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CLUSTERING, CATEGORIZING, AND MAPPING OF SHALLOW COASTAL WATER SOUNDSCAPES

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ABSTRACT

For many of its inhabitants, the underwater soundscape is a rich source of information that may be crucial for their survival. Moreover, in shallow coastal waters where visibility is poor, the importance of sound is emphasized. Yet coastal waters are also rich in anthropogenic sounds which may disturb the ecosystem. Passive Acoustics Monitoring (PAM) is a flexible, non-invasive, and cost-effective solution to acquire information at habitat or community level. Studying the acoustic scene of a habitat in a global, holistic way is known as soundscape analysis. However, there are currently no standardized methods to characterize and understand marine soundscapes in an automated way. Here we propose a methodology for clustering underwater soundscapes and linking the obtained categories to environmental parameters in space and time. This is done using explainable artificial intelligence. The methodology is applied to a PAM dataset collected in the Belgian Part of the North Sea. The obtained categories focus on background sound, which includes all combinations of sounds that occur under certain conditions at specific places. With this information, the marine acoustic scene and its change over space and time can be mapped for the whole area of interest.

Keywords: *soundscape analysis, unsupervised categorization, shallow water, underwater acoustics, shap*

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1. INTRODUCTION

With the increase of human pressure on the ocean in the past decades, it has become necessary to monitor and protect the ocean and its rich natural soundscapes [1]. This can be achieved through Passive Acoustics Monitoring (PAM), which allows for obtaining ecological information from underwater ecosystems. PAM is of particular interest in underwater environments, where other monitoring techniques might be difficult to execute, and because sound plays an important role for most marine species [2].

Soundscape analysis often involves the detection and classification of several sounds, which are usually divided between geophony, biophony, or anthropophony, depending on the nature of the source producing the sound. Detecting these acoustic events allows for tracking the movements and behaviors of marine species, as well as measuring changes in their populations over time. However, soundscape analysis can also be done with a more holistic approach instead of focusing on specific sound events or specific species. This can provide us with information at habitat or community level. This information can then be used to monitor ecosystem changes and the effects of human pressure in certain habitats [2, 3].

Here we focus on soundscape in a holistic sense. We apply the methodology proposed in Parcerisas et al. (2023) [4] to a long-term dataset collected in the Belgian Part of the North Sea (BPNS). The model clusters soundscapes based on acoustic features and explains their occurrence using environmental variables that describe the spatio-temporal context. In this paper, we use this model to create maps for the expected soundscape class for the whole BPNS. Furthermore, we map the expected mean power density at the frequency bands 63, 125 Hz, and

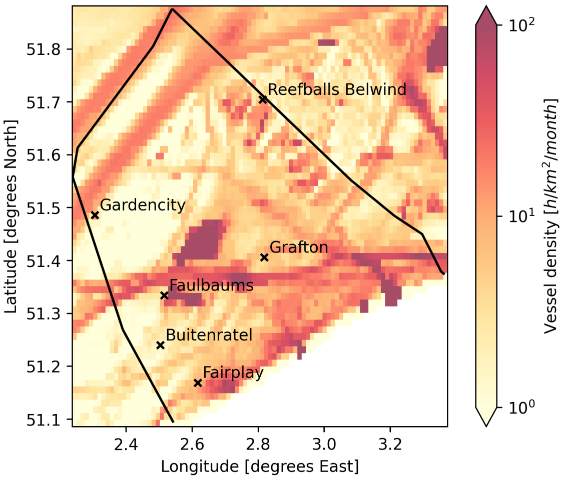

Figure 1. Vessel density from EMODnet [6] in the BPNS, together with the station location of the LifeWatch Broadband Acoustic Network [5]

2000 Hz according to the mean levels of each category and their occurrence.

2. METHODS

We applied the methodology explained in Parcerisas et al. (2023) [4] to long-term data acquired in the framework of the LifeWatch Broadband Acoustic Network [5]. These data were collected using a RESEA 320 recorder (RTSys, France) together with a Colmar GP1190M-LP hydrophone (Colmar, Italy, sensitivity: -180 dB/V re $1\mu Pa$, frequency range -3 dB: 10 Hz to 170 kHz). The acoustic recorders were attached to a steel mooring frame at 1 m above the sea bottom, with no moving parts. 14 different deployments from 6 different stations (see Figure 1) were considered, ranging between March 2021 and September 2022. Because of computing reasons, 10 minutes of every recorded hour was chosen randomly for the analysis.

