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The Caatinga Orchestra: Acoustic indices track temporal changes in a seasonally dry tropical forest

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A R T I C L E I N F O

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A B S T R A C T

Advances in technologies for data acquisition, storage and analysis have boosted Acoustic Ecology studies, but protocols are still lacking. There is a need of more research to understand which methodologies can be applied to answer ecological questions in different environments with varying temporal and spatial dynamics. Tropical forests are generally more complex than temperate ones, both in terms of use of acoustic space and species diversity. The seasonally dry tropical forest (SDTF) in Brazil, known as Caatinga, is a threatened biome, with two marked seasons that shape vegetation and animal activity patterns. In this study, we investigate the applicability of passive acoustics in monitoring SDTF, describing the soundscape and tracking diel patterns and seasonal changes. Combining multiple indices, visualization through false colour spectrograms and clustering, we describe the acoustic activity of the main faunal groups that compose the biophonic orchestra in a SDTF area in the Northeast of Brazil. Distinct patterns were found between day – when birds and wind were the main sound sources – and night – with Orthopterans occupying a large frequency band. Other sound sources in the SDTF soundscape included cicada, rain, and anthropogenic influence such as domestic animals, cars and gunshots. Clustering of eleven acoustic indices was useful to distinguish sound patterns from several sources, especially in the dry season. Further investigation within each cluster showed specific relationships among selected indices and different sound sources. Birds were associated with Entropy of the Spectral Peaks (EPS) and Orthopterans also had a relationship with EPS, as well as with Entropy of Average Spectrum (EAS) and High Frequency Cover (HFC). Variation in diel values of these selected indices, as well as the number of samples included in each cluster category, were successfully used to describe the acoustic activity of Birds and Orthopterans and to track changes between rainy and dry seasons. A better understanding of the soundscape dynamics in a highly seasonal tropical environment was achieved by applying cheap and reliable novel methodologies to study biodiversity in geopolitical regions where funding for conservation initiatives is limited.

1. Introduction

Sounds play a fundamental role for many species and ecosystems, and acoustic data has being used to study vertebrates and invertebrates in a variety of functions and contexts, thus contributing to understanding key ecological processes (Bradbury and Vehrencamp, 1998). Acoustic tools are less invasive and provides data about variation on temporal and spatial patterns of species richness (Depraetere et al., 2012; Duarte et al., 2015), as well as changes in the behaviour of vocal species (Parks et al., 2011). Passive acoustic monitoring has become popular due to recent advances in technologies for data acquisition, storage capacity, analyses methods and tools (Burivalova et al., 2019; Gibb et al., 2019; Merchant et al., 2015). Besides the large amount of data passive acoustic monitoring generates, another major challenge of this method is that it will only work for vocal species that, for most taxa, are difficult to identify from their sounds alone (Gibb et al., 2019).

The popularization of passive acoustic monitoring was followed by the exponential growth of the field of soundscape ecology (Pijanowski

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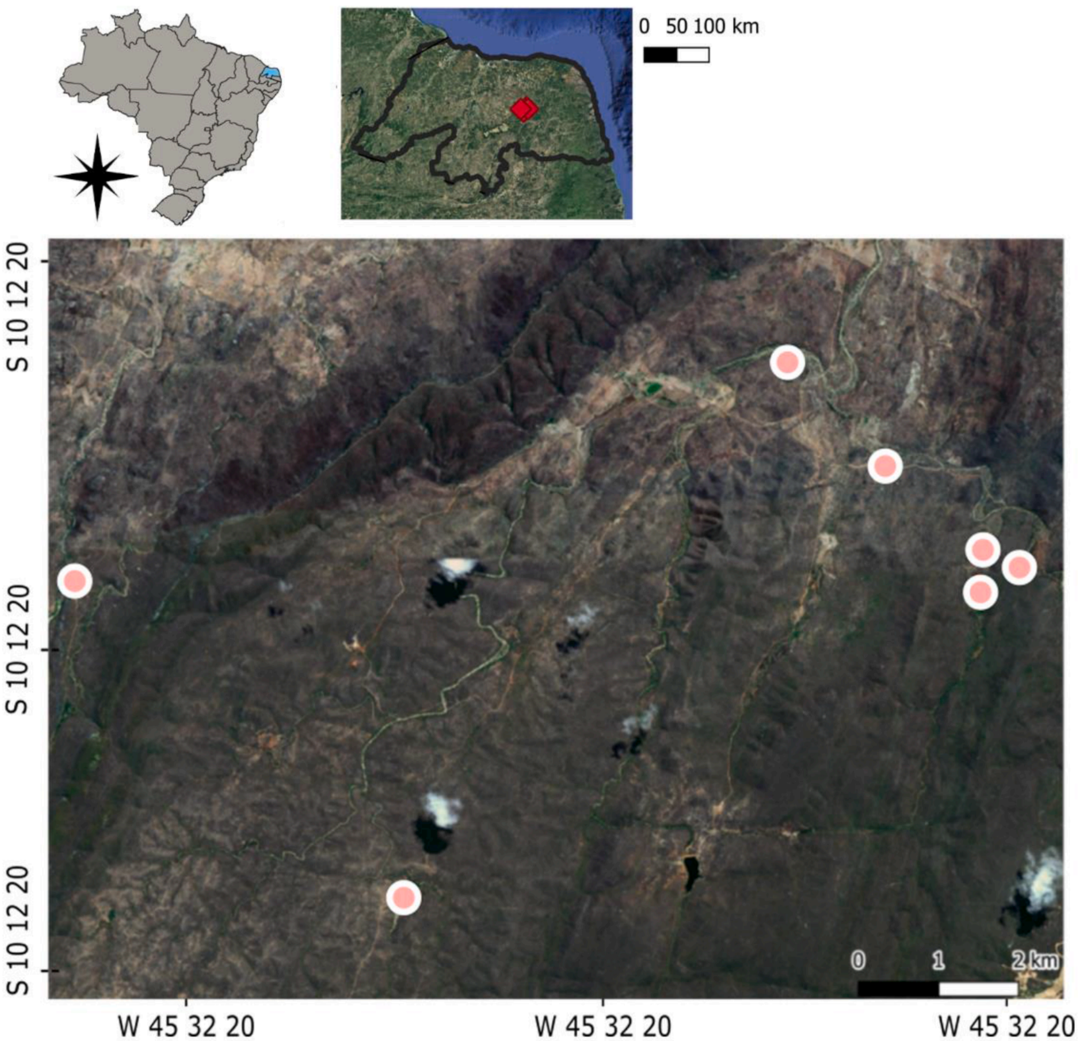

Fig. 1. Site location within an area of Caatinga sampled with Song Meters distributed in the municipality of Lajes, Rio Grande do Norte State, Brazil. Map shows the location of Rio Grande do Norte state (top left), area sampled (in red squares), and location of each recorder (pink circles in the bottom image). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

et al., 2011). The term soundscape appeared for the first time in an urban context (Southworth, 1969) and was used to describe the acoustic characteristics of an given area that reflects their processes (Schafer, 1977) and, in natural environments, creates dynamic acoustic patterns (Pijanowski et al., 2011). We can recognize three different sound sources in a soundscape (Krause, 1987): biophony, arguably zoophony (Ferreira et al., 2018) (sounds produced by animals, usually related to communication), geophony (sounds from physical processes, like wind, rain, thunder), and anthropophony (sounds from human made activities or machines). The study of soundscapes has applications across several temporal and spatial scales to address questions about environmental health, changes in land use, and climate change, to name a few (Blumstein et al., 2011; Burivalova et al., 2019; Buxton et al., 2018; Farina, 2014; Krause and Farina, 2016; Pijanowski et al., 2011; Tucker et al., 2014). The study of soundscape has received much attention from researchers worldwide, however, it is still biased toward temperate regions and in urban areas, with much less attention to more preserved areas of Neotropics (Scarpelli et al., 2019). Therefore it is important to understand the soundscapes dynamics of these areas.

Soundscape ecology in general generates an enormous amount of data, which challenges researchers to deal with data management, fast recovery of reliable information, and ways to visualize and interpret acoustic big data (Phillips et al., 2018; Sueur et al., 2014; Towsey et al., 2014). Acoustics indices are one way to summarise the data in large acoustic recordings files. An acoustic index is a statistic that quantifies some aspects of the structure and distribution of acoustic energy in a recording, and potentially reflects ecological processes (Towsey et al., 2014). The relationship between acoustic indices and community diversity are still poorly understood (Burivalova et al., 2019; Ferreira et al., 2018; Gibb et al., 2019) and, besides the great potential to be used in broad contexts (Aide et al., 2017), most literature focuses on avian communities (Machado et al., 2017; Pieretti et al., 2015; Retamosa Izaguirre et al., 2018; Zhang et al., 2016). Given the diversity of acoustic patterns within audio recordings, it is not expected that a single acoustic index can precisely describe a soundscape (Buxton et al., 2018; Ferreira et al., 2018). Therefore, recent studies propose the combination of several non-redundant indices to accurately summarise soundscapes (Phillips et al., 2018). More visual approaches in characterizing soundscapes rely on the idea that it is nearly impossible to identify patterns in long duration recordings by only listening to them (Sankupellay et al., 2015). To address this limitation, multiple acoustic indices' visualization methods and tools has been proposed using at least two techniques: false colour spectrograms (Sankupellay et al., 2015) and data ordination (Phillips et al., 2018; Sankupellay et al., 2015).

