Ecological Indicators 121 (2021) 107050

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

What does Atlantic Forest soundscapes can tell us about landscape?

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ARTICLE INFO

Keywords:
Acoustic indices
Scale of effect
Soundscape ecology
Landscape ecology

ABSTRACT

The ecoacoustics approach for environmental recordings analysis is used to understand and identify big ecological patterns related to different sound sources, like animals, humans and the environment itself. Sounds can vary according to several features that can be on its surroundings or far away, therefore they are very much reliant on scale. Because humans are changing the environment so much and we cannot account for all those changes in the same speed as they happen, we need fast evaluation tools, such as remote sensing and acoustic monitoring (considered the equivalent of spatial remote sensing for sounds). Considering that the scale of effect was never measured for soundscapes before, we aimed to see in what scale different acoustic indices were responsive. Also, we tested how acoustic indices are influenced by natural vegetation cover. We recorded environmental sounds in Atlantic Forest fragments during three months on the rainy season. Then we calculated different acoustic indices and the percentage of natural vegetation cover in different scales. Our results corroborated our initial hypotheses: different indices respond to different scales and their medians varied according to the amount of vegetation cover on the surroundings. More studies are needed with less fragmented areas, to test indices behaviour in a continuum, but we consider this work an important starting point to understand acoustic indices behaviour in tropical areas, especially in such degraded and threatened area as Atlantic Forest.

1. Introduction

Passive Acoustic Monitoring (PAM) is a tool being used for approximately 30 years now as a biodiversity monitoring tool, with a major increase in publications in the last decade (Sugai et al., 2019). PAM is a non-invasive method that uses autonomous recording units (ARUs) to survey multiple species (Acevedo and Villanueva-Rivera, 2006; Gasc et al., 2015) allowing researchers to monitor several areas at the same time (Deichmann et al., 2017). Besides large spatial coverage, ARUs also can stay in the field for long time periods, and it can be cheaper than traditional methods, such as point counts and transects (Obrist et al., 2015). Moreover, it can be a good repository of acoustic information on habitat biodiversity along the time as recordings can be used as a comparison between different areas and at different time periods (Aide et al., 2013; Deichmann et al., 2018; Sugai and Llusia, 2019).

Data collected using PAM can also provide good insights into ecosystem health and habitat quality (Blumstein et al., 2011; Deichmann et al., 2018). Recordings can provide reliable information on the community (ecoacoustics approach) as well as on focal species (*e.g.*: bioacoustics approach) (Deichmann et al., 2017). The ecoacoustics approach usually do not rely on species identification but instead on the heterogeneity of the acoustic space (Sueur et al., 2008; Gasc et al., 2015; Obrist et al., 2015) among other features. Ecoacoustics is the discipline that allow researchers to identify patterns on recordings (Farina, 2014) like rainfall (Bedoya et al. 2017) daily soundscape patterns (Gage et al., 2017), and acoustic indices patterns (Fuller et al., 2015). Moreover, these patterns can later be correlated with environmental variation acquiring information on possible biodiversity changes (Bedoya et al. 2017). It is expected that acoustic heterogeneity will be positively correlated with biodiversity levels (Sueur et al., 2008; Obrist et al., 2015).

Biodiversity measurements can be challenging as there are several dimensions to be accounted for and natural processes are very complex, so it is hard to simplify this in one or two numbers. To account for this problem, researchers developed ecological/biodiversity indices, which are mathematical formulas that aim to quantify biodiversity worldwide

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https://doi.org/10.1016/j.ecolind.2020.107050
Received 21 April 2020; Received in revised form 7 September 2020; Accepted 6 October 2020
Available online 16 October 2020

(Sueur et al., 2012). Those indices were developed to account for biodiversity richness, abundance and several other measures that are known to be important when studying natural phenomena (Pavoine and Bonsall, 2011). Similarly, in the recent years these indices were adapted to sound data giving rise to what is called acoustic indices (Sueur et al., 2012, 2014). Some studies have tested how acoustic indices behave in different environment (Depraetere et al., 2012; Machado, Aguiar and Jones, 2017; Ferreira et al., 2018; Jorge et al., 2018), but only a few tested the relation of it with landscape composition, configuration and vegetation structure (Bormpoudakis, Sueur and Pantis, 2013; Rodriguez et al., 2014; Fuller et al., 2015; Mullet et al., 2016).

It is already known that sounds vary according to several environmental features, such as, time of day, seasons (Gage & Axel, 2014; Mullet et al., 2017), terrain features and climatic variables (Farina, 2014), like for example rainfall (Sánchez-Giraldo et al., 2020). In addition, they are also influenced by land use and cover since it interferes directly on sound propagation (Morton, 1975). In natural environments, local fauna play an important role, as they are closely related to the ecosystem and its functions (Tucker et al, 2014) and are an important sound source. On the other hand, in urban environments, noise is a real problem connected to some of the same features as natural environments (now modified) and other characteristics, mainly the lifestyle adopted in cities. Urban areas can be an example of a modified landscape impacting on biodiversity. Just as biodiversity, the acoustic community (Farina and James, 2016) is not static, changing over time and space (Lellouch et al, 2014). As we live in a changing world, with more natural environments being converted to agricultural fields, cattle grazing pasture and cities every day, it is of extreme importance to account for biodiversity losses, keeping track of what is being lost, what and how we can still preserve what is left.

Sound is very much dependent on scale as sound attenuates over distance and with obstacles. We have now several acoustic indices developed, and they either propose to account for different characteristics of the acoustic space or to measure different sound features (see Tables 2, 3, 4 and 5 for a complete description of the indices used). Because different indices are expected to address different sound characteristics, choosing the appropriate index is very important. Moreover, as we are still understanding how to take advantage of all indices and possible combinations of them, evaluating the scale of effect (*i.e.*: the significant distance or spatial dimension affecting a sampling unit) is very important. The insights provided can assist to design and assess conservation and restoration actions.

Table 1
Classes created with the natural land uses percentage and a graphic demonstration of the natural vegetation cover found in each one.

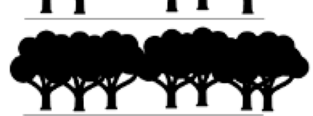
Class	Natural Land Use Range	
C1	0–20%	
C2	21–40%	
C3	41–60%	
C4	61–80%	
C5	81–100%	

Table 2
Acoustic indices calculated based on the waveform converted into decibels.

Indices	Description (from Towsey, 2018)
Background Noise (**BGN**)	Background noise estimate for each minute recording.
Signal to Noise Ratio (**SNR**)	The difference between the maximum decibel value in the decibel envelope and the decibel value of BGN.
Activity (**ACT**)	The fraction of values in the noise-reduced decibel envelope that exceeds the threshold (default = 3 dB).
Events Per Second (**EVN**)	A measure of the number of acoustic events per second averaged over the same noise-reduced one-minute segment. The acoustic event is when the decibel envelope crosses a threshold (default = 3 dB).

Table 3
Acoustic indices derived from the noise reduced decibel spectrogram. Compare acoustic activity in three frequency bands.

Indices	Description (from Towsey, 2018)
Low-frequency Cover (**LFC**)	The fraction of noise-reduced spectrogram cells that exceed 3 dB in the low-frequency band (1–1000 Hz). The technophony is expected to be more present in this band.
Mid-frequency Cover (**MFC**)	The fraction of noise-reduced spectrogram cells that exceed 3 dB in the mid-frequency band (1000–8000 Hz). Most bird's vocalisations are expected to be in this band.
High-frequency Cover (**HFC**)	The fraction of noise-reduced spectrogram cells that exceed 3 dB in the high-frequency band (8000–24000 Hz).

Table 4
Acoustic indices that describe different entropy measures of the distribution of acoustic energy within a recording. Entropy values give a measure of the flatness of the distribution. The following values were subtracted from 1.0 to have a measure of concentration and not dispersion.

Indices	Description (from Towsey, 2018)
Temporal Entropy (**ENT**)	The entropy of the energy (squared amplitude) values of the signal waveform. N = all values in the signal envelope.
Entropy of the Spectral Peaks (**EPS**)	Measure concentration of spectral maxima in the mid-band. N = number of frequency bins in the mid-band.
Entropy of the Average Spectrum (**EAS**)	Measure the concentration of mean energy within the mid-band of the mean-energy spectrum.
Entropy of the Spectrum of Coefficients of Variation (**ECV**)	Like **EAS** but instead the mid-band spectrum is derived from the variance divided by the mean of the energy values in each frequency bin. **ECV** = 1-H_c, where H_c is the entropy of the distribution of the mid-band spectrum composed of coefficients of variation

In this study, we tested how sounds, measured through acoustic indices, vary between different habitat (forest, streams within forest and open matrix), natural vegetation percentage and scale. We predicted that more forested areas would have more influence of biophonic sounds while more open areas would have more influence of anthropogenic sounds. We hypothesized that different indices would respond to different distances, as a result of the sound feature measured. This study innovates on landscape classes determined, which can be useful when classifying heterogeneous environments. Aggregating classes of land cover and use that are more/less natural regarding the wildlife use can be useful to summarise and aid on patterns comprehension. Also, testing the scale of effect of different acoustic indices in relation to their surrounding landscape is a novelty, especially in tropical environment where acoustic indices are still being studied and its unfolding are yet to be discovered.

