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Looking for the -scape in the sound: Discriminating soundscapes categories in the Sonoran Desert using indices and clustering

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ABSTRACT

Soundscapes are increasingly used as innovative entry doors in environmental studies. Facing huge libraries of sound files which cannot be processed manually, acoustic indices provide an overview to the information contained in them, as well as to allow for automatic processing. Studies dealing with such indices have, however, focused more on specific topics or indices than on the overall characteristics of the soundscapes they were analyzing. The aim of this paper is to propose a holistic approach to soundscapes. Our hypothesis is that sufficient number and variety of indices can help frame the characteristics of sound environments and that the use of clustering algorithms allows us to group them in families and study the distribution of those across space and time, revealing a geography that will not necessarily coincide with the obvious landscape/visual geography. To demonstrate this point, we have run indices analysis and classification on a soundscapes database recorded in the Sonoran Desert region (Southeastern Arizona, USA). The results show that sound indices reveal temporal variations and patterns of soundscapes and point out to sometimes surprising similarities between otherwise different environments. As sound indices capture a wealth of information which characterizes the environment at a given place and time, they could be used as proxies to continuous monitoring without having to store extreme amounts of data.

Since Shaffer (1977) popularized the term, soundscapes have been increasingly used as interesting and innovative entry doors in environmental studies, to the point that “soundscape ecology” (Pijanowski et al., 2011) or “ecoacoustics” (Sueur and Farina, 2015; Krause and Farina, 2016) is now a recognizable subfield of ecology. The sonic environment is relatively simple and cheap to record, and it offers many clues about biodiversity and the evolving state of the ecosystems (Burivalova et al., 2018; Ng et al., 2018; Tucker et al., 2014). Soundscapes are considered to be the product of three components (Pijanowski et al., 2011; Farina et al., 2018): the geophony (sounds coming from the weather or the Earth), the biophony (sounds emitted by animals) and the anthropophony (human generated sounds, in which some authors distinguish the technophony, or sounds produced by machines).

As recording and storage devices become cheaper, researchers are faced with huge libraries of sound files which cannot be processed manually (or, rather, by ear). Hence, different methods have been developed to provide shorthand to the information contained in them, as well as to allow for automatic processing. Sound data have a high-dimensional nature, given that a sound file assigns an intensity value to frequency in fine-grained time frames. Indices calculated from the distribution of the intensity of the signal across time and/or frequency have been developed to improve our ability to interpret and visualize important patterns within soundscapes (Sueur, 2018; Farina et al., 2016, 2021; Bradfer-Lawrence et al., 2019). However, they have been mostly used in research focused on specific aspects of the environment (oftentimes the information about biodiversity that could be obtained with the biophony, or environmental information in general), paying less attention to other components (human generated sound but also rain or wind, for example) and also often filtering part of the frequency spectrum accordingly (Gasc et al., 2015; Mullet, 2017). Other research focused on

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specific indices, like acoustic complexity (Pieretti et al., 2011; Farina et al., 2018, 2021) or the Normalized Difference Soundscape Index (Gage and Axel, 2014; Ritts et al., 2016), showing how they reveal a variety of environmental information. In most of the cases (with the exception of Farina *et al.* who use a common acoustic event library for all sites), each recording site is processed separately in these studies, and the samples are not gathered in a single database, which does not allow for the direct comparison of sonic or acoustic patterns across sites. Often, also, the type of environment associated with soundscapes samples is a fixed variable, reflecting what Farina (2014) called the “hegemony of vision” in our perception of the environment.

In this context, the aim of our paper is to test what patterns emerge when gathering samples from different recording sites in one region, and processing those samples in a single database based only on acoustic characteristics. Does a sufficient number and variety of acoustic indices allow for the identification of distinct sonic patterns? What groupings emerge if these patterns are grouped into families using unsupervised clustering algorithms? Do elements of geographical definition, such as the urban/rural divide appear clearly? Or are other geographies or influences revealed?

To respond to these questions, we assembled a sound library from the Sonora Desert (Southeastern Arizona, USA), calculated ten acoustic indices for>14,000 5-minute soundscapes samples, and applied an automatic k-means clustering algorithm on the resulting database. Analyzing the indices, the clusters and their spatial distribution, we discuss the relationship between the sonic environment and the obvious landscape/visual geography, emphasizing how this approach reveals temporal variations and patterns of soundscapes which are not necessarily uniquely bound to certain types of geographical locations, as well as pointing out sometimes surprising similarities between otherwise different environments. Following a trail that Farina et al. (2018, 2021) started exploring with acoustic complexity indices, we conclude by pointing out how calculating enough acoustic indices can lead to the identification of acoustic patterns or signatures which can be used for monitoring changes in sound environments without having to store extreme amounts of data.