All acoustic data were processed using the Python package pypam [7]. Data with a higher sampling rate than 48,000 kS/s were filtered with a low-pass Butterworth order 4 filter and then downsampled to 48,000 kS/s to match the rest of the data. Then the sounds were processed to hybrid millidecade bands [10] because their frequency-dependent bandwidth is well-suited for long-term spectral averages and soundscape comparisons [11]. The hybrid millidecade bands were used as an input for the dimension reduction. In this first analysis, a 1-minute non-overlapping window temporal resolution was chosen for obtaining the spectra for analysis speed. This implies however that short-term patterns smear out and cannot be distinguished.

The hybrid millidecade bands were then clustered in an unsupervised way into several categories using Density-Based Spatial Clustering of Applications with Noise (DBSCAN) from the scikit-learn package [8] after a dimension reduction using Uniform Manifold Approximation and Projection (UMAP) [9]. Different combinations of parameters were checked to try to achieve an optimal distribution of the data for the UMAP reduction, where acoustic sample points were distributed in separate clusters.

To correlate the clusters with the environmental parameters, a Random Forest (RF) was trained to predict the acoustic categories from the environmental parameters. The iterative training scheme of Parcerisas et al. (2023) [4] was followed but the environmental variables used were adjusted to accommodate the shift from a higher spatial resolution and lower temporal resolution to a higher temporal resolution and a lower spatial resolution. The chosen variables are listed in Table 1.

With the obtained RF-model and the available environmental parameters, the presence of different soundscape categories can be predicted in the whole BPNS. This allows for visualizing the different soundscapes present in the BPNS. For each obtained category, the SHAP values [16] were computed. Then, each obtained cluster was assigned a characteristic spectrum by computing the mean power density of the hybrid millidecade bands in that cluster. The mean power density for each month for the hybrid millidecade bands 63 Hz, 125 Hz, and 2000 Hz (center band 2002.16 Hz) was computed and mapped according to the weighted mean considering how often a certain category was predicted. This was done by predicting the expected classes for every hour during a month and then averaging according to the mean value of each cluster at the specified frequency band. The 63 and 125 Hz bands were selected because they are the frequency bands selected by the EU to monitor the Good Environmental Status of marine waters [17]. 2000 Hz was selected because of its higher relevance for marine mammals, in line with other studies [18].

Table 1. Summary of all the used environmental variables

Parameter	**Encoding**	**Source**	**Dependency**
Bathymetry [m]	Converted to positive	EMODnet Bathymetry [12]	Space
Day moment	Categorical encoding	Skyfield [13]	Space, Time
Shipping Density [$km^{-2}month^{-1}$]	None	EMODnet Human Activities [6]	Space, Time
Seabed habitat	Categorical encoding	EMODnet Seabed Habitats [14]	Space
Salinity [PSU]	None	ERDDAP [15]	Space, Time
Surface Temperature [K]	None	ERDDAP [15]	Space, Time
Surface current speed [ms^{-1}]	None	ERDDAP [15]	Space, Time
Height above sea level [m]	None	ERDDAP [15]	Space, Time
Wave period [s]	None	ERDDAP [15]	Space, Time
Wave height [m]	None	ERDAPP [15]	Space, Time
Moon phase [rad]	Cyclic encoding	Skyfield [13]	Space, Time
Week number	Cyclic encoding	NA	Time

3. RESULTS

4 soundscape categories were clearly identified (see Figure 2). The parameters used for the UMAP projection were: number of neighbors=20, minimum distance=0. For the DBSCAN algorithm: minimum samples=240, epsilon=0.5. The obtained RF-model classified the soundscape categories with 91.68% accuracy. The description of each cluster is shown in Table 2. The principal variable selected to explain the clusters was seabed habitat, which in this case was linked to location (see Figure 2). This suggests that the acoustic characteristics of the habitats in the BPNS differ more between habitats than within. Category 1 was not correctly predicted by the model, which suggests that it represents a certain acoustic situation not linked to the selected environmental variables. This hypothesis was supported by the fact that category 1 comprised samples from all the different locations and deployments.

An example of a map of the predicted category in March and November can be seen in Figure 4. Category 0 seems to be the most present, and category 1 seems to be linked to shallower areas. This is also reflected in the frequency distribution. The power density at 63 Hz is low in areas classified as category 2 or 3, probably because 63 Hz is below the cut-off frequency in these shallow areas (Figure 5). In areas classified as soundscape category 0, the level at 63 and 125 Hz is higher than average while it is lower than average at 2000 Hz. By analyzing the obtained SHAP plots per class, it can be seen that category 0 is linked to higher shipping density (see Figure 3 and Table 2)). This is in line with shipping sound production, which is usually characterized by having most of the energy at lower frequencies.

The authors emphasize that this paper reports only a preliminary partial analysis. Several seasonal effects have yet to be explored in detail. Moreover, the limited temporal resolution of 1 minute does not allow for the identification of specific bio-sounds that may contribute to the soundscape only at certain locations and certain times of the year. Further analysis will be reported elsewhere.