Table 5
Acoustic indices that aim to measure species richness acoustically, *i.e.* Ecological indices.

Indices	Description (from Towsey, 2018)
Acoustic Complexity Index (**ACI**) (Pieretti, Farina and Morri, 2011)	It is the average of the mid-band ACI values. Not useful for recordings shorter than 20 s.
Cluster Count (**CLS**)	The number of distinct spectral clusters in the mid-frequency band. Is an attempt to measure the degree of internal acoustic structure, or spectral diversity, within the mid-band where birds' vocalizations predominate. It is expected that more bird species will generate greater vocal diversity which will increase spectral cluster count.
Spectral Peak Density (**SPD**)	A measure of the number of cells in the mid-frequency band spectrogram that are identified as being local maxima.
Normalized Difference Soundscape Index (**NDSI**) (Gage and Axel, 2014)	Calculates the ratio between biophony and technophony in the spectrogram. The NDSI is known to measure habitat ecological health (Kasten et al., 2012).

2. Materials and methods

2.1. Study area

The study was conducted at the Cantareira-Mantiqueira region in São Paulo State - Brazil (Fig. 1). The area is very heterogeneous in terms of both land cover and use. It is possible to identify natural vegetation as well as cities, eucalyptus, yield plantations and pasture areas. The natural vegetation consists in the remaining of Atlantic Forest, the most threaten biome in Brazil. In 2009 there was 12% left of natural vegetation cover in the area (Ribeiro et al., 2009), which is located in the most populated area of the country (Fundação SOS Mata Atlântica, 2016). This biome is considered a biodiversity hotspot since it has suffered from habitat loss and has higher rates of endemic species (Myers et al., 2000). As for the agricultural use of the area, it is mainly dominated by corn, soy, and coffee besides *Eucaliptus* monoculture (São Paulo State Agricultural Extension Service, 2018).

2.2. Data collection

The sound records were collected in an Atlantic Forest area in São Paulo State (Fig. 1) as aforementioned, during the rainy season (from October 2016 until January 2017). Despite the rainy days, which were excluded from the analysis when too noisy, we believe this is the best period of the year to capture the most active soniferous species because it coincides with the reproductive period of most species. During reproductive season the animal community gets especially active exhibiting several different behaviours and therefore being the best period of the year for acoustic monitoring (Duarte et al., 2015). Sound data was acquired using 22 Song Meters 3 (Wildlife Acoustics) at 48 kHz sampling rate, 16 bits recordings. The sounds were recorded in *.wav* format file in 22 data collection points spatially distributed (Fig. 1). Those points were placed in three different habitat types: Open (mainly agricultural matrix and pasture areas), Forest (Atlantic Forest remnants) and Stream (forest fragments near water bodies) (Fig. 2). During the first month, Forest habitat were sampled (October to November), then we sampled Open habitat (November to December) and, lastly, we sampled Stream habitat (December to January). The sampling effort was spread across months due to logistic constraints and equipment availability. Because all the data was collected in the same period of the year (mid spring till mid-summer) and being a tropical country where variation of temperature within seasons is not considered significant, the month

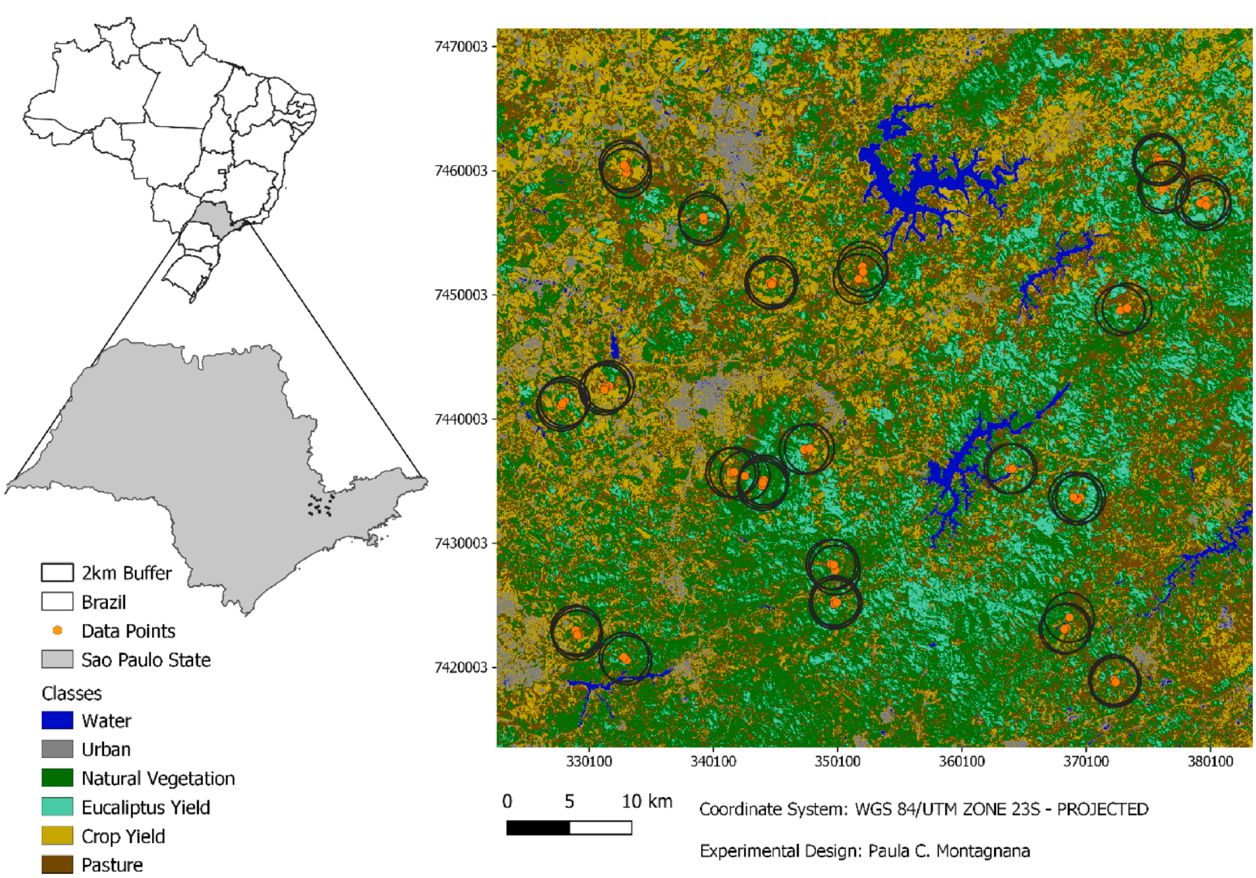


Fig. 1. Study area showing São Paulo State location in Brazil and Data Points in the state. Data collection points are also shown in zoom, with the larger buffer tested (2 km) and the land use and land cover classes from the image classification.

Fig. 2. Representation of the environments recorded, being (1) pasture areas; (2) forest areas; (3) stream areas.

factor was not considered in the analysis. Those areas were chosen using remote sensing techniques and then the best site to place the recordings were slightly adapted when in the field.

Because not all areas and recorders had the same subsampling (especially due to recorders failure or setbacks in the field) we chose to subsample the days for analysis. In this way, we analysed 15 out of 30 days of data collection whenever it was possible. This was made to minimize differences in recordings (i.e. we tried to pick up always the same days between areas). Even so, some recorders did not have 15 complete days of recordings and for these ones we picked up only complete days. Our data collection protocol is in Supplementary Material. Using this schedule, we had approximately 7 h recording per day, per recording times 15 days, i.e. 102 h per recorder, totalling 2,244 h recordings.