1. Context and research questions

1.1. Context: Soundscapes and acoustic indices

Acoustic indices quantify the amount of acoustic energy, its distribution across the frequency spectrum (or across specific frequency intervals), and ratios between specific frequency bands, some of which are used by given acoustic communities (Farina, 2014; Farina et al., 2018; Bradfer-Lawrence et al., 2019). As Buxton et al. (2018) show in their study where they counted>60 sound indices developed by researchers, most of them are linked with the study of biodiversity or environmental/ecological topics. For instance, acoustic indices have been widely used to study the presence and diversity of specific bird communities (Gasc et al., 2015; Machado et al., 2017; Mammides et al., 2017; Towsey et al., 2014). But, as Sueur et al. (2014) demonstrate, indices also allow us to access general characteristics or detect changes over time in the places where the recordings were done. As one example, Depraetere et al. (2012) have used them to track animal diversity in general. The use of indices for assessing biodiversity in urban contexts is, however, controversial (Fairbrass et al., 2017) or at least requires precautions because of the background noise formed by human technophony (Dein and Rüdisser, 2020).

The relationship between indices and characteristics of the recording locations have also been studied. Bradfer-Lawrence et al. (2019) show that after enough data are acquired, standard error deviance stabilizes, which makes it possible to point out habitat characteristics. Fairbrass et al. (2017) point out that three indices (*acoustic entropy*, *acoustic evenness* and *NDSI* – see below) are strongly correlated with landscape characteristics. Similarly, Thoret et al. (2020) use an innovative model of hearing to see how amplitude and frequency cues captured by the human hearing system are key to identify different natural soundscapes. Last, Farina et al. (2016, 2021) have used acoustic complexity indices to compare several Mediterranean soundscapes and extract key characteristics.

In most of these studies, the “landscape” is, however, a fixed variable and data are sometimes filtered so as to exclude parts of the sonic environment which are considered noise (for instance, oftentimes, the technophony). This may construct what Farina (2014) called the “hegemony of vision” in our perception of the environment – since the type of environment is a priori considered to be uniquely linked with the recorded soundscape – which may preclude other approaches in which soundscapes reveal a different geography than the (essentially visual) one we are familiar with.

2. Methodology

2.1. Recordings: Location and material

This study uses a collection of recordings made in the Sonoran desert region around the city of Tucson (Fig. 1) in July-September 2018 (monsoon season) and April-June 2019 (dry season). Soundscapes were recorded with four SM4 devices (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) in 18 sites spanning from the center of the city to *peri*-urban environments to wildlife preserves in mountain areas. The elevation of sites is diverse, ranging from 699 m for Whispering Hills to 1,746 m for Chuparosa Inn, reflecting the diversity of the area.

Recording parameters were 24 kHz dual channel and the resulting files were coded in wav (i.e. with no compression). Continuous recording was used in each site, but the duration of the recordings as well as the number of campaigns in each site vary. Recordings total 1,174 h and were broken down in 14,093 5-minute samples. Only the left channel, which was issued from a high-sensitivity external microphone installed about 100–120 cm above the ground, was used.

Following the remark by Farina et al. (2018) that soundscapes require a holistic approach to understand their relationships with the environment, we processed the recordings without prior filtering or removal of frequency bins frequently considered as noise. All recorded sonic components were thus taken into account in the analysis. Likewise, although the recordings originated from an array of different environments, ranging from urban to isolated rural, the processing was done independently of these *a priori* categories. All samples were put in the same database, and indices calculation and k-means clustering were performed regardless of location. The location/landscape parameter was only used afterwards to see whether it appeared to influence the results. To highlight this point, we present most of the figures with sites grouped in “urban” and “rural” categories.