4. DISCUSSION AND CONCLUSIONS

The prediction of the categories for the whole BPNS showed that this is an acoustically dynamic area, being influenced both by time and space. The category prediction by the RF-model seemed to be influenced mainly by the seabed habitat and shipping density (Table 2). Even though all the data were collected with the same instru-

Table 2. Manual description of the SHAP values of each category.

Category	Description
0	seabed habitat 5.27, high shipping, high salinity
1	(not a soundscape class) high shipping, seabed habitat A5.25 or A5.26, high temperature
2	seabed habitat A5.23 or A5.24, low shipping
3	low shipping, seabed habitat A5.25 or A5.26

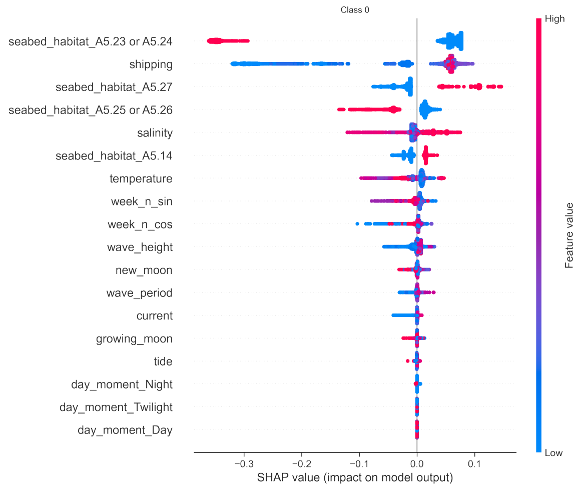

Figure 3. SHAP values of the obtained category 0 resulting from the trained RF-model.

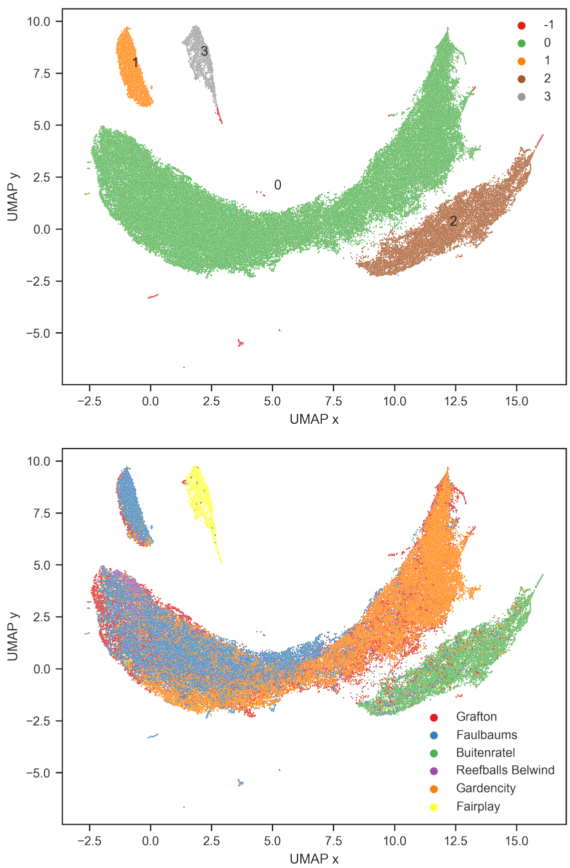

Figure 2. Top: Obtained clusters using DBSCAN in the UMAP space. -1 represents samples classified as noise and not belonging to any cluster. Bottom: distribution of the stations in the UMAP space.

mentation, the data clustered clearly according to the location where it was recorded 2. This indicates that different locations in the BPNS have different soundscapes and they can be distinguished from each other.

The shipping density used in the model represents the monthly average computed from the Automatic Identification System (AIS) data and considering all types of vessels. Therefore, further work is necessary to also include vessels which do not use AIS, and also to investigate if different shipping activities (e.g. fishing, tanker...) influence the soundscape categories in different ways. Furthermore, using AIS data at a higher time resolution (e.g. daily or hourly average) would provide a more dynamic understanding of the effects of shipping noise on the obtained soundscape categories.

Unsupervised categorization of soundscapes can be used as a tool to understand and predict the long-term soundscape. The different categories can then be acoustically characterized by looking at the mean spectrum per category. Furthermore, these categories can be placed in an environmental context using explainable artificial intelligence (XAI), so we can understand when and where they occur. This is especially interesting in dynamic shallow areas such as the BPNS, where propagation patterns are complex to model.