To identify land use cover of the study area we used Landsat 8 OLI/TIRS Collection 1 – Level 2 imagery (Path: 219, Row: 76, Image Date: 7th of July 2016) which comes pre-processed with final surface reflectance values, corrected for most atmospheric disturbances, and with a spatial resolution of 30x30 meters (U.S. Geological Survey). The Landsat 8 data was combined with the following remote sensing methods so land-use data could be incorporated in our study. To perform the remote sensing operations included the Semi-Automatic Classification Plug-in (SACP) (version 6.2.5) (Congedo, 2016) available for free use in the QGIS (version: 3.2.3 - Bonn) software interface (QGIS, 2020). A supervised classification using a Maximum Likelihood Algorithm and Landsat 8′s spectral bands (2 thru 7) was undertaken using manually selected regions of interest (ROIs) which served as the land use class training samples. The dominant land uses that are found in the study area include: native vegetation, urban, yield, eucalyptus plantations as well as pastures. After visually examining the histogram distributions and

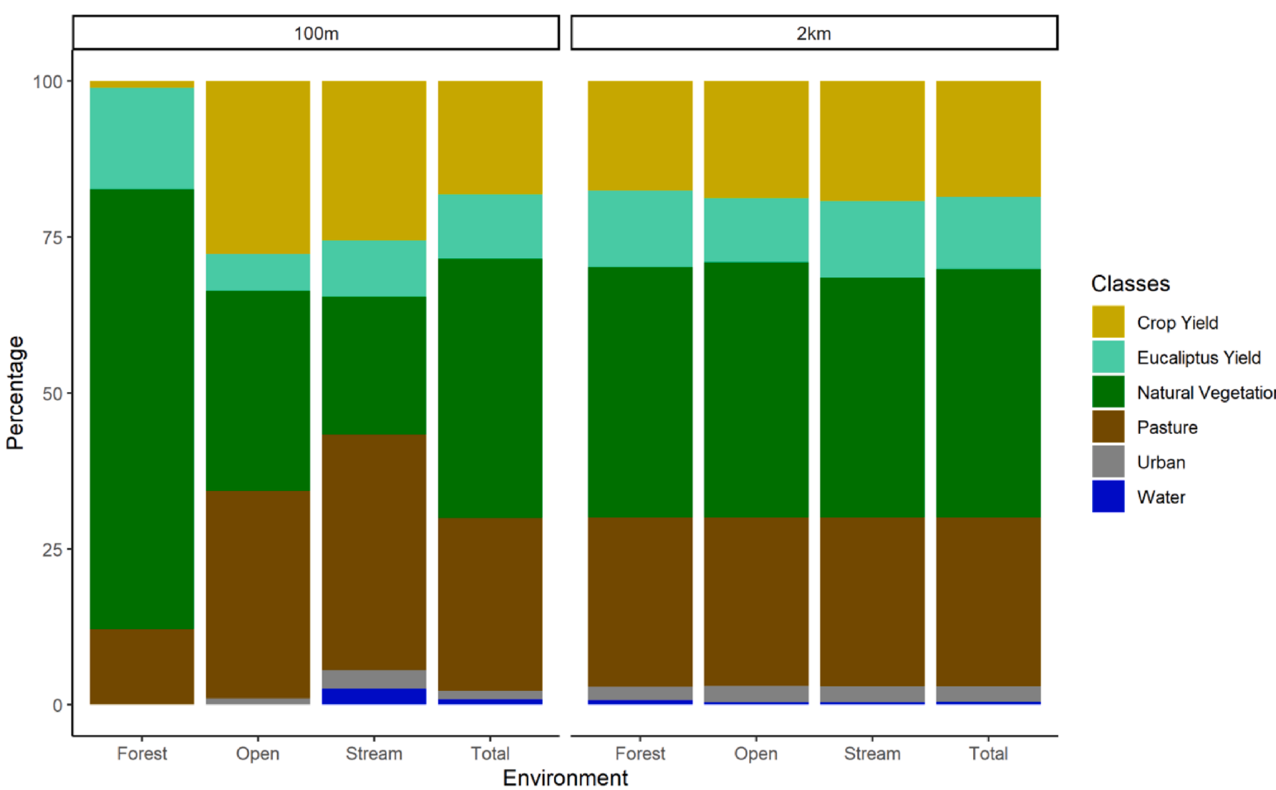


Fig. 3. Percentage of classes of land use and vegetation cover by environment in buffers of 100 m and 2 km.

analysing the separability statistics of the training ROIs' spectral signatures for each of the Landsat 8 spectral bands, the ROI samples were determined to be acceptable. Once the Maximum Likelihood Algorithm was run the classification results were validated using an accuracy assessment generated error matrix, with which the error matrix values were determined to be within an acceptable range.

We quantified the amount of native vegetation in different buffer sizes (from 100 m to 2 km) for each acoustic sampling unit. The different buffer sizes were determined to check the scale of effect for each index. The buffer sizes tested are represented in Fig. 4.

2.3. Environment and naturalness classes

For each habitat studied (Forest, Open and Stream) we identified different land uses and measured the percentage of natural vegetation (Fig. 3), for the bigger and smaller buffer sizes we draw (100 m and 2 km). In Forest habitat we had a higher percentage of natural vegetation class than in Open and Stream habitat ($F_{54,2} = 31.7$, $p < 0.001$) when considering the 100 m buffer. When we increase buffer size for 2 km, the difference between environments did not change ($F_{54,2} = 0.143$, $p = 0.867$) (Fig. 3). The other buffers were not tested here because the differences between acoustic indices and natural vegetation classes were not meaningful for them. For classes results, different indices responded differently to the scales tested, so they are presented grouped by the scale they were responsive to.

We then defined classes according to the percentage of natural vegetation plus water on each buffer – these were the land uses we considered as natural. The classes created are represented in table 1.

To measure the scale of effect we determine five different buffer sizes around the data collection points. The sizes chosen were 100 m, 200 m, 500 m, 1 km, and 2 km (Fig. 4). As we had no literature to base the sizes chosen, the smaller one was draw accordingly to pixel size. We had 30 m pixel size, so 50 m buffer was not good in terms of spatial resolution, therefore we chose 100 m to start with. Then we increased buffer size until the one we thought it would be good enough considering attenuation effects, which was 2 km. The sizes were arbitrarily chosen based sound propagation theory in different environments (Farina, 2014).

2.4. Sound analysis

We subsampled the full dataset into 15 days and analysed the recordings in the three different areas mentioned in the sound collection section (Open, Forest and Stream). The Stream points were chosen because this sample was initially developed for amphibians, which can be found usually near water and they were forested areas near water bodies. We then took advantage from the dataset to analyse using a different approach. We used *AnalysisPrograms.exe* (Towsey et al, 2018) to analyse our data, developed by the *Ecoacoustics Research Group* at the *Queensland University of Technology*. The software takes long recordings, splits them into 60 seconds and calculate several summary and spectral indices from the recordings (as described in section 3.4.1). The R scripts used to analyse the recordings can be found in the Supplementary Material.

We inspected the false colour spectrogram to check if geophony (like rain or wind) were not interfering too much in the recordings, as we collected data near water and during the rainy season, both being potential masking sources for biophony. This is an important point as wind and rain are important part of the soundscape, but at the same time they usually happen occupying all frequencies, masking other important sounds. When heavy rain or wind events are found, it is usual to remove