2.2. Indices selection and calculation

After a literature review (principally Sueur et al., 2014; Buxton et al., 2018; Sueur, 2018; Bradfer-Lawrence et al., 2019; Farina, 2014; Farina et al., 2021), indices were chosen to be computed for each of our 5-minute samples. We selected generalist indices (those which are not targeting a specific animal community and not *a priori* selecting only a part of the audio spectrum), that covered different characteristics of sound (e.g., complexity, entropy, amplitude). We started with a selection of ten such indices covering a wide array of acoustic characteristics, a number which would best guarantee coverage of most of the information contained in the sonic environment. The selected indices had proven to be useful in previous environmental studies (Bradfer-Lawrence et al., 2019). The indices were: *bioacoustic index*, *amplitude* (*M index*), *temporal entropy*, *spectral entropy*, *acoustic entropy* (*H-index*), *acoustic diversity* (*ADI*), *acoustic evenness*, *acoustic complexity* (*ACI*), *number of frequency peaks* and *Normalized Soundscape Difference Index* (*NDSI*) (Table 1). All indices were calculated using R 3.6.2 from R Core Team (2019) using

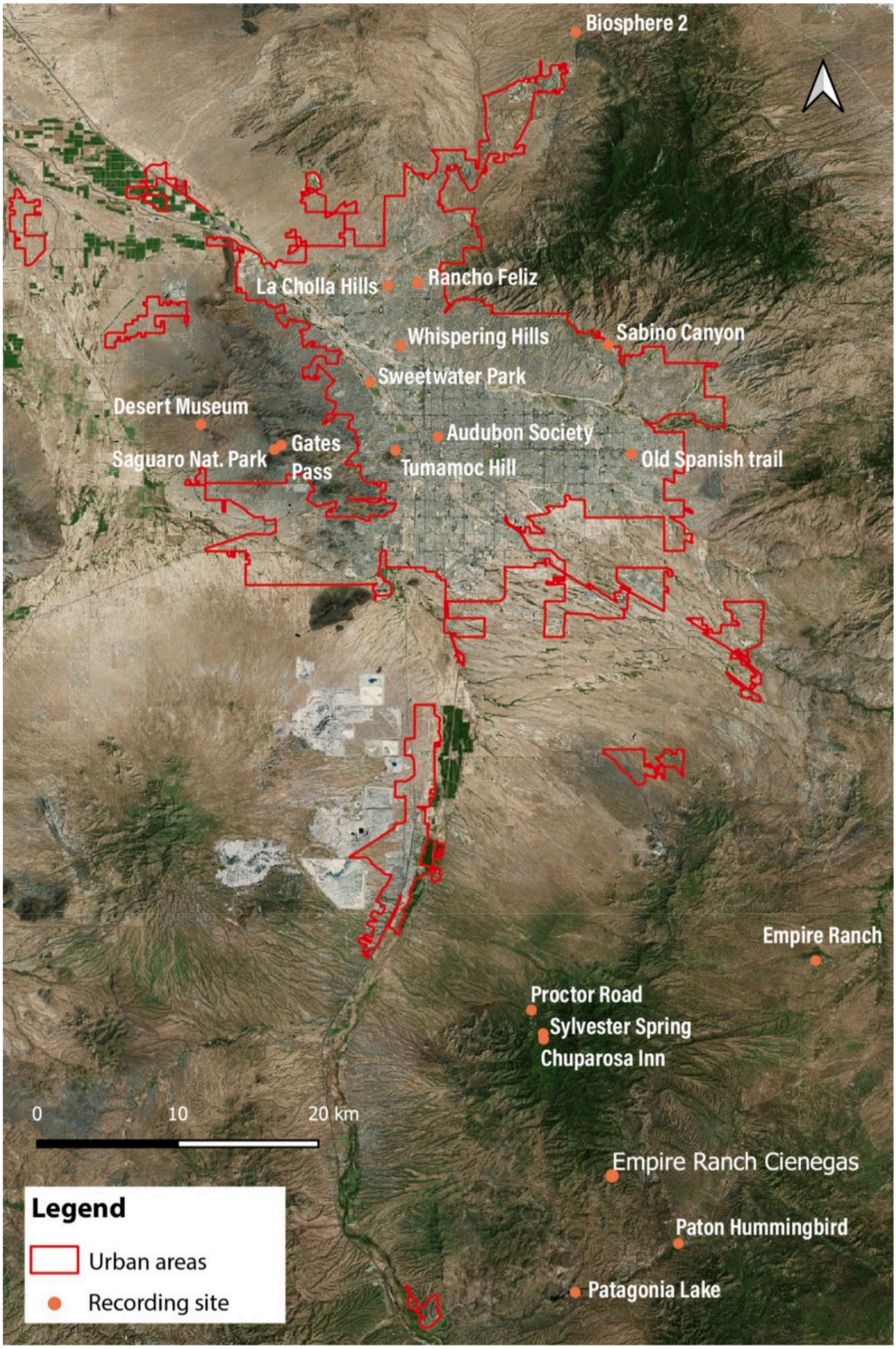

Fig. 1. Map of the study area (background image BING © Microsoft).