Here we use multiple visualization tools to validate the applicability of passive acoustic monitoring and soundscape characterization in a seasonally dry tropical forest (SDTF), aiming to point out weaknesses and strengths of this methodology in such a unique environment. A detailed understanding of the soundscapes patterns present in the area can be a valuable tool for environmental monitoring, to understand general changes in the patterns of animal's activity, and even to identify where to focus efforts in species identification (i.e. identifying the files where the birds are, instead of manually looking for them). This paper also aims to contribute by generating prior baseline data to monitor how the construction of a massive windfarm complex in the area will influence the soundscape and biodiversity in the future (Dahl et al., 2012).

The SDTF in Brazil, called Caatinga, has two distinct seasons: dry and rainy. The vegetation cover among seasons changes drastically (Fig. A1), as well as the animal activity, since the reproductive period of birds, anurans, mammals and insects in the area is highly dependent on the water supply (Santos et al., 2011).

The objective of this study was to describe the dynamics of the Brazilian Caatinga soundscape and track diel patterns and seasonal changes. Specifically, we aimed to answer: (1) Can acoustic indices be used to discriminate sound sources in the Caatinga soundscape? (2) Are there diel patterns in the soundscape? (3) Which animal groups contribute to changes in the observed diel patterns in the soundscape? (4) How do soundscapes change between rainy and dry season?

We hypothesize that a combination of acoustic indices are required to discriminate among sound sources. We expect that in such tropical environments, birds will dominate the diurnal period and insects will fill in the nightscape. Anurans are not expected to be present since recording sites were not close to water bodies (information about the sampling sites are in Appendices, Table A1). We also expect less contribution by aviafauna to recordings during the dry season, as climate is less favourable to birds in this season (i.e. limited water and food resources). Regarding insects, we do not expect the daily activity period to change from dry to wet season. We expect that the number of individuals, and even species, will reflect more intense use of the acoustic space during the wet season, when most insect species are exploiting the abundance of water as a resource for adults and early stages of their life cycles.

2. Methods

2.1. Study area and sampling sites

Seasonally Dry Tropical Forests represent 20% of the world's tropical forests (Hansen et al., 2010), and are distributed within the Americas, Africa, Eurasia and Australasia (Miles et al., 2006). These forests share some similarities such as a significant numbers of endemic species which are susceptible to desertification processes and climate change (Aguirre-gutiérrez et al., 2020; Miles et al., 2006), and are often not prioritised in conservation actions (Santos et al., 2011). Those characteristics make the Tropical Dry Forests the most endangered of all tropical forests (Dirzo et al., 2011). Within Brazil, the SDTF is distributed over nine states in an area of 836,00 km^2 (MapBiomas, 2019), where average annual rainfall ranges from 200 to 800 mm and the rainy season lasts for 3 to 5 months (Olmos et al., 2005). Usually the rainy season in the study area begins in February, and in 2017 we had a considerable amount of rainfall registered until July.

The study area is located within Serra do Feiticeiro (Fig. 1) which is the most pristine Caatinga area in Rio Grande do Norte State (Cordero-Schmidt et al., 2017; Marinho et al., 2018; Vargas-Mena et al., 2018). Besides the conservation importance, there is no legal protection inside the area or surrounding landscape, and a massive windfarm has been planned to be constructed in the next few years. A total of seven sampling sites were monitored and the distance between them varied between 200 and 2,000 m (Fig. 1). The recorders were distributed so that our sample was representative of the landscape in the region. Sites varied in vegetation structure, distance from roads, and terrain inclination. Additional information about sampling sites are presented in the Appendices (Table A1 and Fig. A1).

2.2. Data acquisition

In each of the five sampling sites, we installed one autonomous recorder (Song Meter SM3®, Wildlife Acoustics, Inc., Concord, Massachusetts), with an omnidirectional waterproof microphone, attached to a tree at 1.5 m high. The sensors were programmed to record one minute every 15 min at a sample rate of 44.1 kHz and 16 bits, in wav format. Data were collected in 2017 over 26 consecutive days each season (Rainy, from 12 June to 07 July 2017. Dry, from 13 December 2017 to 09 January 2018) simultaneously on all the five sites (Fig. 1). Due to equipment malfunction, data from one of the recorders from the 2017 rainy season was removed from analyses. Additionally, two SM2 + with the same specifications were used during the 2018 rainy season, also recording for 26 days, in two other sites simultaneously (Fig. 1). Slight improvement in signal-to-noise ratios in the Song Meter model SM3 compared to SM2 + does not impact the measured acoustic indices (Wildlife Acoustics, Inc.).

2.3. Data processing

To extract biological information from the audio data, we manually counted sonotypes in a subsample of the recordings (1-minute every 30 min on files from 3 consecutive days, for each season, N = 290). We define sonotype as a note or series of notes with a distinct pattern that may represent a species vocalization (Aide et al., 2017; Ferreira et al., 2018). The use of this approach has some limitations, although for insects and amphibians one sonotype generally equals one species, in birds we have a different scenario. The same species of bird can have a wide vocal repertoire, including mimetic signals from other species, which may lead us to biases in the number of species resulting from this approach. Nonetheless, it is valid since the limitations of identifying sounds at the species-level is well understood (Aide et al., 2017) and our aim was not identifying species, but identifying patterns in animal acoustic activity. Insects are currently the most difficult taxa in terms of species identification from vocalisation. One weakness of this methodology for soniferous insect species is that their vocal parameters have a strong association with body size and environmental conditions such as humidity and temperature (Robinson and Hall, 2002). Thus, a single insect species comprised by individuals with size variation could be accounted for two or more times. Another limitation is that some insect species differ acoustically with the pulse rate of their calls (Mendelson and Shaw, 2002), which is almost impossible to detect via manual listening, so the number of sonotypes may underestimate the actual insect diversity.

Sound patterns were detected using aural and manual inspection of files for their spectral features in Raven Pro 1.5® (Cornell Lab of Ornithology, Ithaca, NY). Sounds were labelled as present/absent according to four categories of biophony: birds, insects, anurans, or mammals. We also registered the presence of geophony (e.g. wind, rain) and antropophony (e.g. vehicles, gunshots). Each file was assigned to one to four labels, and the dominant category of sound within each file was also registered.

Once the recorders are exposed to adverse conditions in the field, it is common that some files are damaged, and no information can be extracted from the spectograms (Sankupellay et al., 2015). Although it is also a common practice to manually remove files with too much wind, rain or anthropogenic noise, here we use all undamaged files, since we consider that those sound sources are also part of the soundscape and should be accounted for.

2.4. Acoustic indices

The acoustic indices calculations and visualization were generated using Analysis Program. A comprehensive guide and the scripts to run the analysis are available at https://github.com/QutEcoacoustics/audio-analysis. In total, we use 14 Summary and six Spectral Indices (see

Table 1
Acoustic indices calculated for soundscape data from a pristine region within Caatinga, a seasonally dry tropical forest of Brazil. Indices were calculated using the Analysis Program. For details about calculations, see references. Note that ACI, ENT, EVN, BGN, PMN, R3D were calculated at both spectral and summary versions. The spectral calculations were used to build False Colour Spectrograms.

Index	Index Name	Description	Reference
ACI	Acoustic Complexity Index	Originally developed to reflect bird activity, excluding constant and low frequency sounds (like human generated noise). Very sensible to other sound sources, like rain. In this study, based on bird species observed, we chose to use the frequency band of 0.5 to 11 kHz.	Pieretti et al., 2011; Towsey, 2017
ENT	Temporal Entropy	Measurement of acoustic energy concentrated in each frequency bin (Spectral Temporal Entropy), across the wave envelope.	Towsey, 2017
EVN	Events per second	Average number of times the decibel envelope crosses a BGN + 3 dB threshold, per second.	Towsey, 2017
BGN	Background noise	Noise profile calculated from the decibel waveform. Note that this index is used to calculate others (like EVN).	Towsey, 2017
SNR	Signal to noise Ratio	Difference between the BGN value and the maximum value in the decibel envelope.	Towsey, 2017
ACT	Activity	Fraction of values in the 30 s decibel envelope that exceed 3 dB above the BGN value. Constant sounds with high signal to noise ratio (like cicada chorus) are reflected in high ACT values.	Towsey, 2017
HFC	High Frequency Cover	Fraction of the noise-reduced decibel spectrogram in the high frequency band (11–22.050 kHz) that exceed 3 dB above BGN.	Towsey, 2017
MFC	Mid Frequency Cover	Fraction of the noise-reduced decibel spectrogram in the mid frequency band (0.5–11 kHz) that exceed 3 dB above BGN.	Towsey, 2017
LFC	Low Frequency Cover	Fraction of the noise-reduced decibel spectrogram in the low frequency band (below 0.5 kHz) that exceed 3 dB above BGN.	Towsey, 2017
EAS	Entropy of Average Spectrum	Concentration of mean energy in the mid-band of the mean energy spectrum.	Towsey, 2017
EPS	Entropy of the Spectral Peaks	Concentration of spectral maxima values in the mid frequency band (0.5 – 11 kHz).	Towsey, 2017
ECV	Entropy of Coefficient of Variation	Similar calculation to EAS, but in ECV the mid-band spectrum is derived from the variance divided by the mean of the energy values in each frequency bin.	Towsey, 2017
CLC	Cluster Count	Measure of the degree of internal acoustic structure, or spectral diversity, within the mid-band. Therefore, it is an index that can reflect bird diversity.	Towsey, 2017
SPD	Spectral Peak Density	A measure of the number of cells in the mid-frequency band that are identified as being local maxima. Not normalized to be independent of frame size and frame overlap.	Towsey, 2017
R3D	Three Ridge Indices	Combination of maximum values of three ridge indices (horizontal, upward slope, downward slope) which attempts to detect harmonic structures in the mid-band.	Towsey, 2017

section "Data visualization" below) (Table 1). The summary indices represent a single statistic calculated across a broad frequency range to measure different aspects of the acoustic energy within that time-period, in our case, 30 s. Meanwhile, the spectral indices are vectors calculated within predefined frequency bands and time periods, but also summarise several aspects of the acoustic energy distribution (Towsey, 2017).

