) where distributions for the Ambient class decrease, with the exception of the 0.1-1.1 kHz frequency band. Three frequency bands in the Hs (c) increase in the Ambient class, with the 0.1-1.1 kHz frequency band decreasing. The NDSI (d) distributions change the least. Distributions in the high band (anthro band 2-10 kHz and bio band 10-48 kHz) increase in the Ambient class and the standard deviation increases by 0.01. Distributions decrease in the Ambient class in the med band (anthro band 1-2 kHz and bio band 2-10 kHz) with the standard deviation decreasing by 0.04. In the low band (anthro band 0.1-1.1 kHz and bio band 2-48 kHz) the distributions differ most significantly between the two clear peaks, with an elevated probability density function in the Ambient class. All indices and frequency ranges have significant overlap between the distributions of the classes.

4 DISCUSSION

We have presented a method in which distribution changes in acoustic indices can be examined in the same ambient soundscapes with the presence of a known, major soundscape driver by sampling data from the same location and time to include one hierarchically labelled class. SPD's were used to establish differences in the soundscapes. All PSD percentiles increased for frequencies less than 5 kHz when vessels were known to be present, and clear peaks in the rms and 99th percentile were seen in the Whistle class between 5-20 kHz (Fig. 2). Elevated PSD percentiles in frequencies above 20 kHz in the Whistle class were likely due to the co-occurrence of clicks and burst pulses, which were seen in the LTSA (Fig. 3). Overlapping whistles, clicks and burst pulses were anecdotally noted during the labelling process. SPD's of Ambient and Vessel classes were more similar, with the Ambient class quieter below 5 kHz (Fig. 5).

In Tolsta, index distributions presented in Fig. 4 changed consistently across all frequency bands except for the 0.1-1.1 kHz frequency band, in which whistles do not occur. **ACI** values increased in the Whistle class, likely caused by changes in frequency across short temporal periods characteristic of delphinid whistles. **BIO** index values decreased with an increase in standard deviation in the Whistle class. The **NDSI** distributions all decrease for the Whistle class in the med (anthro band 1-2 kHz and bio band 2-10 kHz) and low (anthro band 0.1-1.1 kHz and bio band 2-48 kHz) bands. A decrease in the **NDSI** can be

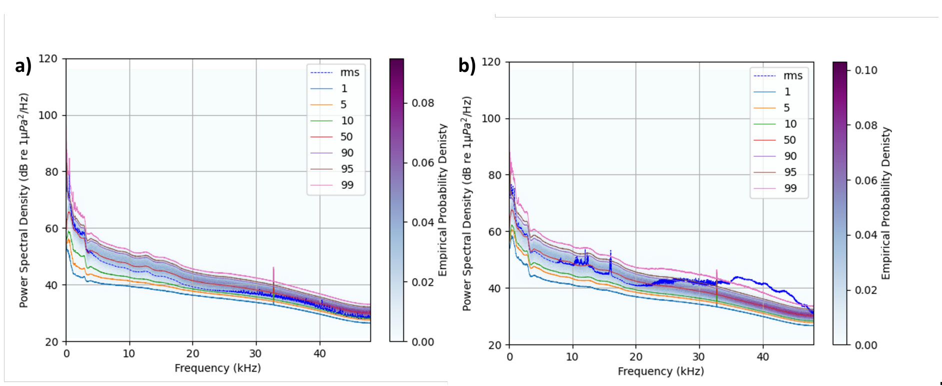

Figure 5: Spectral Probability Densities from Hyskier in July, using only ambient labels (a) and vessel labels (b). PSD percentile levels are similar above 20 kHz, aside from the rms and and 99th percentile level increasing in the vessel class. The difference between the 99th and 1st percentiles is larger in the Vessel class below 20 kHz, with the greatest difference below 5 kHz.