Table 1
Acoustic indices along with their associated ecological phenomena, technical definition, parameters used in this experiment, and the functions used to calculate them. Indices with (*) were retained for the final cluster analysis.

Index	Associated Soundscape Quality	Technical Definition	Parameters	R Implementation
Acoustic Complexity Index (*)Pieretti et al. (2011)	Quantification of biotic song, which is hypothesized to be associated with intensity variability in frequencies.	Absolute amplitude difference between a frequency bin and the same frequency in the successive STDFT window averaged over all frequencies and time steps.	• STDFT Window Length: 512 • STDFT Overlap: 50% • STDFT Window Type: Hamming	***Package:*** seewave***Function:*** ACI()
Acoustic Diversity Index (*) Villanueva-Rivera et al. (2011)	Quantification of the evenness of frequencies bands, with extremes associated with either high noise or total silence.	The Shannon index of equal-sized frequency bins in a STDFT which exceed a given dB threshold and do not exceed a given frequency.	• Max Frequency: 10000 Hz • dB Threshold: −50 • Size of Frequency Bands: 1000 Hz	***Package:*** soundecology***Function:*** ad()
Acoustic Entropy Index (*) Sueur et al. (2008b)	Quantifies relative number of species.	The product of the spectral and temporal entropy indices.	See parameters for spectral and temporal entropy indices.	***Package:*** seewave***Function:*** H()
Acoustic Evenness IndexVillanueva-Rivera et al. (2011)	Quantifies diversity of frequencies. No exact ecological association can be found in the literature.	The Gini index of equal-sized frequency bins in a STDFT which exceed a given dB Threshold and do not exceed a given frequency.	• FFT Window Length: 512 • FFT Overlap: 0 • Window Type: Hanning	***Package:***Soundecology***Function:*** acoustic_evenness()
Amplitude Index (*) Depraetere et al. (2012)	Quantifies the volume of the soundscape.	Median of Amplitude Envelope.	Envelope Type: Hilbert	***Package:*** seewave***Function:*** M()
Bioacoustic Index (*)Boelman et al. (2007)	Quantifies relative avian abundance.	The area under the curve of the dB mean frequency spectrum between two given frequencies after subtracting the minimum amplitude within that frequency range.	• FFT Window Size: 512 • Minimum Frequency: 500 Hz • Maximum Frequency: 12,000	***Package:*** Soundecology***Function:*** bioacoustic_index()
Frequency Peaks Number (*)Gasc et al. (2013)	General measurement of overall diversity of sound.	The number of points in the mean spectrogram where the slope of the spectrogram exceeds a specified value and is followed by a fall in which the absolute value of the spectrogram's slope also exceeds a given, possibly different, value.	• Left Minimum Amplitude Slope: 0.04 • Right Minimum Amplitude Slope: 0.04	***Package:*** seewave***Function:***Calculate mean spectrum using meanspec(), which is fed to seewave's fpeaks(), which is then fed to the built-in function nrows().
Normalized Difference Soundscape Index (*)Kasten et al. (2012).	Quantifies the ratio of human-generated sound to that of non-human biological sound.	Ratio (b-a)/(b + a) where *a* and *b* indicate the sum of the frequencies within the Welch frequency spectrum which correspond to the anthrophony and biophony frequency bands, respectively.	• Anthrophony: 1–2 kHz • Biophony: 2–8 kHz	***Packages:*** soundecology andseewave***Functions :*** Use soundscapespec() to calculate the frequency spectrum of the soundscape, which is then fed as an argument to the ndsi() package in soundecology.
Spectral Entropy Sueur et al. (2008b)	Quantifies the noisiness of a soundscape.	The Shannon Evenness of the mean frequency spectrum, i.e., the Shannon entropy of the spectrum scaled by the log of the number of frequency bins.	• FFT Window Length: 512 • FFT Overlap: 0 • Window Type: Hanning	***Package:*** seewave***Function:*** seewave's meanspec () is used to calculate mean spectrogram of sound, which is then used as an argument insh(), which is also in seewave.
Temporal Entropy (*) Sueur et al. (2008b)	Quantifies the degree of amplitude modulation within a soundscape.	The Shannon Evenness of the amplitude envelope, i.e., the Shannon entropy of the amplitude envelope scaled by the log of the envelope's sample number	Envelope Type: Hilbert	***Package:*** seewave***Function:*** After using env() from seewave to calculate the amplitude envelope, pass the results to th(), which is also in seewave.

packages *Seewave* (Sueur et al., 2008a) and *Soundecology* (Villanueva-Rivera and Pijanowski, 2018).