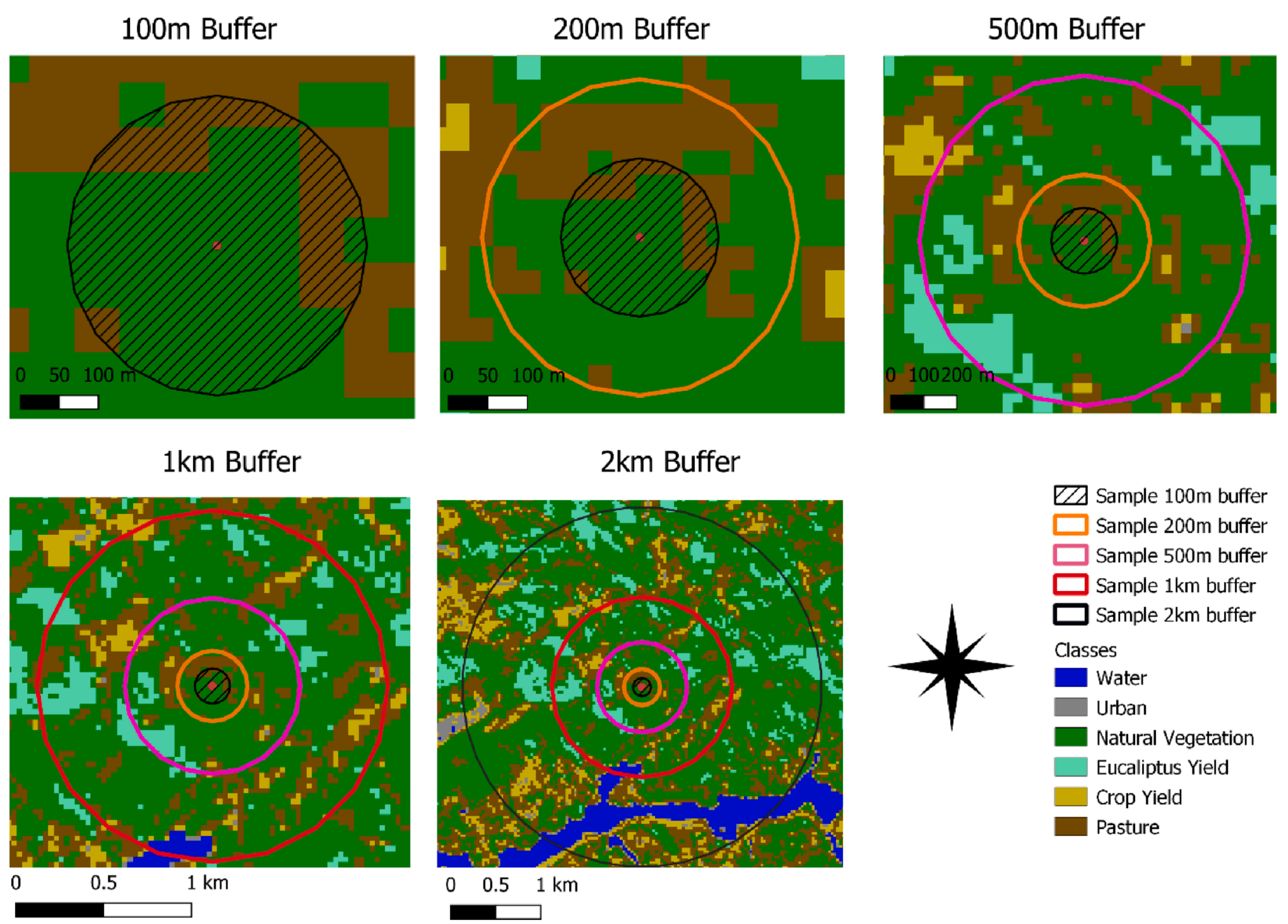


Fig. 4. Different buffers tested and corresponding land use and cover.

them from the dataset, because they can interfere in the analysis and bias them towards geophonic sounds, and usually there are other important sounds being masked so the results may not always show other underlying processes happening.

2.4.1. Acoustic indices

The software calculates the most used and acknowledged acoustic indices (see tables 2, 3, 4 and 5 for detailed description of calculated indices). Those indices can be divided into subgroups according to their calculation methods and they cover the most important acoustic features that need to be accounted for when analysing sound data using ecoacoustics - for a complete description of the methodology used by the software, see Towsey, 2018. The minutes with high levels of rainfall were completely excluded from the recordings therefore, we assume rain is not one the of the main sources of sound influencing the indices.

2.5. Statistical analysis

As acoustic indices are calculated in the most varied ways, we started the analysis by scaling the data in order to be able to compare the results. After performing normality and homogeneity tests, we found out the data was not normally distributed, so we did non-parametric tests for the whole dataset. The chosen statistical test was Kruskall Wallis, because for a Generalised Linear Model the pseudo R^2 was very low (0.2). We also tested the data for spatial autocorrelation through Moran's I (max. value observed was 0.37, $p < 0.05$ – low spatial autocorrelation) to exclude the hypothesis that spatial distribution of the points was the explanation for similarity between them. We did not test nor exclude indices that were highly correlated because we wanted to investigate the results of individual indices in face of the scale of effect and different landscape classes. As we are identifying patterns in a tropical area which there has much yet to be explored, we calculated and analysed all available indices, testing which ones would be related to landscape at what scale. Moreover, each index was tested independently so there was no redundancy of explanation by not removing the highly correlated ones.

3. Results

There was significant difference between the three environments analysed (Forest, Open and Stream) and some the acoustic indices tested. Only the 100 m and 2 km (smaller and bigger sizes) buffer sizes were meaningful. We found that Activity, Events per Second and High Frequency Cover were common to both environment analysis and 100 m buffer, while different indices that did not have significant results before respond to the 2 km buffer (Signal to Noise Ratio, Mid Frequency Cover, Low Frequency Cover, Temporal Entropy, Entropy of Variance Spectrum and Cluster Count). The complete results for all indexes, environment and buffer sizes tested can be found in Supplementary Material.

3.1. Acoustics and environment (Forest, Open, Stream)

Background noise Kruskal-wallis results did have a higher median in Stream habitat when compared to the Open habitat ($X^2 = 6.579$, DF = 2, $p < 0.05$) (Fig. 5). For Activity we found lower medians in Forest and Stream environments while Open habitat had a bigger range of values ($p < 0.001$) (Fig. 5) ($X^2 = 12.169$, DF = 2, $p < 0.005$), more like Stream values than Forest. Events Per Second had similar results with Activity ($X^2 = 11.674$, DF = 2, $p < 0.005$) (Fig. 5).

High-Frequency Cover varied the most in Forest areas, followed by Open areas, which do not differ statistically according to Kruskal-wallis results ($X^2 = 14.342$, DF = 2, $p < 0.005$). Stream areas showed less variability and lower medians with no statistical difference from Forest ($p < 0.001$) (Fig. 5). For entropy indices, Stream medians were statistically different from Open ($p < 0.05$) and Forest ($p < 0.05$). Kruskal-wallis results for Entropy of Spectral Peaks were $X^2 = 7.521$, DF = 2, $p < 0.05$ and for Entropy of the Average Spectrum were $X^2 = 14.208$, DF = 2, $p < 0.005$ (Fig. 5).

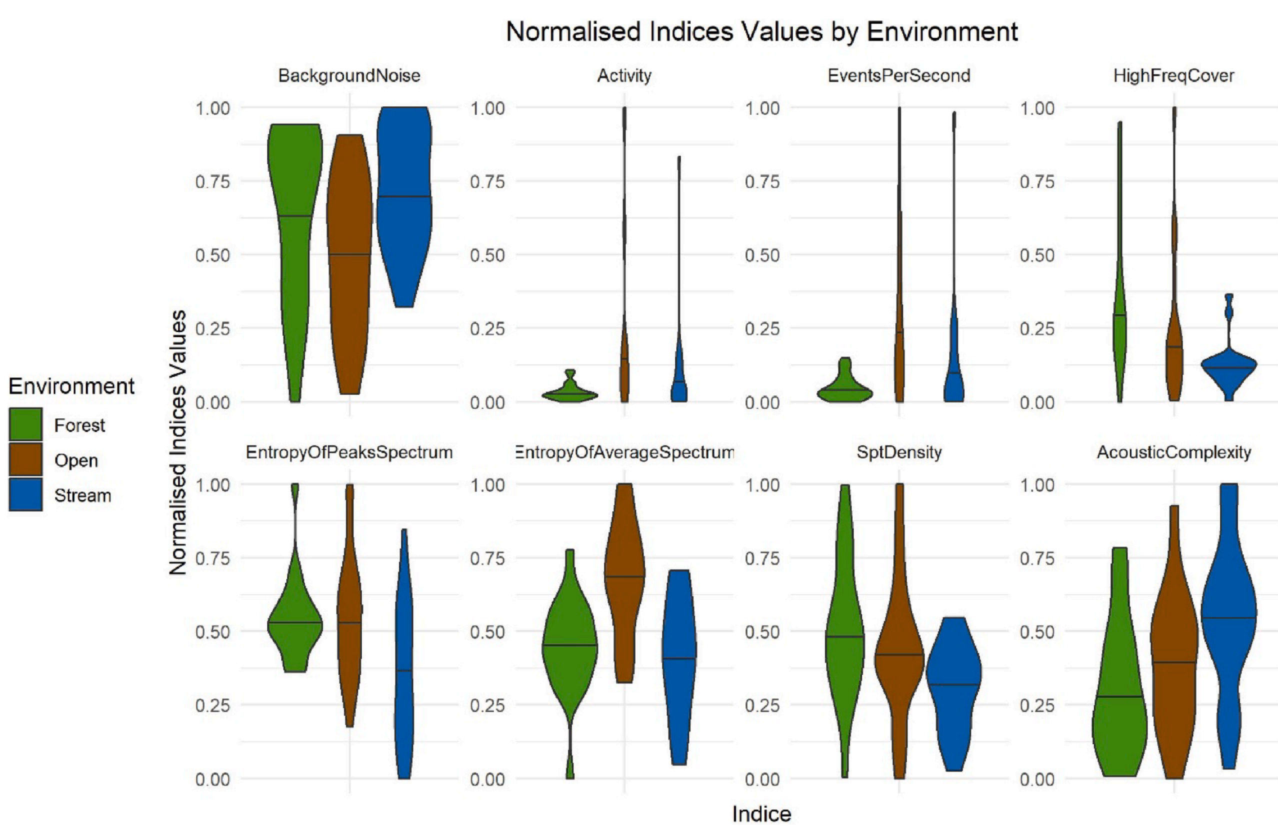


Fig. 5. Normalised indices values per environment.