2.5. Data visualization

Sound visualization is an important tool and it is based on the assumption that the human pattern perception is better at integrating long visual representations than long aural stimuli (Sankupellay et al., 2015). The use of False Colour Spectrograms (FCS) capitalizes on the human capability to discriminate red, green, and blue and is generated based on a combination of acoustic indices. Three different orthogonal indices are assigned to one of three colours (red–greenblue, RGB). The pixel size depends on the sampling rate (vertical axis) and temporal resolution (horizontal axis). Six acoustic indices were used in two different visualization combinations: ACI-ENT-EVN and BGN-PMN-R3D. Those indices are the default on the Analysis Programs, and are complementary and non-redundant.

2.6. Clustering the dataset

The k-means is one of the most popular and relatively simple clustering algorithms and requires that a fixed number of clusters is determined prior to the analysis. The algorithm used here was a variation of the k-means, known as k-means++, that results in more accurate centroids and minimizes the distance between points within each cluster (Campbell et al., 2006). To determine the ideal number of clusters, we used a smaller dataset with high biophonic activity. Days with rain, strong winds and recorder malfunction were discarded by inspecting the False Colour Spectrograms. This smaller dataset consisted of eight days, two for site 02 and two on site 03 (see Table A1), in each of the two seasons (rainy and dry). The indices were normalised between the 2nd and 98th percentiles bounds and scaled between 0 and 1. We generated a correlation matrix to remove highly correlated summary indices (Pearson's correlation > 0.75) (Gage et al., 2017). In total, we used 11 of the 14 summary indices (Appendices, Table A2, Fig. A3).

We tested two indices that are metrics for evaluating clustering algorithms: Silhouette Index (Rousseeuw, 1987; R Package *cluster*, Maechler et al., 2018) and Dunn Index (Dunn, 1974; R Package *clValid*, Brock et al., 2008). As observed by Phillips et al. (2018), although these are the most commonly used indices for this purpose, they do not always reflect the best discrimination of acoustic signatures. The Silhouette Index achieved best values for our sample with five clusters, which is a low number to represent complex acoustic communities (Phillips et al., 2018), and the Dunn Index showed very low values, from which we couldn't take any conclusion (Fig. A4). Considering the limitations of such validation metrics, we decided to manually browse 376 files and labelled sonotypes as: Orthopteran, Cicada, Birds, Wind, Quiet, Clipping, Frogs, Donkey, Anthropophony. Within Orthopteran, Cicada and Birds we also created a "Low activity" subcategory which was used when the acoustic signals were faint (low signal to noise ratio) or appeared only sporadically in the file. When $k = 50$, the number of clusters assigned to each manually labelled class reached a plateau, which suggests that all different spectral patterns within that category were accounted for. The exception was Orthopteran, which kept increasing, and an explanation may be the great number of files containing Orthopteran vocalization, and not necessarily an effect of the number of clusters. Therefore we used the optimal number of clusters as 50.

The complete dataset comprises >24,000 one-minute files from all seven different sampling sites. Previous inspection of the False Colour Spectograms showed similar soundscape patterns among sites. Therefore, we use the entire dataset without exploring the inter-site differences. The files were further divided into 30-seconds segments to

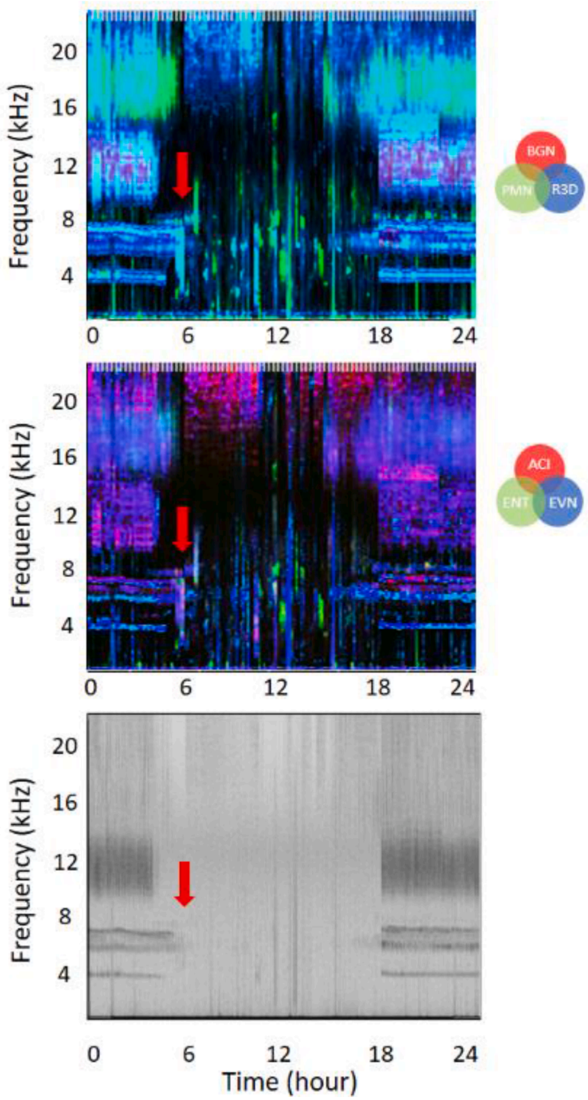

Fig. 2. Examples of 24-hour visualization of Caatinga soundscape data, Brazil, using one-minute samples every 15 min. A total of 96 files were used to compose these images, no gaps between them. On top, two False Colour Spectrograms, using three different indices to compose each of the two Red-Green-Blue visualizations. The indices and colours used in each FCS are indicated beside each image. In the bottom, in the greyscale spectrogram of the same period, FFT = 1024, 50% overlap. Red arrows indicate the dawn chorus. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

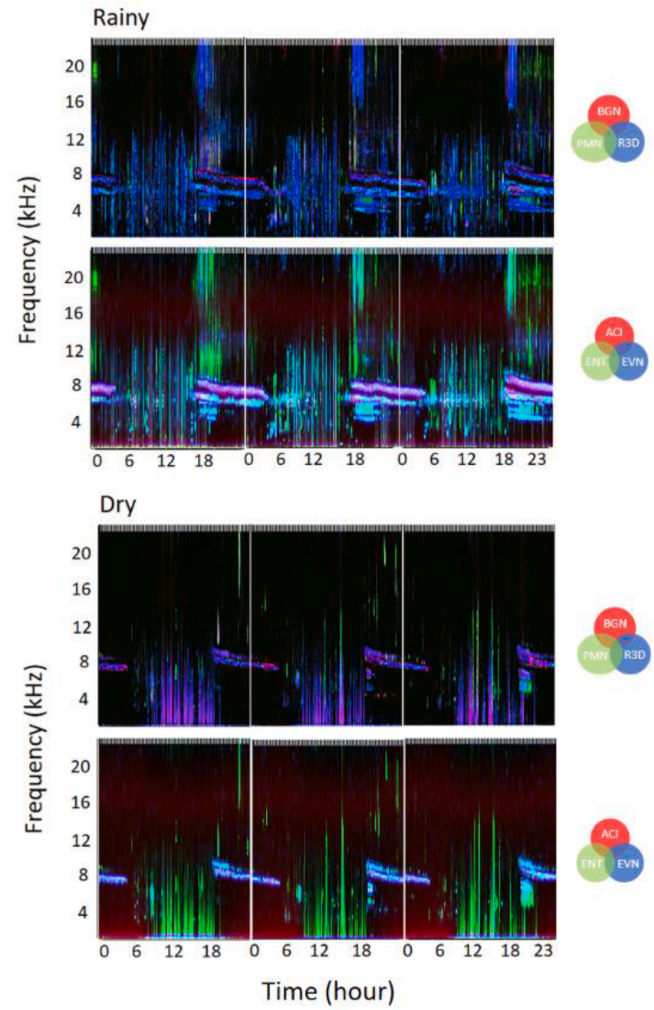

Fig. 3. Examples of 24-hour Caatinga soundscape visualisations, Northeastern Brazil, using False Colour Spectrograms. Three days in the rainy season (top) and three days in the dry season (bottom). Top images (for both seasons) were made using the indices ACI-ENT-EVN. Bottom images (for both seasons) were made using the indices BGN-PMN-R3D.

achieve a better resolution and avoid losing data due to clipping. Files were removed from further analyses by excluding those with Clipping Index values >500. The Clipping Index is a measure of the proportion of audio segment that presented clipping, a distortion of the soundwave that compromises the information, indices calculation and, thus, would affect the clustering. We normalized the rest of the data and excluded the correlated variables (as explained above), then we performed a k-means++ clustering, using k = 50, maximum number of iterations = 500 (Campbell et al., 2006; R Package 'LICORS', Goerg and Goerg, 2013).