In order to give a good view of the acoustic characteristics of the samples it is important that the indices are not correlated with one another. In order to check for this, we ran a Pearson correlation test which showed that some were very highly correlated (>0.8) and gave redundant information. For this reason, we decided to exclude *acoustic evenness* and *spectral entropy*, using the eight other indices as dimensions to characterize our samples.

2.3. K-means analysis

K-means analysis (MacQueen, 1967; Jin and Han, 2011) allocates individual points in a sample to clusters by calculating the distance between each point and the center of each cluster calculated in an n–dimensional space, where n is equal to the number of parameters (here indices) that are associated with each observation. The algorithm will proceed in several passes, trying to optimize clusters by minimizing the mean distance between points and centers for each cluster at each iteration. The algorithm ends after a predefined number of iterations.

K-means is an unsupervised clustering algorithm. While supervised learning algorithms exploit data which has already been labeled or given a class, unsupervised learning algorithms use data which has not yet been labeled, which suits our approach of soundscapes where we did not want to provide a priori information beside the acoustic characteristics of each sample. However, unsupervised algorithms often require the desired number clusters as one of the entry parameters. To determine the optimal number for our sample, we first calculated the average silhouette metric (fviz_nbclust function in R) using CLARA clustering (Charrad et al., 2014; Kaufman and Rousseeuw, 1990). This metric is an effective way to gauge the quality of a clustering solution. The average silhouette metric peaked at both 2 and 9 clusters. As two clusters would not have brought enough information, we opted for 9 clusters and ran the k-means on the 8 remaining indices using the R-package of the same name, with a max-iteration of 30 (increasing beyond this did not noticeably change the results).

A Pearson correlation analysis was run between the clusters and each index to ensure that no single parameter explained the distribution. As no significant correlation was found, the classification was considered to represent adequately the complexity of the soundscapes that are being studied.

Once the clusters were calculated and each sample assigned, we determined in each cluster the five sample that were closest to the center and we proceeded to aural analysis of these samples to determine what type of soundscape the cluster was representative of. The interpretation grid for characterizing these samples was based on grading from 1 to 5 the importance of the three components of the soundscapes (geophony, biophony, techno/anthropophony), the presence or absence of peculiar sound events (e.g., a plane taking off, howling coyotes) and the presence or absence of continuous background sound (e.g., insect stridulation). Table 3 summarizes the main characteristics of these soundscapes.

3. Results

3.1. Results of indices calculation

Looking at the values of the indices for each sample gives a first idea of the characteristics of soundscapes across our sample (table 2). Those can be further understood by looking at the average diel metrics (Fig. 2) which show how they vary (or not) according to the time of the day. As we wanted to see the influence of the location parameter on these values, we differentiate urban and rural sites in these results.

The *bioacoustic index* shows peaks which clearly reflects the dawn chorus of many animal species, corresponding to the observation of Fuller et al. (2015). The dusk chorus also appears, but it is less pronounced. The index falls at night and during the peak of the day. Indices values for urban and rural sites have very similar profiles, with higher values for the urban ones. The *amplitude index* also displays a peak at dawn, stronger in urban areas than in the country. Its higher values, however, are reached at the beginning of the afternoon, with noticeable peaks for both urban and rural sites.

Temporal entropy has the same global profile for rural and urban areas, although its decrease during the day in rural zones is much more pronounced than in urban zones. This profile is explained by insect choruses and specific urban noise (e.g., air conditioning units) dominating the nighttime sound environment. As these sounds are focused on specific frequencies, entropy is high. During the day, sounds are more diverse, leading to a more even occupation of the frequency spectrum, reflected in lower entropy. This is more pronounced for rural areas where the constant technophony noise is less present.