Spectral Peak Density (SptDensity) had the highest median in Forest, followed by Open habitat. Lower values were found in Stream ($X^2 = 8.177$, DF = 2, $p < 0.05$) (Fig. 5) with Forest and Stream differing statistically ($p < 0.05$). Acoustic Complexity Index had higher values in Stream, followed by Open habitat and lowest medians found in Forest ($X^2 = 8.546$, DF = 2, $p < 0.05$) (Fig. 5) differing statistically from Stream ($p < 0.05$).

3.2. Acoustics and natural land cover

3.2.1. 100 Meters buffer size

Activity ($X^2 = 12.973$, DF = 4, $p < 0.05$) and Events Per Second ($X^2 = 12.299$, DF = 4, $p < 0.05$) results were similar across different land use classes. Classes 1 and 2 (lower percentage of native vegetation cover) had higher variation and higher medians, while class 3 had less variation as well as lower values. For both indices (Activity and Events Per Second), class 3 was statistically different from Classes 1 and 2 ($p < 0.05$) (Fig. 6).

High-Frequency Cover presented more variation and higher medians in classes 2, 4 and 5 and lower medians in classes 1 and 3. Class 1 was statistically different from classes 2, 4 and 5 ($X^2 = 14.756$, DF = 4, $p < 0.005$) (Fig. 6) meaning that less natural vegetated areas presented lower levels of high frequency cover.

Acoustic Complexity Index had higher range of values in class 1, and lower values and variance in class 3 ($X^2 = 12.585$, DF = 4, $p < 0.05$). The median values differed statistically between classes 1 and 3 ($p < 0.05$) (Fig. 6).

3.2.2. 2 km buffer size

Signal to Noise Ratio was found to have more variation in less forested habitats (Fig. 7) with higher medians in habitat with less than 20% of vegetation cover ($X^2 = 12.297$, DF = 3, $p < 0.05$). Class 1 was statistically different from Class 2 ($p < 0.05$). Mid Frequency Cover results had higher values for class 1 which was statistically different from class 2 ($p < 0.05$) ($X^2 = 8.104$, DF = 3, $p < 0.05$). Low Frequency cover values had higher values in class 1, and small variation in values in classes 1 and 5 ($X^2 = 8.223$, DF = 3, $p < 0.05$) (Fig. 7). Entropy indices had higher values in class 1, with other medians being pretty much similar. For Temporal Entropy, class 1 was statistically different from class 2 ($p < 0.05$). The chi-square results for Temporal Entropy were ($X^2 = 10.204$, DF = 3, $p < 0.05$) and for Entropy of the Spectrum of Coefficients of Variation ($X^2 = 8.070$, DF = 3, $p < 0.05$) (Fig. 7). Cluster count had higher values in class 1, which was statistically different from class 2 ($p < 0.05$). We also found less variation in class 5 ($X^2 = 13.191$, DF = 3, $p < 0.005$) (Fig. 7).

4. Discussion

The classes here presented were used to group the areas with similar amount of natural land cover, because this would decrease the variability in this feature therefore being a good way to explain and represent our results. We know this means some information will be lost on the details of the spatial dimension, but, on the other hand, this gives us some important insight about acoustic indices and tropical modified environment, and the generalisation can be good for the development of further experimental design. Moreover, another study have used the same approach of classifying environment into categories in order to evaluate the differences in acoustics between them (Carruthers-Jones et al., 2019).

The non-natural classes designated in our study are mainly formed by *Eucaliptus* monoculture, pasture among other agricultural fields, being the area mostly rural and not urban or industrial dominated. In this way, most animals (especially the ones more vocally active, like birds and insects) use the agricultural matrix especially for feeding and generally do not interpret those areas as non-habitat. Moreover, because of fragmentation, highly mobile animals can use both forest and

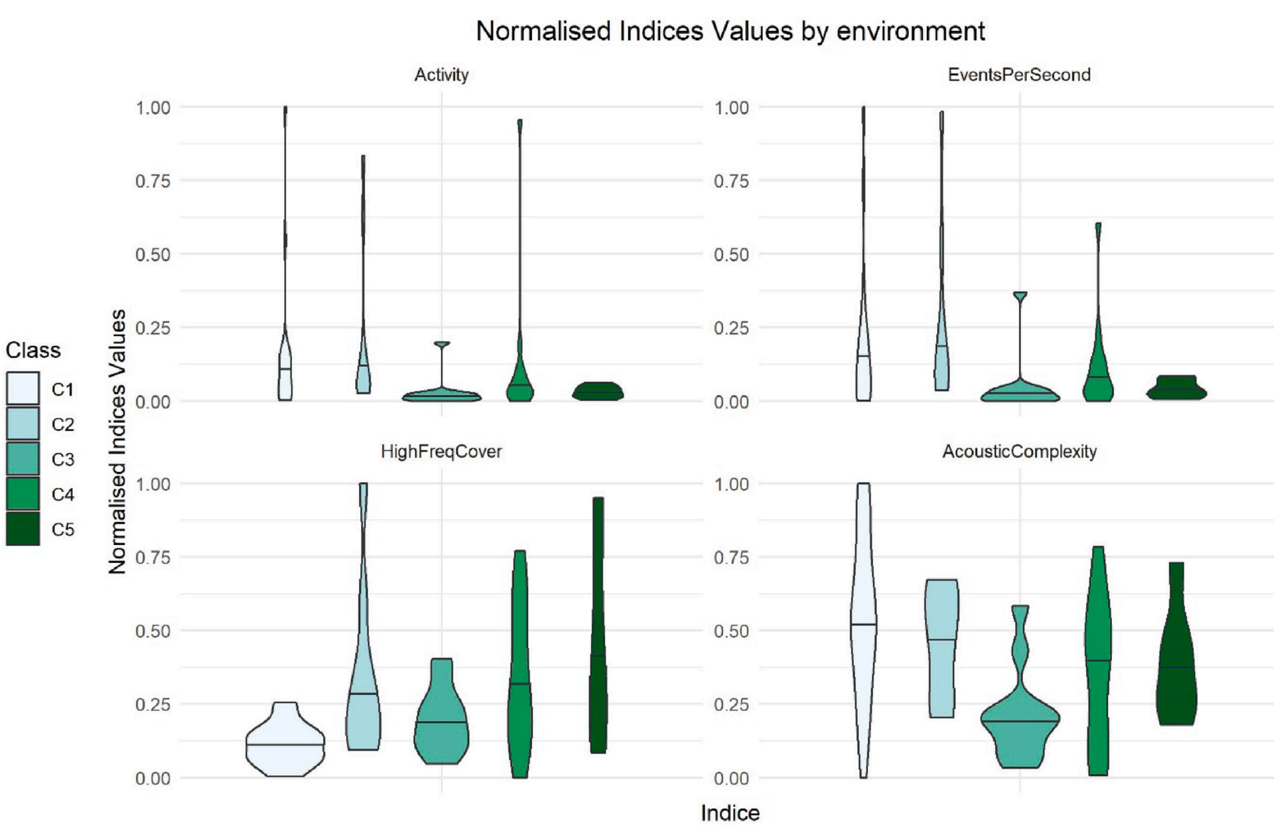


Fig. 6. Significant indices normalised values by classes for 100 m buffer size.