We validated the content of clusters by manually verifying 10 files within each cluster, in a total of 500 files. Each file was labelled with one to four classes (birds, orthopterans, cicadas, wind, rain, quiet) which were further ranked by importance (i.e., the amount of occupation of the acoustic space). We compared the number of files in each label category between the seasons, for the entire dataset, by using a Pearson's Chi-squared test (R package 'stats', R Core Team, 2018).

2.7. Clusters visualization

We chose the Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) for data visualization. UMAP is a technique for data reduction, and presents some advantages compared to other popular data reduction algorithms, such as PCA and SammonMap (McInnes et al., 2018). The UMAP analyses were generated in R using 'umap' package (Konopka, 2018) and the graphs were created using 'ggplot2' package (Wickham, 2016).

2.8. Relationship between clusters and acoustic indices

To understand the weight of acoustic indices on each cluster we use radar plots analysis (R package 'fmsb', Nakazawa, 2019), for each one of the 25 clusters associated with a single label. Besides using the normalized values, we also reduced the noise by using a medoid value for each variable (Phillips et al., 2018), which allowed us to easily visualize which variables have the most influence on each cluster.

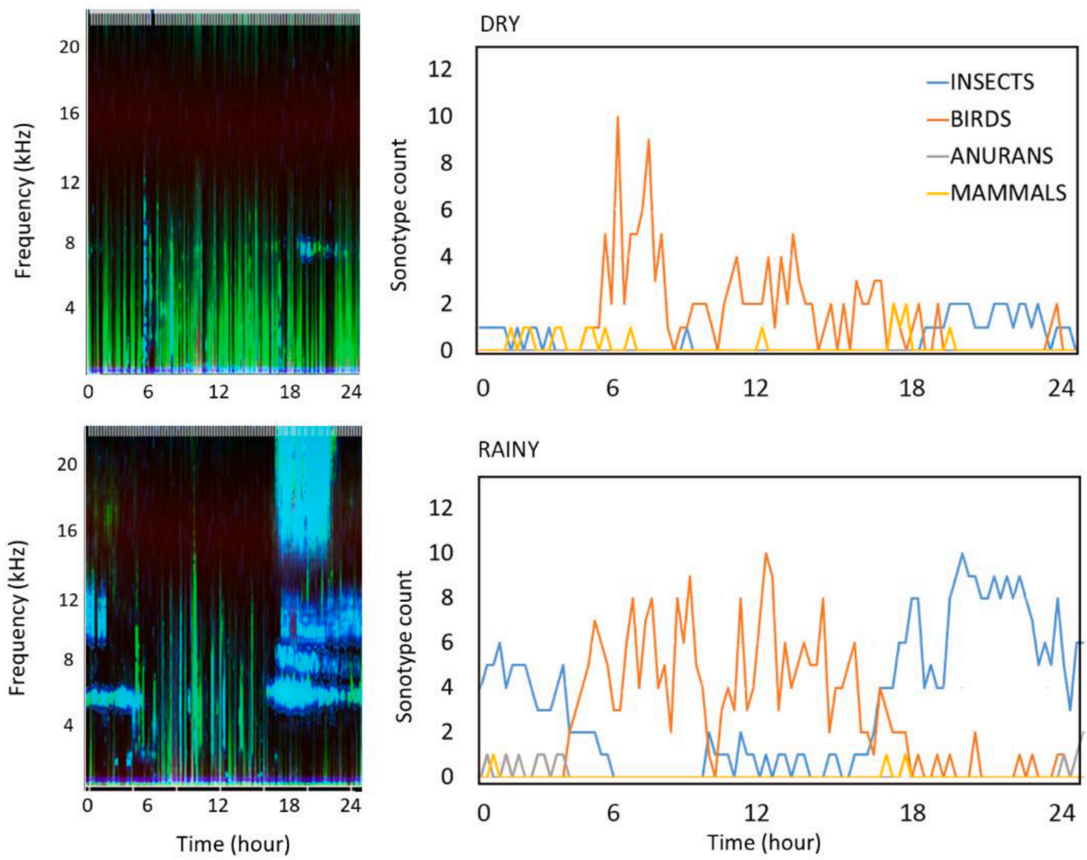

Fig. 4. Comparison between False Colour Spectrograms and graphs with the number of sonotypes manually identified for each animal category. Note that during the dry season the wind dominates the FCS visualizations and impairs inferences on acoustic activity diel fluctuations.

Table 2
Number of clusters and files assigned to each label category extracted from Caatinga soundscape data, Northeastern Brazil. The clusters are divided into those assigned to only one label, to two labels and, three or more/inconsistent labels. Percentages were calculated from the total number of files for each season, and are shown within parenthesis. Significant differences between seasons are indicated as *(p < 0.001). See Table A3 for statistics.

Label	Number of clusters	Files assigned (%)	
		Dry	Rainy
Birds *	1	0	637 (2.56)
Cicadas *	1	204 (0.82)	5 (0.03)
Orthopterans *	10	1,793 (12.72)	6,155 (24.8)
Quiet *	5	3,691 (26.18)	2,301 (9.27)
Wind *	8	4,545 (32.24)	3,358 (13.52)
Total	25	10,233 (71.96)	12,456 (50.6)
Birds + Orthopterans *	4	246 (1.74)	2,246 (9.04)
Birds + Wind *	3	1,749 (12.4)	1,434 (5.77)
Birds + Quiet	1	317 (2.24)	455 (1.83)
Orthopterans + Cicadas *	2	225 (1.6)	770 (3.1)
Orthopterans + Quiet *	1	214 (1.51)	513 (2.06)
Orthopterans + Wind *	3	97 (0.68)	1,970 (7.93)
Birds + Rain *	1	66 (0.46)	206 (0.84)
Wind + Rain *	1	0	831 (3.34)
Total	16	5,828 (20.63)	8,425 (34.22)
Birds + Orthopterans + Wind *	4	292 (2.07)	2,043 (8.29)
Inconsistent *	5	856 (6.07)	1,694 (6.82)
Total	9	1,148 (8.1)	3,737 (13.7)

2.9. Diel and seasonal patterns

To understand how the diel and seasonal patterns could be identified using the clusters, we chose 5 days per season in each sample point and looked for the relationship between the time of the day (24hs) and the number of files associated to each sound label. We also used the acoustic indices that most influence each cluster (from the radar plots) as a measure of the contribution of each one of our main biophonic labels.

3. Results

3.1. Visualization using False Colour Spectrograms (FCS)

We compared the spectrograms (examples can be found in Appendices, Fig. A2) with the FCS to verify which sound sources were contributing more to the observed patterns (Fig. 2). In a 24 h timeframe, it is possible to visualize the nocturnal insects at the grey scale spectrogram, but not the diurnal biophonic activity, which are easily observed in the FCS. This is especially evident for short duration signals, the case for most bird calls, and an example can be seen in the dawn chorus (indicated with red arrows in Fig. 2).

Although the bird activity is visible during twilight and daylight (from 04 h30 to 17 h30), the characteristics of the sounds produced by this group are not easily visualized and individualized with the FCS technique in our recording scheme (Fig. 3). On the other hand, insects presented clear patterns of occupation of acoustic space and were better visualized in the FCS, since their vocalizations occupy narrower frequency bands with long durations. Thus, it may be possible to estimate the number of sonotypes by counting different bands. The activity at night was dominated by Orthopterans, but it is also possible to identify Cicada's calls as horizontal bands during the day between 5 and 7 kHz in

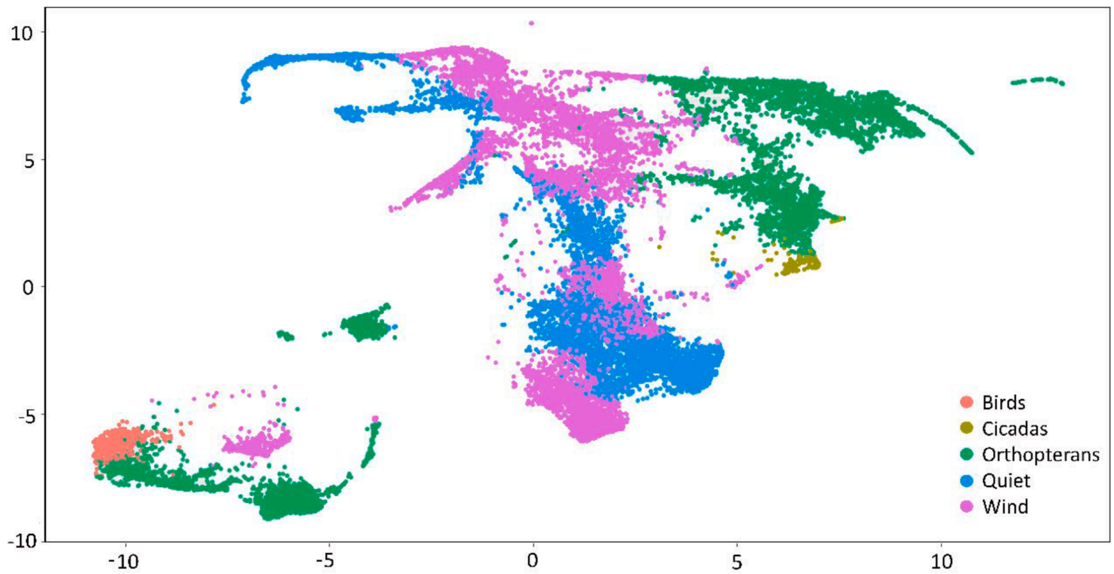

Fig. 5. Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) Clusters visualization from Caatinga soundscape data, Northeastern, Brazil. The colours represent single-label files.