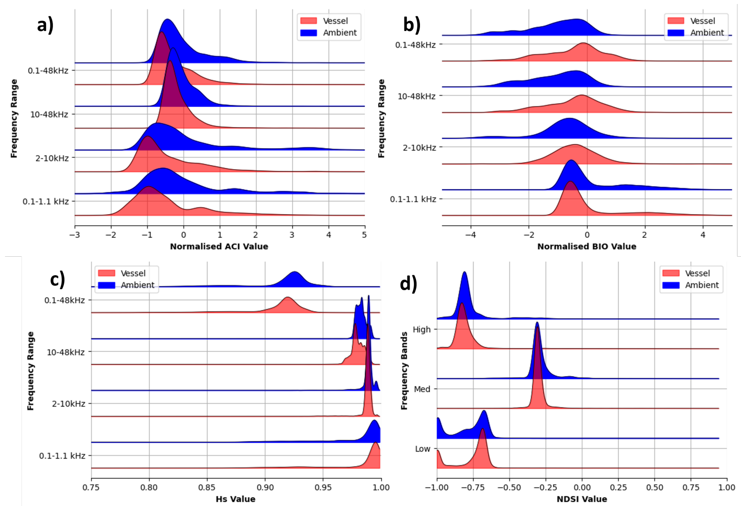

Figure 6: Ridgeline plots showing index distributions from the Ambient and Vessel classes in Hyskier in July. Changes in distributions are small. All ACI (a) percentile values decrease in the Vessel class, whilst all BIO index (b) distributions increase. Hs distributions (c) increase slightly across all frequency ranges with the exception of 0.1-1.1 kHz frequency band. The NDSI (d) distributions are similar between classes, with an increase in the standard deviation in the med band and small differences in the shape of the low band distributions in the Ambient class.

caused by a quieter maximum band in the bio range, or a louder maximum band in the anthro range. From the SPD's in Fig. 2, it can be seen that the decrease in PSD as a function of frequency is greater between 0-5 kHz in the Whistle class, meaning a greater disparity between the anthro and bio bands in both the med and low frequency ranges and lower **NDSI** values. The standard deviation of the high band (anthro band 2-10 kHz and bio band 10-48 kHz) increases in the Whistle class which is consistent with a less stable soundscape as indicated by the greater spread of the empirical probability density values seen in the SPD (Fig. 2).

Index distributions also changed between the Ambient and Vessel classes in Hyskier (Fig. 6), though distributions were more similar than between the Whistle and Vessel classes in Tolsta. Comparisons must be made with care, but this is also seen in a greater similarity between the SPD's of the Vessel and Ambient classes. The most significant changes are seen in the **ACI** and the **BIO** index. **ACI** distributions increase and **BIO** index distributions decrease in the Ambient class, though the distributions are similar in the **BIO** index. This is the same trend of an increase in the **ACI** corresponding to a decrease in the **BIO** index as seen in Tolsta. **NDSI** values are highly similar between the classes, which is consistent with similar SPD shapes and stable soundscapes with empirical probability densities clustered around the median value in both classes (Fig. 5). As in Tolsta, **NDSI** values are predominantly less than 0, as is expected in soundscapes in which ambient levels decrease with increasing frequency as is seen in the SPD's from both locations.

The aim of this study was to establish if there were significant changes in the distributions of acoustic indices when calculated from the same data set sampled for periods in which different classes were present. Differences in index distributions in frequency ranges corresponding to the classes considered are clear, with differences between whistles and vessels the most significant. A full interpretation of the changes in indices is beyond the scope of this paper. For example, the **BIO** index decreasing when calculated over frequencies including whistles could be caused by numerous factors such as the co-occurrence of clicks and burst pulses, and the co-occurrence of multiple whistles of differing frequencies, both of which were observed when labelling. This provides further evidence that any future pipeline would likely require multiple indices to be calculated for each window of data to allow a rigorous interpretation of values, and discriminate between different causes of, in this example, a low **BIO** index.

5 CONCLUSION

We have presented evidence that soundscape drivers comprising at least 40% of a soundscape significantly change distributions of four commonly used indices. Changes in distributions were consistent with the frequency ranges of the noise classes considered, and the corresponding spectral probability densities. Whilst index distributions calculated across the whole frequency range differed between classes, the interpretation of these changes would be difficult without indices calculated over frequency ranges determined by the signals of interest. These results suggest indices reflect relevant spectro-temporal features of marine soundscapes in the West of Scotland, though further research is required before standardised methodologies are developed. As index distributions overlap significantly, the results also suggest future pipelines would require multiple indices to be considered.

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