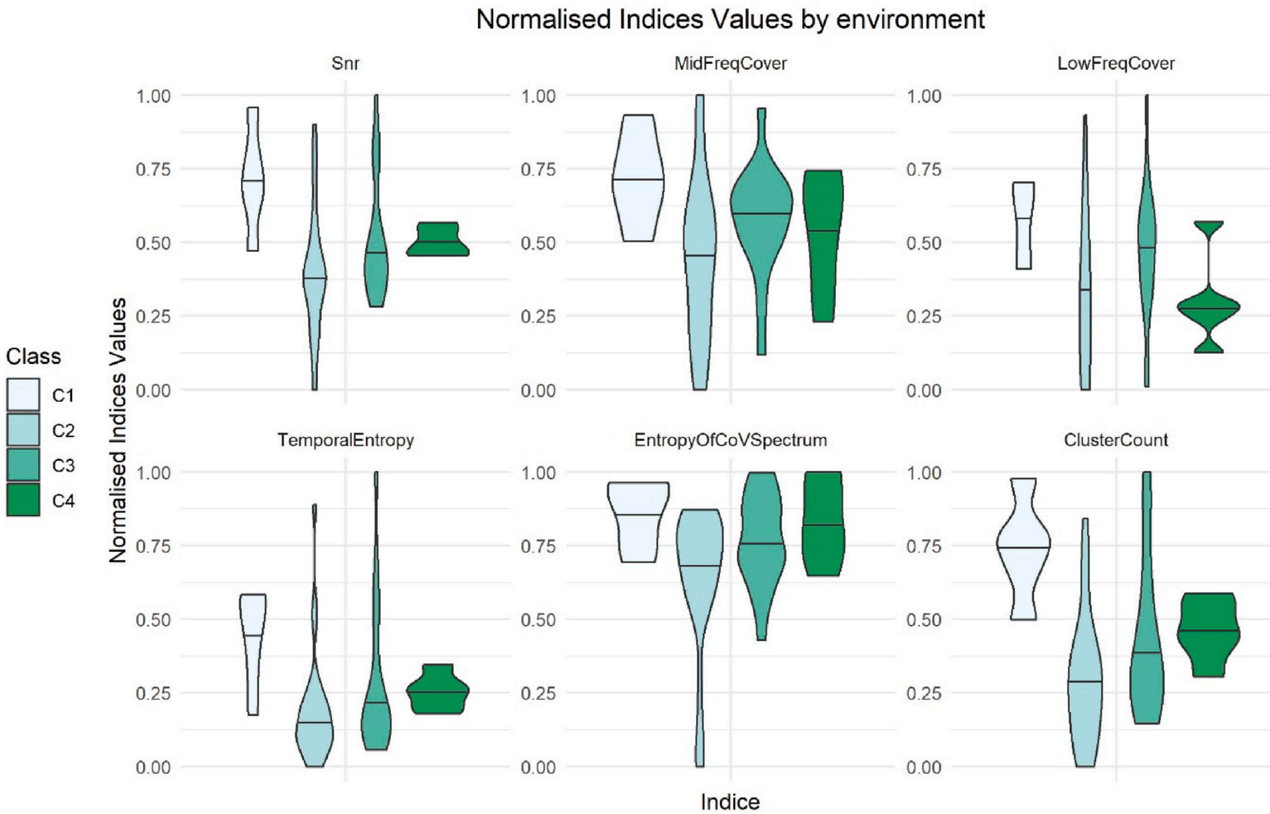


Fig. 7. Significant indices normalised values by classes for 2 Kilometres buffer size.

agricultural matrix depending on the roughness of the matrix. We did not quantify what types of monoculture in each patch, but the area is dominated by *Eucaliptus* and pasture in its majority and it also counts with some monoculture like corn, soy and coffee (São Paulo State Agricultural Extension Service, 2018). There is evidence that agricultural matrix combined with forest patches can sustain high levels of biodiversity, without accounting for functional attributes even though they represent an important process sustained by biodiversity (Magioli et al., 2016). The values for Normalized Difference Soundscape Index (NDSI) were not statistically significant among areas but all our values were above 1. High values of this index (around 1) indicate good habitat quality (Gage and Axel, 2014), corroborating that even though it is an area modified by human actions and highly fragmented, it is still used and occupied by wildlife.

The sampling scheme of the audio recordings have long periods of non-recording which is not ideal for ecoacoustics analysis. However, the "silent" minutes are around midday and late night, which are periods known to be quieter in terms of biodiversity. Besides, as aforementioned, the data was collected in 2016 and with the main objective of sampling frogs. In 2016 there were severe constraints on data storage and analysis, so the experimental design was developed attempting to maximize the efforts but at the same time limited by such logistic restrictions. The data was collected in the rainy season because it coincides with the reproductive period for most soniferous species at this region (Haddad and Sazima, 1992; Rodrigues et al., 2005). Although rainfall is one of the main sources of geophonic sounds (Sánchez-Giraldo et al., 2020) and this is important in terms of soundscapes dynamics, heavy rain can mask other sounds. Because of the possible masking effect, we decided to exclude rainy minutes.

Even though we did not test nor exclude the highly correlated indices, our results using different scales showed that the redundancy on indices was removed by the scale effect. This is evident as we had different indices responding to the different scales tested. Moreover, our results showed consistency among the scales: the same indices that had significant results for the environment analysis appeared in the 100 m scale buffer (*i.e.*: Activity, Events Per Second and High Frequency Cover), demonstrating that those indices are consistently more affected by their direct surroundings in this dataset. On the other hand, the results for 2 km buffer indicates indices that rely on a broader scale and therefore spatial context. So, as expected, we successfully demonstrated that different indices are responsive to different scales. This is very important given the fact little is known about soundscapes in natural tropical areas (Scarpelli et al., 2019). Also, these results can help to shape further research, in which depending on the focal group and the question, some indices can be more useful than others. We also believe these results are an important step for designing experiments. As for the scale of analysis, we found meaningful results for the smaller (100 m) and largest (2 km) sizes tested. We believe this is meaningful in terms of general recommendations, although we do not recommend the use of these exact sizes of the buffer. This is mainly because we did not test any value outside this limits and therefore more studies are still needed in order to define the exact scale of effect (as well pointed out by the reflection proposed by Jackson and Fahrig (2015).

Background Noise higher values in stream areas may be due to noise of running water nearby the recorder, which is one of the major interferences in communication for terrestrial environments (Brumm and Slabbekoorn, 2005). Background noise, also known as "keynote sounds", are directly influenced by geography, vegetation and animals living in an area (Dumyahn and Pijanowski, 2011). The detection of these keynotes sounds is important because it can decrease the efficiency of acoustic communication, by masking effect (Lugli and Fine, 2003; Brumm and Slabbekoorn, 2005). The masking effect happens when the animal cannot effectively send the signal because another source of sound (which may be another signal or just noise) happens at the same time in the same frequency band or with same/higher levels in terms of Decibels (Rabin and Greene, 2002). For analysis purposes, after this index is calculated, the value found for each recording is subtracted from the decibel envelope, so we assume that those interfering sounds will not affect in the forthcoming indices (Towsey, 2018).

Activity and Events per Second had similar patterns and similar values after the index was normalised. The bigger range of Activity and Events Per Second found were in Open habitats with 0 until 40% natural land cover (C1 and C2) which can be explained by sound attenuation, which is less prone to happen in areas with less obstacles (Tarrero et al, 2008).

Signal to Noise Ratio was higher in C1 than in other classes, meaning that louder sounds (in dB) happened in areas with less vegetation. It is expected that those areas are more susceptible to louder noise since they have fewer obstacles which could attenuate sound (Fricke, 1984), therefore louder sounds would be expected to travel further distances.

Low Frequency Cover had higher values in C1 and more variation in habitat C2 and C3. Lower frequencies are known to be occupied by anthropogenic sounds, which are supposed to be more present in human-dominated environments (Eldridge et al, 2016) and the opposite is also true, more naturally vegetated areas usually are less dominated by noise derived from human activity (Farina, 2014). The meaningful buffer size of 2 km for this index is expected because low frequency sounds usually can travel further distances without signal decaying (Padgham, 2004). Also, anthropogenic noise is generally louder (in dB) than most natural sounds (with some exceptions especially regarding geophony) therefore they can be detected within bigger distances.

Mid Frequency Cover had its higher values in C1 and a bigger range of values in C2, C3 (as Low Frequency Cover) and C4. Mid Frequency Cover is expected to measure decibels in the frequencies 1000–8000 Hz, which are usually occupied by biophony – mainly birds and some insects. The values found can be explained by the fact that this index measures the sound in dB and as aforementioned less forested areas are expected to have sound waves travelling further with less attenuation.

High Frequency Cover (HFC) was higher and more varied in Forest habitats and the medians were also higher in the areas with more proportion of natural land uses. We manually inspected the recordings and found out that the higher frequencies were usually occupied by bats (social calls, since we did not measure ultrasound) and insects (mainly cicadas). Bats are known to avoid noisier areas because this can decrease rates success on foraging (Schaub, Ostwald and Siemers, 2009) and they also tend to avoid more open areas because they can be more predated and those areas have usually less food resources and roosting sites (Estrada et al., 1993). The meaningful buffer size for HFC was 100 m as expected, since higher frequency waves' attenuation is distance-dependent (Cosens and Falls, 1984; Morton, 1975). Besides, higher frequencies suffer more from obstacles attenuation than lower frequency waves (Fricke, 1984).

Temporal Entropy had higher values in C1 habitats, and similar values for the remaining classes. This index presented very low variation for all habitats. Entropy is expected, in general, to have higher values in areas with high biodiversity (Sueur et al, 2008) which is the theoretical basis for the development of these indices. *AnalysisPrograms.exe* does a mathematical manipulation of the index value after it is calculated so it is a measure of temporal energy concentration – i.e. that higher values indicate more energy concentrated over frequencies bins (Towsey et al., 2014). Therefore, we would expect that C1 habitats would have more energy in lower frequency bands, since those habitats would be expected to have more influence anthropic changes and consequently, noise (Farina, 2014). At the same time, Entropy concentration giver the inverse measure of expected biodiversity because animals usually spread their signals across the frequency bins, being less agglomerated.