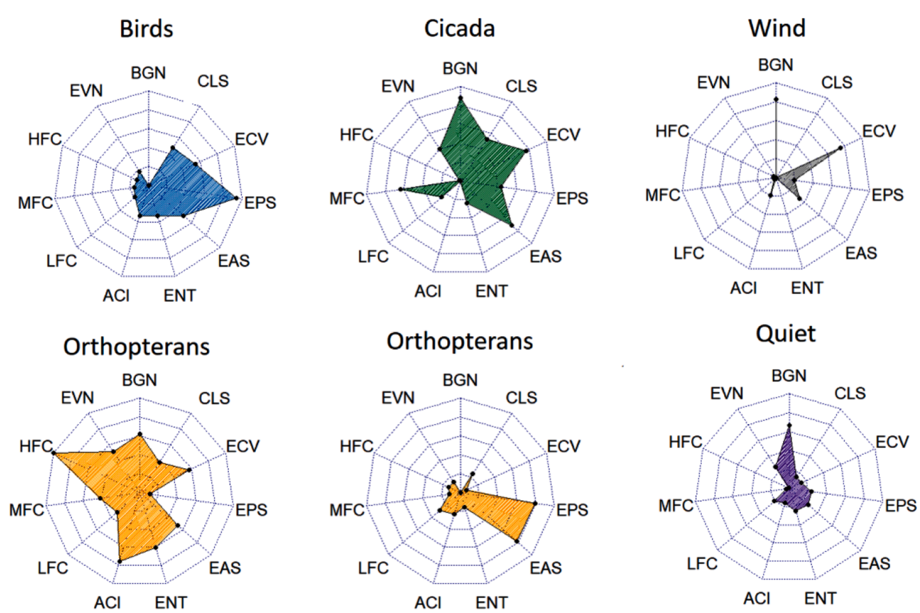

Fig. 6. Radar plots showing the indices weights in clusters associated with a single label from Caatinga soundscape data, Northeastern Brazil. Y axis shows the medoid of each normalised index. Details about the indices are presented in Table 1. Note that there are two "Orthopterans" clusters with distinct patterns, the one on the left reflecting acoustic activity from family Tettigoniidae.

the rainy season (Fig. 3).

The background noise representing the low intensity wind can be observed as the reddish colours (Fig. 3, bottom FCS). In the dry season, strong winds directly hitting the microphone show as a distinct pattern of green (vertical stripes on the FCS, Fig. 4), and are a limitation for the use of FCS. However, FCS makes it possible to detect a decrease in animals' acoustic activity compared to the rainy season, which is a benefit of this visual analysis.

3.2. Data clustering

The number of clusters labelled as each of the categories (Birds, Cicadas, Orthopterans, Quiet and Wind) can be seen on Table 2. The first part of the table lists only the clusters assigned to a single label. During the dry season, >70% of the clusters fit into this single label-category, but during the rainy season, the percentage drops to 50%. In both seasons, the clustering was more successful in grouping files with Wind, Orthopterans and with very low acoustic activity (Here referred as Quiet). The frequency of all categories, except Birds + Quiet, were significantly different between seasons (Table A3).

The distribution of the clusters is shown in Fig. 5. We chose to show only the files assigned to a single label, because the visualization of clusters assigned to multiple labels jeopardizes interpretation of the results due to the great number of different colours used. The clusters distribution grouped together the categories Wind and Quiet, as expected. Also, we labelled as Wind, files with different intensities of wind. Thus, files with presence of low wind could have been confounded with those labelled as Quiet.

Clusters labelled as Orthopterans varied in activity level, which resulted in the presence of this label in different groups of clusters. The

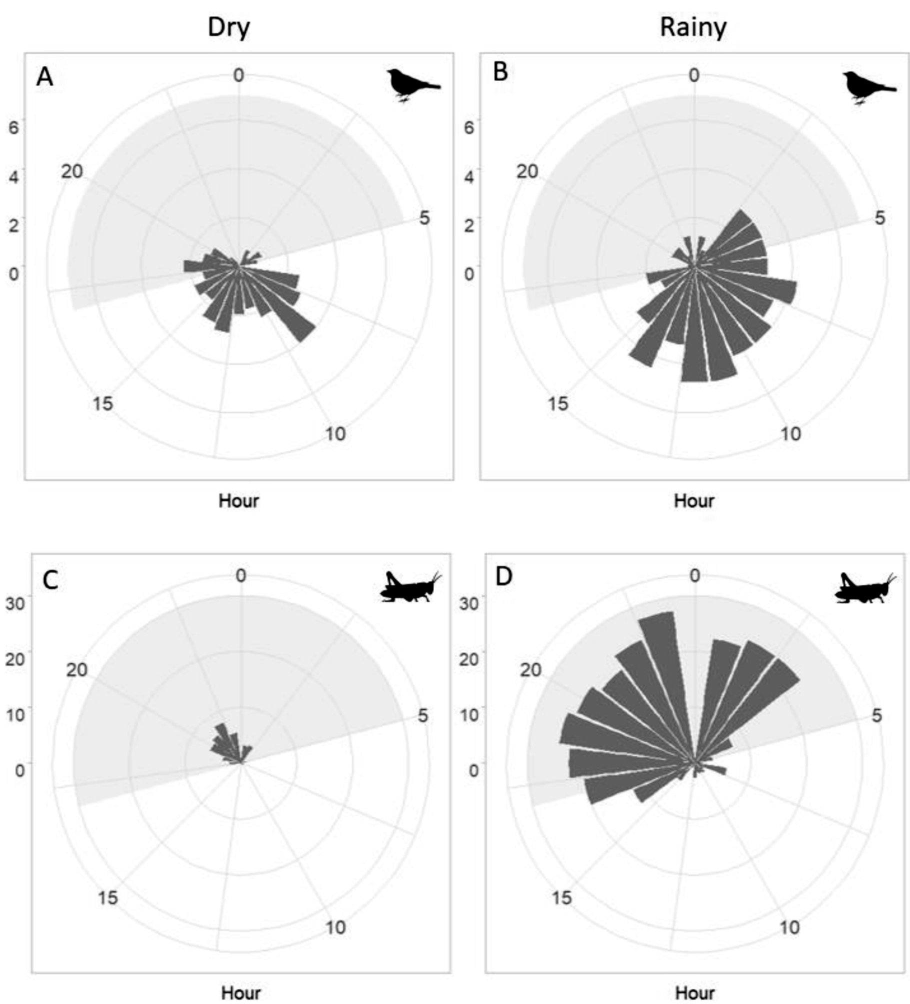

Fig. 7. Diel patterns (shaded area represents nigh time) of acoustic activity presence of the most representative groups (Orthopterans and Birds) during Dry and Rainy seasons, extracted from Caatinga soundscape data, Northeastern, Brazil. A and B refer to number of files labelled as Birds, and C and D to the ones labelled as Orthopterans throughout 24 h, using the average number of files of a subsample of five consecutive days from each of the four recorders. Note that the y axis scales are different for birds and orthopterans, due to the difference in number of files assigned to each category.