The obtained power density distribution maps per frequency band give insight into the expected levels per frequency in the whole BPNS. Using hybrid millidecade

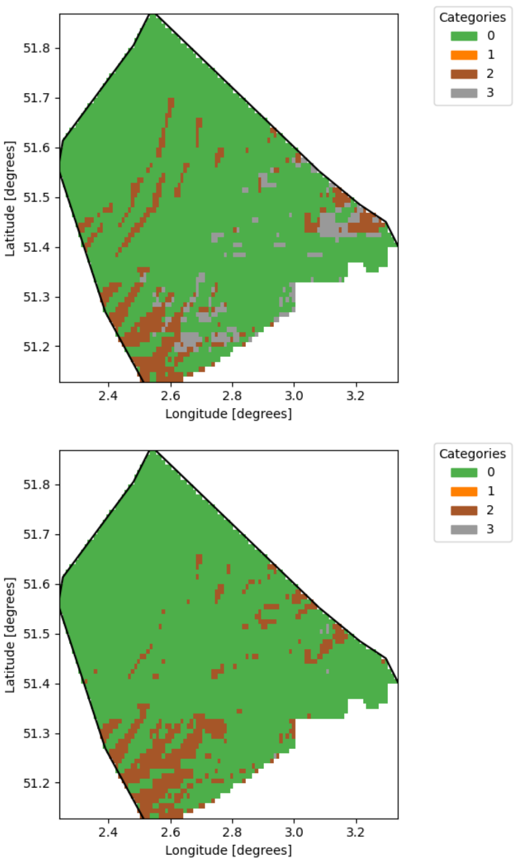

Figure 4. Predicted soundscape categories in the BPNS (black line is the delimitation of the Exclusive Economic Zone) according to the environmental parameters using the RF-model, from two randomly selected timestamps. Top, prediction of 8th of March of 2022 at 12:00 am. Bottom, prediction of 25th of November at 00:00 am.

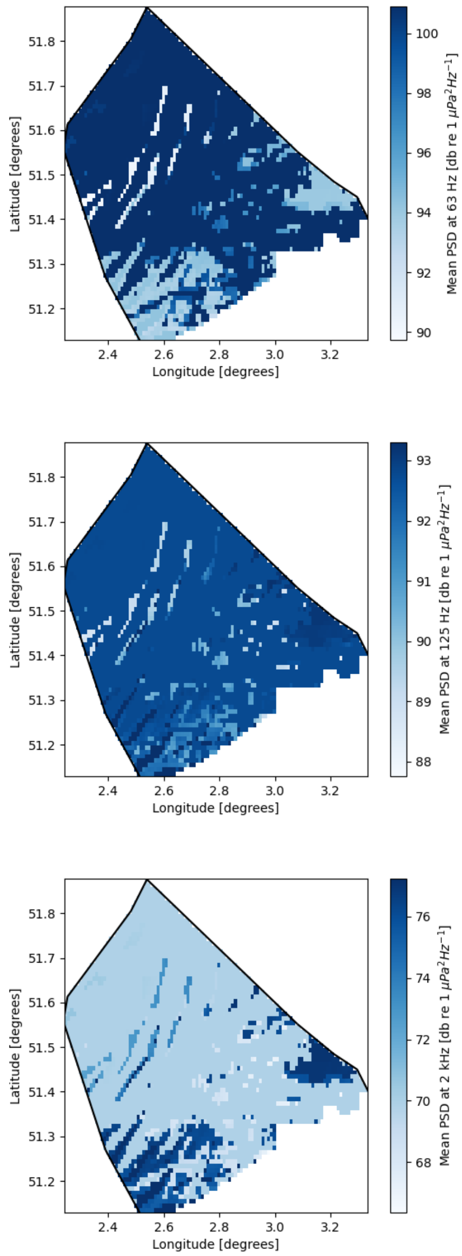

Figure 5. Predicted mean power density for the three selected frequency bands during January 2022. Categories predicted hourly for the entire month. Mean power density computed considering the assigned power density at each frequency for each category and its hourly occurrence during the month. Top, 63 Hz. Middle, 125 Hz. Bottom, 2000 Hz.

bands instead of one-third octave bands (used in [4]) is suitable for long-term soundscape prediction. The obtained categories are then less dynamic in space and time and more linked to habitat (see Figure 2). Furthermore, in the long-term dataset there are less combinations of spatial features than in Parcerisas et al. (2023) [4]. The obtained clusters are probably not shaped by short biological sounds but by longer, continuous sounds. This is obtained by choosing a lower time resolution of 1 second power spectrum density averaged in 1 minute. Computing the hybrid millidecade bands this way, as proposed by [10], smooths out transient sounds.

The obtained distribution of categories and their evolution in time can help us understand the different acoustic scenes and their variability. This can be used to detect anthropogenic noise pollution, or rapid degradation of ecosystems [19]. This suggests that hybrid millidecade bands averaged in 1-minute bins are suitable for habitat discrimination but are not sensitive to the sound correlated to other temporal environmental data, which contributes to the soundscape in a finer time resolution.

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