Entropy Peak Spectrum presented higher medians in forested and open areas. Entropy of the Average Spectrum was higher in Open areas, lower in Forest and Stream areas. For Entropy of the Spectrum of Coefficients of Variation, we found higher medians for Class 1, with other values being pretty much alike. This means that entropy indices did not present a consistency among them. For some, forested areas had energy more concentrated and for others, open areas had more concentration of energy, indicating that those indices need to be tested carefully, checking the actual recordings so the patterns found can be explained. We expected to find lower values in forested areas, because energy is supposed to be more evenly distributed in places with higher biodiversity levels. At the same time, we expected to find energy more aggregated in the Open habitat, as a result of the influence of technophony.

Spectral Peaks Density had the highest median in Forest environments similarly to Open habitat while lower values were found in Stream ones. This means that in Open and Forest habitat, dB values exceed the limit of 6 dB on the contrary of Stream ones. In this case, we could argue that the meaning for this index is different in both habitats. In Open habitat, as aforementioned we expect louder sounds to be detected within greater distances because there will be less obstacles to attenuate it and besides we expect more interference of anthropogenic sounds (Eldridge et al., 2016) which are usually by nature louder than other sources. In Forest habitat we expect that these values are a result of the biophony due to the fact this is the supposed to be the predominant sound source in these habitats. This is a good example of how the context matters in the use of acoustic indices for conservation and monitoring and how acoustic indices help identifying features and checking points, but some degree of manual inspection is still necessary.

Acoustic Complexity Index presented higher values in Stream environments and habitats with less natural cover. We found this index to be a good measure of geophony (rain) and insect signals. On the other hand, studies in a different part of Brazil found no significant correlation of this index with any group (Ferreira et al, 2018).

For Cluster Count we found higher medians in C1 and lower similar values in the remaining classes. This index is expected to indicate recordings with higher number of birds calling, because it measures the number of clusters in the mid-frequency bands, usually occupied by birds. We would expect that habitats with low levels of native vegetation would have fewer birds than habitats with higher proportion of native vegetation cover (Marsden, Whiffin and Galetti, 2001). At the same time, our non-natural classes are dominated by pasture and *Eucaliptus*, which can be used by wildlife for foraging, shelter and other behaviours.

5. Conclusion

This study is a good starting point to better understand how acoustic indices reflect tropical ecoacoustics dynamics. Moreover, it gives insights and knowledge on how landscape and soundscape are related, indicating how acoustic indices behave in different fragmented areas, as well as how direct landscape reflects in its values. We tested and found out at what scale different acoustic indices are affected, which is of extreme importance not only for the experimental design step but also for analysis and interpretation of results.

We believe there are other important variables (such as climatic, for example) that should be tested to check their relationship with sounds since they have an important role in both sound propagation and in animal's behaviour and ecology. We also recommend the test of landscape, patch and class metrics (such as connectivity, patch size and edge/core area relationship) since not only the proportion but configuration of natural land uses can be important, especially in highly fragmented areas. Also, we know that sounds vary greatly throughout the day, so maybe another interesting approach would be accounting for those differences in time-blocks.

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.

Acknowledgements

MCR thanks FAPESP (process #2013/50421-2), CNPq (processes # 312045/2013-1; #312292/2016-3) and PROCAD/CAPES (project #88881.068425/2014-01) for their financial support. MDAS acknowledge CAPES for her fellowship. All authors acknowledge the reviewers that contributed to improve the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.107050.

References

Acevedo, M.A., Villanueva-Rivera, L.J., 2006. Using Automated Digital Recording Systems as Effective Tools for the Monitoring of Birds and Amphibians. Wildl. Soc. Bull. 34 (1), 211–214. https://doi.org/10.2193/0091-7648(2006)34[211:UADRSA]2.0.CO;2.

Aide, T.M., et al., 2013. Real-time bioacoustics monitoring and automated species identification. PeerJ 1, e103. https://doi.org/10.7717/peerj.103.

Bedoya, C., et al., 2017. 'Automatic identification of rainfall in acoustic recordings. Ecol. Indicat. Elsevier Ltd 75, 95–100. https://doi.org/10.1016/j.ecolind.2016.12.018.

Blumstein, D.T., et al., 2011. Acoustic monitoring in terrestrial environments using microphone arrays: Applications, technological considerations and prospectus. J. Appl. Ecol. 48 (3), 758–767. https://doi.org/10.1111/j.1365-2664.2011.01993.x.

Bormpoudakis, D., Sueur, J., Pantis, J.D., 2013. Spatial heterogeneity of ambient sound at the habitat type level: ecological implications and applications. Landscape Ecol. 28 (3), 495–506. https://doi.org/10.1007/s10980-013-9849-1.

Brumm, H. and Slabbekoorn, H. (2005) 'Acoustic Communication in Noise', Adv. Study Behav. pp. 151–209. doi: 10.1016/S0065-3454(05)35004-2.

Carruthers-Jones, J., et al., 2019. The call of the wild: Investigating the potential for ecoacoustic methods in mapping wilderness areas. *Sci. Total Environ.*. Elsevier B.V. 695, 133797 https://doi.org/10.1016/j.scitotenv.2019.133797.

Congedo, L. (2016) Semi-Automatic Classification Plugin Documentation. https://doi.org/10.13140/RG.2.2.29474.02242/1.

Cosens, S.E., Falls, J.B., 1984. A comparison of sound propagation and song frequency in temperate marsh and grassland habitats. Behav. Ecol. Sociobiol. 15 (3), 161–170. https://doi.org/10.1007/BF00292970.

Deichmann, J.L., et al., 2017. 'Soundscape analysis and acoustic monitoring document impacts of natural gas exploration on biodiversity in a tropical forest. Ecol. Indicat. Elsevier Ltd 74, 39–48. https://doi.org/10.1016/j.ecolind.2016.11.002.

Deichmann, J.L., et al., 2018. It's time to listen: there is much to be learned from the sounds of tropical ecosystems. Biotropica 1–6. https://doi.org/10.1111/btp.12593.

Depraetere, M., et al., 2012. Monitoring animal diversity using acoustic indices: Implementation in a temperate woodland. *Ecol. Ind.*. Elsevier Ltd 13 (1), 46–54. https://doi.org/10.1016/j.ecolind.2011.05.006.

Duarte, M.H.L., et al., 2015. The impact of noise from open-cast mining on Atlantic forest biophony. Biol. Conserv. 191, 623–631. https://doi.org/10.1016/j.biocon.2015.08.006.

Dumyahn, S.L., Pijanowski, B.C., 2011. Soundscape conservation. Landscape Ecol. 26 (9), 1327–1344. https://doi.org/10.1007/s10980-011-9635-x.

Eldridge, A., et al., 2016. 'A new method for ecoacoustics? Toward the extraction and evaluation of ecologically-meaningful soundscape components using sparse coding methods'. Peer J. 4, e2108 https://doi.org/10.7717/peerj.2108.

Estrada, A., Coates-estrada, R., Meritt Jr, D., 1993. 'Bat Species Richness and Abundance in Tropical Rain Forest Fragments and in Agricultural Habitats at Los Tuxtlas, Mexico. Ecography 16, 309–318.

Farina, A. (2014) Soundscape ecology: Principles, patterns, methods and applications, Soundscape Ecology: Principles, Patterns, Methods and Applications. doi: 10.1007/978-94-007-7374-5.

Farina, A., James, P., 2016. 'The acoustic communities: Definition, description and ecological role, BioSystems. Elsevier Ireland Ltd 147, 11–20. https://doi.org/10.1016/j.biosystems.2016.05.011.

Ferreira, L.M., et al., 2018. What do insects, anurans, birds, and mammals have to say about soundscape indices in a tropical savanna. Journal of Ecoacoustics 2, p. PVH6YZ. https://doi.org/10.22261/JEA.PVH6YZ.

Fricke, F., 1984. Sound attenuation in forests. J. Sound Vib. 92 (1), 149–158. https://doi.org/10.1016/0022-460X(84)90380-8.

Fuller, S., et al., 2015. 'Connecting soundscape to landscape: Which acoustic index best describes landscape configuration?', *Ecological Indicators*. Elsevier Ltd 58, 207–215. https://doi.org/10.1016/j.ecolind.2015.05.057.

Fundação SOS Mata Atlântica (2016) 'Relatório Anual 2016', pp. 88.

Gage, S.H., et al., 2017. Acoustic patterns at the Samford Ecological Research Facility in South East Queensland, Australia: The Peri-Urban SuperSite of the Terrestrial Ecosystem Research Network. *Ecol. Inf.*. Elsevier B.V. 38, 62–75. https://doi.org/10.1016/j.ecoinf.2017.01.002.