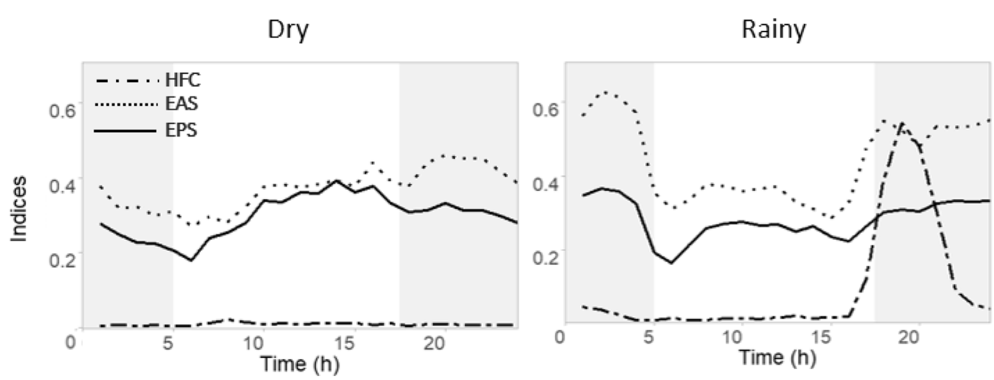

Fig. 8. Fluctuations in the mean value of three different indices along the 24 h, each one associated to one biophonic group: EPS (Entropy of Spectral Peaks, associated to Birds), HFC (High frequency Cover, associated to Tettigoniidae orthopterans), and EAS (Entropy of Average Spectrum, associated to other Orthopteran families). We used the average calculated from a subsample of five days from four recorders in Caatinga, Northeasthern, Brazil.

group located in the upper right of Fig. 5 corresponded to the low activity level, mainly in the dry season, but also in late night hours in the rainy season (an UMAP with files coloured as dry and rainy season is shown in Fig. A5). Files labelled as Birds were segregated from most of the other files but presented some similarities with part of the files labelled as Orthopteran during the rainy season.

3.3. Relationship between clusters and acoustic indices

The weight of indices in each cluster was explored using radar plots (Fig. 6). Orthopteran clusters presented two different patterns, one linked to EPS (Entropy of Peaks Spectrum) and EAS (Entropy of Average Spectrum) and other highly influenced by HFC (High Frequency Cover). This last one reflects acoustic patterns of the Tettigoniidae family, which produce high frequency sounds (Montealegre-Z and Mason, 2005). The clusters labelled as Quiet, Wind, and Cicada presented high values of

Fig. A1. Examples of areas sampled. Note the differences in top photos, taken at the same place during rainy and dry seasons.

Background Noise (BGN). EPS, although important to describe Orthopteran activity, showed the highest values in the clusters labelled as Birds.

3.4. Diel and seasonal patterns

The diel patterns of the main biophonic sources contributing to the soundscapes and their variation between seasons is presented in Fig. 7. In graphs A to D we used the number of files assigned to each animal taxa according to the clustering presented in Section 3.2. Fig. 7 shows similar general patterns of biophonic activity as those generated by manual identification (shown in Fig. 4). Fig. 7 also shows that acoustic activity from insects and birds are almost mutually exclusive, showing little temporal overlap, markedly in the dry season. Fig. 8 shows the temporal dynamics of three indices that are most representative in the clusters labelled as Birds (EPS), mid-frequency band Orthopteran (EAS) and high-frequency band Orthopteran (HFC). It is interesting to observe that Orthopterans belonging to the Tettigoniidae family (HFC) had a distinct temporal pattern compared to other Orthopterans, being active only at dusk in the rainy season. EPS has a strong association with both Birds and Orthopteran clusters. Therefore, the diel pattern of EPS is different between seasons, following the acoustic activity of Birds in the dry season, but also influenced by Orthopteran activity in the rainy season.

4. Discussion

We use acoustic indices to identify sound patterns and describe the temporal patterns of biophony in the Caatinga, Brazil. We use the False Colour Spectrograms technique and a clustering analysis of eleven acoustic indices to discriminate the main sound sources present in Caatinga soundscape. We found that during the day, the acoustic space was filled by bird calls and wind, while at night insect (Orthopteran) activity was most prevalent. Biophony (both birds and insects) were more active during the rainy season. In the dry season, wind was predominant in our recordings. Finally, we determined the acoustic indices that best capture the sounds of birds (EPS), Orthopterans (EAS, EPS and HFC) and wind (BGN).

4.1. Acoustic indices

The use of multiple acoustic indices achieves good results in tracking the daily and seasonal activity patterns in the soundscape. Previous works in similar biomes using single acoustic indices were able to use

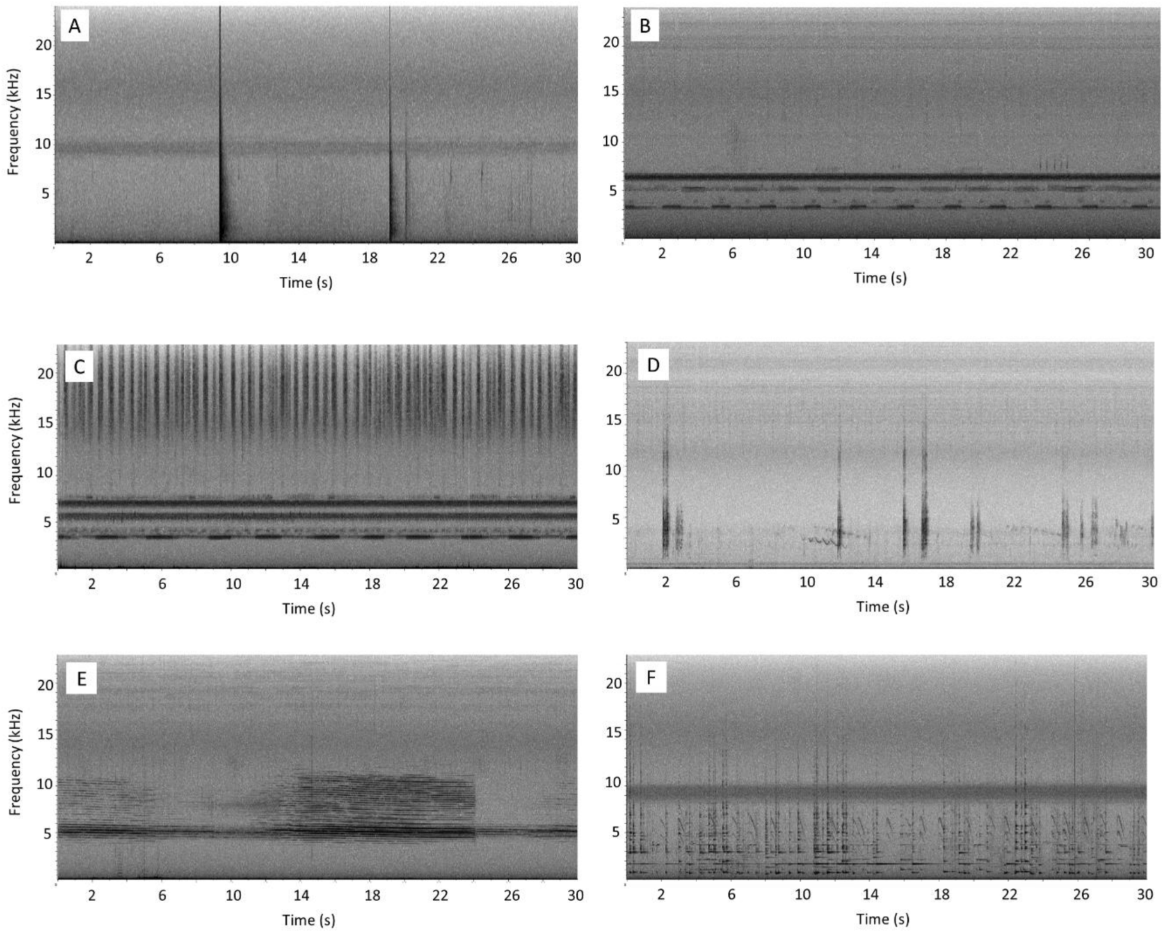

Fig. A2. Grey scale spectrograms of six distinct acoustic patterns: Gunshots (A), Orthoptera (B), Orthoptera with high frequency band stridulation (C), Birds (D), Cicada (E) and Bell (F).

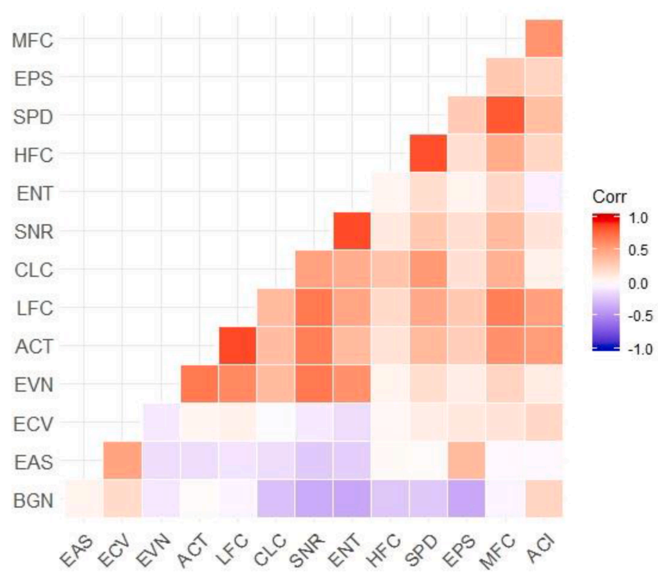

Fig. A3. Correlogram of fourteen Acoustic Indices, calculated for the entire dataset.

them to find variation in the soundscapes and acoustic activity between seasons, forest cover (Rankin and Axel, 2018), impact from open mining (Duarte et al., 2015), and distance from roads (focusing on birds, Machado et al., 2017). With a focus on multiple taxa, four acoustic indices (Acoustic Diversity, Evenness, Entropy, and Normalized Difference Soundscape) were correlated with insects' richness, but the relationship with bird acoustic activity wasn't clear (Ferreira et al., 2018). Our approach uses a combination of indices to produce more reliable characterization of acoustic signals, allowing us to differentiate sound sources within the environment more precisely. The use of multiple indices has been suggested to increase the reliability of these metrics in environmental monitoring (Eldridge et al., 2018; Towsey et al., 2014).

4.2. Visualization through FCS

The use of False Colour Spectrograms has some advantages based on the human capabilities of rapidly processing visual information. FCS provide a quick and reliable look at the data in its entirety and show daily acoustic patterns, also enabling the identification of the main factors responsible for the Caatinga acoustic signature and the variation between dry and rainy seasons.

Visible acoustic activity patterns were different between seasons, especially when comparing the two main sources of biophony - birds and insects. As expected, these animals showed higher acoustic activity in the rainy season, considering the reproductive period of these groups is linked to the food and water availability during the wet season (Cavalcanti et al., 2016; Wolda, 1988). The observed temporal segregation in acoustic activity between these two faunal groups suggest temporal partitioning of the soundscape but we can also speculate about acoustic crypsis of insects during birdś activity period, or acoustic avoidance (as coined by Curio, 1976). Acoustic avoidance may indicate a possible

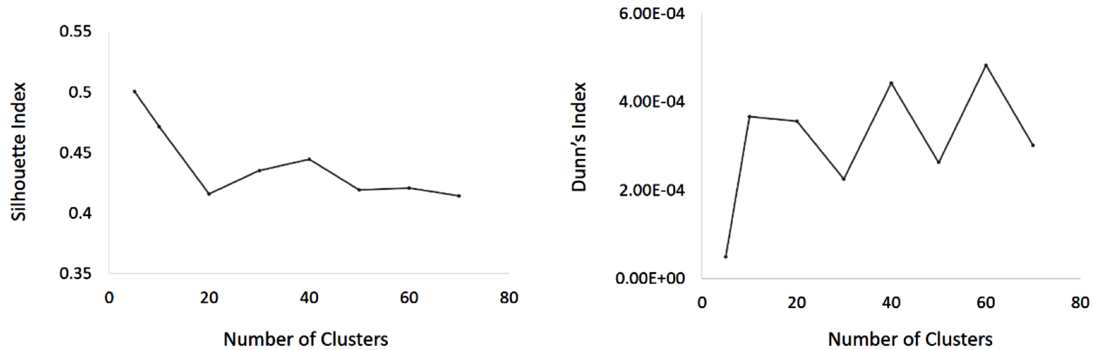

Fig. A4. Dunn's Index and Silhouette Index values for different number of clusters proposed to group acoustic data from Caatinga soundscapes, Northeastern Brazil.

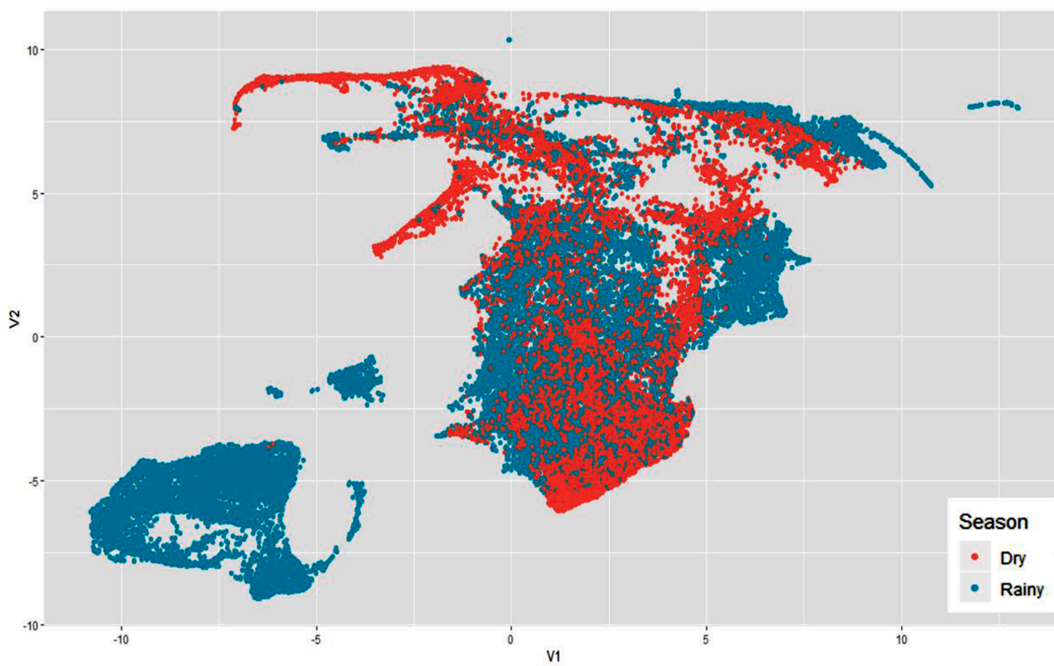

Fig. A5. Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) Clusters visualization. The colours represent files recorded in the dry and rainy seasons.

ecological prey-predator relationship and/or evolutionary processes of predation avoidance at play. Bird guilds that are fully or partially insectivorous account for 78% of all bird guilds in the region (Cavalcanti et al., 2016).

Consistent with our expectation, the wind was the main factor affecting data integrity and signal detectability. Wind is constant at the Serra do Feiticeiro, which also attracts windfarms companies to the region, where a large windmill complex is planned to be built in the next few years. The wind (and resulting overload and clipping in the recordings) was more pronounced in the Dry season when vegetation structure - leafless trees and absence of herbs - allows wind to directly hit the microphones. Strong winds might also act as a masking agent of acoustic communication and can negatively influence an animal's decisions to call during windy periods, which would in turn affect the dynamics of the soundscape. Removing all those files was an option, but we believe that it would not realistically depict the sampled soundscapes. In addition, we wanted to take on the challenge of investigating soundscape sampling in areas with open vegetation, as dry forests and savannas.

The potential to identify groups or even species using FCS was explored by Towsey et al. (2018) and Indraswari et al. (2020). Acoustic space partitioning among insect species is clearly observed in the 24-hour FCS of Caatinga which is a greater temporal scale that usually investigated (Schmidt and Balakrishnan, 2015). While vertical stratification of insects assemblages is often observed in areas with high canopy (Jain and Balakrishnan, 2011), our area is dominated by shrubs and small trees. Therefore, we suggest that the main strategy for acoustic masking avoidance among insects is frequency partitioning. In this sense, the FCS can allow studies of acoustic niche partitioning at a broader scale.

4.3. Clustering evaluation

We evaluated how effective was clustering of the summary indices by listening to a sample of each cluster, examining the False Colour Spectrograms, UMAP visualization and investigation of daily patterns. Additionally, we determined how the main environmental sound sources affected the indices, inferring which index best predicts the occupation of acoustic space by each sound source.

Entropy of Spectral Peaks (EPS) is a measurement of concentration of spectral maxima in the mid-band (Towsey, 2017), in our case from 0.5 to 11 kHz, a frequency band occupied by Birds, but with influence from insect stridulation as well. The index presented higher values in clusters classified as containing acoustic activity from Birds but was also present

Table A1
General description of sampling sites used in the study, Caatinga biome, Northeastern, Brazil. *Please note the region has an unpredictable rain regime and intermittent rivers that may flow once in every five years. To measure the nearest water body, we considered only the ones that have water most part of the year (in most cases, human-made reservoirs).

Site	Coordinates	Habitat	Elevation (m)	Nearest road (m)	Nearest water body (m) *
1	5°47′2.1″S 36°8′58.1″O	Rocky ground, vegetation composed mostly by shrubs and cactus.	224	600	2900
2	5°47′42.1″S 36° 8′3.0″O	Terrain inclination around 30°, SM installed in a hill, exposed to wind gusts. Vegetation include trees and shrubs.	268	650	2100
3	5°47′49.5″S 36°8′19.9″O	Close to a dry water course, Terrain inclination around 30°. Vegetation composed of trees, bromeliads, and cactus. Presence of large rocks, used as shelter by bats, small mammals and lizards.	257	600	2300
4	5°46′19.6″S 36°9′38.7″O	Open area, used as cotton plantation in the past, in regeneration. Vegetation dominated by shrubs, herbs and cactus.	223	320	1230
5	5°49′56.20″S 36°12′10.3″O	Human made reservoir. As one of the largest in the region, it contains water most part of the year. Poaching is common during the dry season in the area.	303	130	50
6	5°47′38.1″S 36° 8′17.6″O	Area dominated by herbs and sparse trees.	243	30	2200
7	5°47′48.4″S 36°14′25.6″O	SM positioned on top of a cave, used by bat colonies and other small mammal species and lizards. Vegetation is mostly composed by shrubs and small trees.	325	100	2200

in Orthopteran clusters. The 24 h variation observed in Fig. 8 corroborate this finding. In the dry season, when Orthopteran activity is low, the EPS values increase during the day, in a pattern that resembles the Birds Activity pattern. On the Rainy season, when Orthopterans are highly active, they appear as the main driver to both EPS and EAS daily variation.