Gage, S.H., Axel, A.C., 2014. Visualization of temporal change in soundscape power of a Michigan lake habitat over a 4-year period. *Ecol. Inf.*. Elsevier B.V. 21, 100–109. https://doi.org/10.1016/j.ecoinf.2013.11.004.

Gasc, A., et al., 2015. Acoustic indices for biodiversity assessments: Analyses of bias based on simulated bird assemblages and recommendations for field surveys. *Biol. Conserv.*. Elsevier B.V. 191, 306–312. https://doi.org/10.1016/j.biocon.2015.06.018.

Haddad, C. F. B. and Sazima, I. (1992) 'Anfíbios anuros da Serra do Japi', História natural da Serra do Japi: ecologia e preservação de uma área florestal no sudeste do Brasil, (July), pp. 188–211.

Jackson, H.B., Fahrig, L., 2015. Are ecologists conducting research at the optimal scale? Glob. Ecol. Biogeogr. 24 (1), 52–63. https://doi.org/10.1111/geb.12233.

Jorge, F.C., et al., 2018. The effectiveness of acoustic indices for forest monitoring in Atlantic rainforest fragments. *Ecol. Ind.*. Elsevier 91 (April), 71–76. https://doi.org/10.1016/j.ecolind.2018.04.001.

Kasten, E.P., et al., 2012. The remote environmental assessment laboratory's acoustic library: An archive for studying soundscape ecology. *Ecol. Inf.*. Elsevier B.V. 12, 50–67. https://doi.org/10.1016/j.ecoinf.2012.08.001.

Lellouch, L., et al., 2014. Monitoring temporal change of bird communities with dissimilarity acoustic indices. Methods Ecol. Evol. 5 (6), 495–505. https://doi.org/10.1111/2041-210X.12178.

Lugli, M., Fine, M.L., 2003. Acoustic communication in two freshwater gobies: Ambient noise and short-range propagation in shallow streams. J. Acoust. Soc. Am. 114 (1), 512–521. https://doi.org/10.1121/1.1577561.

Machado, R.B., Aguiar, L., Jones, G., 2017. Do acoustic indices reflect the characteristics of bird communities in the savannas of Central Brazil? *Landscape Urban Plann.*. Elsevier B.V. 162, 36–43. https://doi.org/10.1016/j.landurbplan.2017.01.014.

Magioli, M., et al., 2016. Connectivity maintain mammal assemblages functional diversity within agricultural and fragmented landscapes. Eur. J. Wildl. Res. 62 (4), 431–446. https://doi.org/10.1007/s10344-016-1017-x.

Marsden, S.J., Whiffin, M., Galetti, M., 2001. Bird diversity and abundance in forest fragments and Eucalyptus plantations around an Atlantic forest reserve, Brazil. Biodivers. Conserv. 10 (5), 737–751. https://doi.org/10.1023/A:1016669118956.

Morton, E.S., 1975. Ecological Sources of Selection on Avian Sounds. Am. Nat. 109 (965), 17–34. https://doi.org/10.1086/282971.

Mullet, T.C., et al., 2016. 'Temporal and spatial variation of a winter soundscape in south-central Alaska. Landscape Ecol. Springer, Netherlands 31 (5), 1117–1137. https://doi.org/10.1007/s10980-015-0323-0.

Mullet, T. C., Farina, A. and Gage, S. H. (2017) 'The Acoustic Habitat Hypothesis: An Ecoacoustics Perspective on Species Habitat Selection', Biosemiot. Biosemiot. doi: 10.1007/s12304-017-9288-5.

Myers, N. et al. (2000) 'Biodiversity hotspots for conservation priorities.', Nature, 403 (6772), pp. 853–8. doi: 10.1038/35002501.

Obrist, M. K. et al. (2015) 'Chapter 5 Bioacoustics approaches in biodiversity inventories by Bioacoust. Int. J. Animal Sound Record., (October), pp. 68–99.

QGIS (2020) QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.org.

Padgham, M., 2004. Reverberation and frequency attenuation in forests–implications for acoustic communication in animals. J. Acoust. Soc. Am. 115 (1), 402–410. https://doi.org/10.1121/1.1629304.

Pavoine, S., Bonsall, M.B., 2011. Measuring biodiversity to explain community assembly: A unified approach. Biol. Rev. 86 (4), 792–812. https://doi.org/10.1111/j.1469-185X.2010.00171.x.

Pieretti, N., Farina, A., Morri, D., 2011. A new methodology to infer the singing activity of an avian community: The Acoustic Complexity Index (ACI). *Ecol. Ind.*. Elsevier Ltd 11 (3), 868–873. https://doi.org/10.1016/j.ecolind.2010.11.005.

Rabin, L.A., Greene, C.M., 2002. Changes to acoustic communication systems in human-altered environments. J. Comp. Psychol. 116 (2), 137–141. https://doi.org/10.1037/0735-7036.116.2.137.

Ribeiro, M.C., et al., 2009. The Brazilian Atlantic Forest: How much is left, and how is the remaining forest distributed? Implications for conservation. *Biol. Conserv.*. Elsevier B.V. 142 (6), 1141–1153. https://doi.org/10.1016/j.biocon.2009.02.021.

Rodrigues, M., et al., 2005. Aves do Parque Nacional da Serra do Cipó: o Vale do Rio Cipó, Minas Gerais, Brasil. Revista Brasileira de Zoologia 22 (2), 326–338. https://doi.org/10.1590/S0101-81752005000200005.

Rodriguez, A., et al., 2014. Temporal and spatial variability of animal sound within a neotropical forest. *Ecol. Inf.*. Elsevier B.V. 21, 133–143. https://doi.org/10.1016/j.ecoinf.2013.12.006.

Sánchez-Giraldo, C. et al. (2020) 'Ecoacoustics in the rain: understanding acoustic indices under the most common geophonic source in tropical rainforests', Rem. Sens. Ecol. Conservat., pp. 1–14. doi: 10.1002/rse2.162.

São Paulo State Agricultural Extension Service, 2018. Levantamento Censitário das Unidades de Produção Agropecuária do Estado de São Paulo – LUPA. http://www.cdrs.sp.gov.br/projetolupa/.

Scarpelli, M. D. A. et al. (2019) 'Gaps in terrestrial soundscape research: it's time to focus on tropical wildlife', Sci. Total Environ. Elsevier B.V., p. 135403. doi: 10.1016/j.scitotenv.2019.135403.

Schaub, A., Ostwald, J. and Siemers, B. M. (2009) 'Foraging bats avoid noise', Journal of Experimental Biology, 212(18), pp. 3036–3036. doi: 10.1242/jeb.037283.

Sueur, J., et al., 2008. Rapid acoustic survey for biodiversity appraisal. PLoS ONE 3 (12). https://doi.org/10.1371/journal.pone.0004065.

Sueur, J., et al., 2012. Global estimation of animal diversity using automatic acoustic sensors. Available at: Sens. Ecol.: Towards Integrat. Knowled. Ecosyst. 101–119 http://sueur.jerome.perso.neuf.fr/WebPage_PapersPDF/Sueuretal_INEE_2012.pdf.

Sueur, J., et al., 2014. Acoustic Indices for Biodiversity Assessment and Landscape Investigation. ACTA Acustica United With Acustica 100, 772–781. https://doi.org/10.3813/AAA.918757.

Sugai, L.S.M., et al., 2019. Terrestrial Passive Acoustic Monitoring: Review and Perspectives. Bioscience 69 (1), 5–11. https://doi.org/10.1093/biosci/biy147.

Sugai, L.S.M., Llusia, D., 2019. (2019) 'Bioacoustic time capsules: Using acoustic monitoring to document biodiversity. *Ecol. Ind.*. Elsevier 99, 149–152. https://doi.org/10.1016/j.ecolind.2018.12.021.

Tarrero, A.I., et al., 2008. Sound propagation in forests: A comparison of experimental results and values predicted by the Nord 2000 model. Appl. Acoust. 69 (7), 662–671. https://doi.org/10.1016/j.apacoust.2007.01.007.

Towsey, M. et al. (2014) 'Visualization of long-duration acoustic recordings of the environment', Procedia Computer Science. Elsevier Masson SAS, 29(Krause 2008), pp. 703–712. doi: 10.1016/j.procs.2014.05.063.

Towsey, M. et al. (2018) 'Ecoacoustics Audio Analysis Software v18.03.0.41'. doi: 10.5281/ZENODO.1188744.

Towsey, M. (2018) The calculation of acoustic indices derived from long-duration recordings of the natural environment. Brisbane.

Tucker, D., et al., 2014. Linking ecological condition and the soundscape in fragmented Australian forests. Landscape Ecol. 29 (4), 745–758. https://doi.org/10.1007/s10980-014-0015-1.