Entropy of Average Spectrum (EAS) was highly correlated to Orthopteran acoustic activity. The index is a measure of the concentration of mean energy within the mid-band of the mean-energy spectrum. These insects were predominant within the mid-band, particularly at night, sometimes filling almost the entire mid-band frequency. Nonetheless, other clusters with high Orthopteran acoustic activity showed a different pattern, with high values of High Frequency Cover (HFC). This index is a measure of the energy concentration on high frequency bands (here, from 11 to 22 kHz), assumed to be indicating acoustic activity from Tettigoniidae. The Background Noise (BGN) was highly correlated with two of our cluster categories, Quiet and Wind.

Within the same taxa some similarities in the sound characteristics are expected, reflex of physiological constraints, such as sound production mechanisms. For example, most orthopterans will produce sound by stridulating (Montealegre-Z and Mason, 2005; Riede, 1998), resulting in similar soundscape patterns. On the other hand, acoustic communities are highly influenced by their species composition and other environmental factors that may lead to a change in the use of acoustic space.

We found different results in how sound sources affect acoustic indices in Caatinga than what has been observed in other studies with similar methodology (Phillips et al., 2018). Compared to Phillips et al. (2018), insect clusters also presented high values of EAS, but the authors did not find the HFC related to these animals. Besides the differences in insect assembly, this can also be a result of the sampling frequency used and the values applied to be considered as Low, Medium and High frequency in calculations. The HFC was more related to cicada activity. The bird clusters also presented differences, being more related to MFC, LFC and even ACI, while in our work, was more related to EPS.

4.4. Insects

The use of acoustic monitoring has the potential to become a key tool in the study of insects communities (Lehmann et al., 2014), even accelerating the discovery of new species. Besides that, there is a lack of consistent and reliable acoustic libraries for the Insect group. For example, there are at least ten thousand Orthoptera species that produce sound as a form of communication, but only 10% of those are included in digital acoustic libraries (Riede, 2017). The disproportionally large occupation of acoustic space by insects in our data called our attention to the importance of considering this group in ecoacoustics studies. Especially in semi-arid environments, insects represent an important food source for other animals and, although there is a consensus that they are good bioindicators (Brown, 1991), there is limited evidence to support this assumption.

In humid tropical environments, there is almost no variation between the insect abundance through the seasons, but a reduction can be observed in tropical environments with a severe dry season, as the Caatinga. This reduction can be caused by several factors as stress related to food decline, which can lead to adaptations that include dormancy, diapause or migration (Pinheiro et al., 2002).

The temporal vocalization patterns in Orthoptera are variable and dependent on environmental features - especially humidity and temperature. These patterns can be continuous through the day, have peaks on dusk, peaks on dawn, only during the night, only during the daylight (Fischer et al., 1996). In tropical regions, it is common to have a nocturnal pattern, as observed in our Caatinga data. Predator avoidance is probably one of the major factors leading to this acoustic pattern. Orthopteran species living in open vegetation (as the Caatinga) are easily visualized by birds, thus are more nocturnal, in comparison to species living in dense vegetation (Robinson and Hall, 2002). Changes in frequency features related to temperature changes through the night were also visible in our FCS, which is similar to previous research (Phillips et al., 2018). The temperature does not affect the frequency directly, but the wave sound speed in the medium (Endler et al., 2000).

One limitation in the use of passive acoustic monitoring to study insects relies on the fact that information degradation in these animals can occur at short distances. The interval between pulses in orthopterans

Table A2
Correlation Matrix of fourteen indices for the complete dataset. Absolute values of Pearson's Correlations > 0.75 are in bold. The eleven indices used after removal of the high correlated ones are presented in bold.

	BGN	SNR	ACT	EVN	HFC	MFC	LFC	ACI	ENT	EAS	EPS	ECV	CLS	SPD
BGN	1	0.420	0.254	0.205	0.342	0.313	0.313	0.120	0.370	0.071	0.523	0.137	0.386	0.398
SNR	0.420	1	0.792	0.733	0.154	0.431	0.810	0.181	0.895	0.220	0.186	0.116	0.558	0.314
ACT	0.254	0.792	1	0.828	0.172	0.449	0.866	0.140	0.618	0.177	0.200	0.121	0.456	0.330
EVN	0.205	0.733	0.828	1	0.099	0.256	0.747	0.077	0.634	0.125	0.091	0.119	0.389	0.188
HFC	0.342	0.154	0.172	0.099	1	0.520	0.196	0.319	0.107	0.040	0.136	0.029	0.423	0.878
MFC	0.313	0.431	0.449	0.256	0.520	1	0.526	0.398	0.375	0.017	0.248	0.043	0.611	0.837
LFC	0.313	0.810	0.866	0.747	0.196	0.526	1	0.175	0.708	0.153	0.239	0.100	0.496	0.388
ACI	0.120	0.181	0.140	0.077	0.319	0.398	0.175	1	0.173	0.044	0.041	0.050	0.231	0.365
ENT	0.370	0.895	0.618	0.634	0.107	0.375	0.708	0.173	1	0.202	0.131	0.113	0.498	0.256
EAS	0.071	0.220	0.177	0.125	0.040	0.017	0.153	0.044	0.202	1	0.411	0.524	0.130	0.033
EPS	0.523	0.186	0.200	0.091	0.136	0.248	0.239	0.041	0.131	0.411	1	0.095	0.247	0.261
ECV	0.137	0.116	0.121	0.119	0.029	0.043	0.100	0.050	0.113	0.524	0.095	1	0.035	0.045
CLS	0.386	0.558	0.456	0.389	0.423	0.611	0.496	0.231	0.498	0.130	0.247	0.035	1	0.639
SPD	0.398	0.314	0.330	0.188	0.878	0.837	0.388	0.365	0.256	0.033	0.261	0.045	0.639	1

Table A3
Statistical comparison between the proportional numbers of files assigned to each cluster label in the two seasons. Df = 1 for all cases.

Label	Files assigned		X^2	p-value
	Dry	Rainy		
Birds	0	637	533.69	≪0.001
Cicadas	204	5	232.74	≪0.001
Orthopteran	1793	6155	2509.2	≪0.001
Quiet	3691	2301	894.13	≪0.001
Wind	4545	3358	753.38	≪0.001
Subtotal	10,233	12,456		
Birds + Orthopteran	246	2246	1200.6	≪0.001
Birds + Wind	1749	1434	334.37	≪0.001
Birds + Quiet	317	455	0.004	0.95
Orthopteran + Cicadas	225	770	147.02	≪0.001
Orthopteran + Quiet	214	513	41.08	≪0.001
Orthopteran + Wind	97	1970	1308.8	≪0.001
Birds + Rain	66	206	31.01	≪0.001
Wind + Rain	0	831	608.64	≪0.001
Subtotal	5828	8425		
Birds + Orthopteran + Wind	292	2043	299.63	≪0.001
Inconsistent	856	1694	299.63	≪0.001
Subtotal	1148	3737		

calls is an important information which could be lost in distances as short as 2 m, once the echoes derived from the signals fill the spaces between them (Simmons, 1988). When we explore the greyscale spectrograms of our data, we observe that only part of the orthopteran signals presents resolution enough to make posterior comparisons with databases to identify species.

4.5. General conclusions about the use of passive acoustic monitoring in SDTF

The development of the acoustic ecology field with improved processing and analyses of time series can provide much information about the environment to managers, ecologists and conservationists (Burivalova et al., 2019; Almo Farina and Gage, 2018). Here, we provided baseline information that can be used in the future to inform land managers about changes caused by the construction of a windfarm complex in the area. Besides impacts from the construction, such as habitat displacement (Dohm et al., 2019) and collision (Drake et al., 2015), previous studies suggest that windfarms can cause acoustic impact on animals in the area (Rabin et al., 2006; Zwart et al., 2016).

Our main challenges working with acoustic data in a dry forest was the constant presence of wind, particularly in the dry season, when vegetation loses foliage. The strong presence of insects in our recordings, compared with the relatively low abundance of birds, brings our attention to the importance of insects in the Caatinga soundscape, a group that still receive less of a focus in ecoacoustics research than other animal groups (Aide et al., 2017). Some acoustic indices are dependent on the frequency band selected for inclusion in the calculations (i.e., the frequency range is adjustable) which can bias the interpretation of the soundscape. We highlight the importance of considering insects and wind in both experimental design and analyses. Despite these challenges, our approach was able to track seasonal changes and patterns of animal activity, reflected in the use of acoustic space.

This paper contributes to a better understanding of the soundscape dynamic in a highly seasonal tropical environment. Soundscape ecology and its translation into acoustic indices to study ecological processes in tropical environments is still very incipient. Seasonally dry tropical forests, such as Caatinga, are globally threatened and receive less funding for conservation initiatives when compared to other tropical environments (Dirzo et al., 2011; Santos et al., 2011), which makes it even more important to explore affordable and efficient methods to study biodiversity in these regions.

CRediT authorship contribution statement

E. G. Oliveira: Conceptualization, Formal analysis, Methodology, Project administration, Visualization, Writing - original draft, Writing - review & editing. **M. C. Ribeiro:** Funding acquisition, Supervision, Writing - review & editing. **P. Roe:** Resources, Software, Supervision, Writing - review & editing. **R. S. Sousa-Lima:** Conceptualizaton, Methodology, Resources, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices

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