Acoustic and *spectral entropy* have exactly the same profiles, which is why the second was dropped for the cluster analysis, as it was redundant. There seems to be a clear urban/rural difference in this profile. Urban areas tend to have a much flatter curve, with entropy a bit higher during the day than at night, contrary to what Fuller et al. (2015) observed. Rural areas have a much higher contrast between day and night and display a clear peak during the morning. The same occurs with *acoustic diversity* and (although inverted) with *acoustic evenness*. We did not, however, observe higher *H* or *ADI* indices at night in rural areas (quite the opposite, contrary to Fuller et al., 2015). *ADI* seems to be higher in rural areas.

Acoustic complexity is higher during the day in rural areas and slightly lower at night. Its curve is much flatter for urban areas, while the night/day contrast for rural areas is very strong. *Number of Peaks Index* registers sharps bursts in a frequency interval and is a proxy for sonic activity, either from the fauna or human induced. As we can see, in rural settings there are peaks (during the night and from 8 to 10 AM) and periods of much less developed sonic activity. Urban areas have lower values in general, except for a very sharp peak at dusk.

NDSI, which examines the ratio between biophony and anthropophony (table 1) also seems to mark a distinction between urban and rural sites. If the general profile is similar, the urban sites have much flatter curves, reflecting the constant technophony which overlaps biophony. Conversely, the rural profile is sharply contrasted, with very important drops at dawn and dusk. The night/day contrast for the NSDI is consistent with the observations of Fuller et al. (2015).

3.2. Cluster analysis

The classification regrouped all samples in 9 clusters. We investigate here how this distribution relates with place and time.

As we can see in table 3, if the whole library is quite well balanced between day and night recordings, clusters 5 and 6 are almost exclusively composed of night samples (83 and 85%), while clusters 2 and 4 are composed of day samples (81.3 and 93.5%). The others are more balanced. They see, however, a 2/3 vs 1/3 repartition between day and night for three of them. We can conclude from this that, regardless of location, night soundscapes are more homogeneous and day soundscapes more diverse.

Looking at the clusters' diel distribution (Fig. 3), their profiles as a

Table 2
Average values of the 8 indices retained for the clustering analysis by site (U = urban; R = Rural).

Location	Altitude (m)	Bioacoustic Index	Amplitude	Temporal entropy	Acoustic entropy	Acoustic diversity	Acoustic complexity	NDSI	Nbr Peaks
Audubon Society (U)	728	131.1	0.14	0.98	0.72	1.39	186.22	0.09	0.42
Biosphere2 (R)	1,158	106.7	0.05	0.98	0.64	1.17	177.17	0.89	0.42
Chuparosa Inn (R)	1,726	149.1	0.09	0.99	0.69	1.35	152.71	0.14	0.01
Desert Museum (R)	841	106.4	0.07	0.98	0.34	0.22	169.70	0.40	0.09
Empire Ranch (R)	1407	112.5	0.09	0.97	0.32	0.27	172.64	0.14	0.00
Gates Pass (R)	940	111.1	0.08	0.98	0.51	0.80	163.20	0.72	0.36
Rancho Feliz (U)	774	123.1	0.09	0.98	0.71	1.22	162.28	0.85	1.22
Whispering Hills (U)	699	120.9	0.19	0.98	0.52	0.54	164.48	0.20	0.29
Patagonia Lake (R)	1198	125.4	0.03	1.00	0.47	0.93	173.18	0.65	0.01
Paton H/bird (R)	1230	139.2	0.07	0.99	0.61	1.22	167.10	0.07	0.00
Proctor Road (R)	1395	120.6	0.07	0.97	0.36	0.10	167.90	0.09	0.00
La Cholla Hills (U)	732	133.7	0.08	0.99	0.51	0.60	159.65	0.14	0.13
Sabino Canyon (U)	825	116.1	0.05	0.99	0.45	0.34	164.83	0.05	0.19
Saguaro NP (R)	990	128.8	0.08	0.98	0.59	0.99	163.22	0.28	0.50
Sylvester Spring	1649	116.8	0.05	0.99	0.45	0.43	156.04	−0.16	0.01
Sweetwater Park (U)	714	140.3	0.14	0.98	0.55	0.68	162.18	0.18	0.29
Old Spanish Trail (U)	813	136.1	0.07	0.99	0.63	0.78	161.26	0.34	0.24
Tumamoc Hill (U)	821	126.4	0.09	0.98	0.49	0.16	160.70	−0.32	0.03
Total		**126.2**	**0.09**	**0.98**	**0.54**	**0.68**	**163.66**	**0.25**	**0.29**

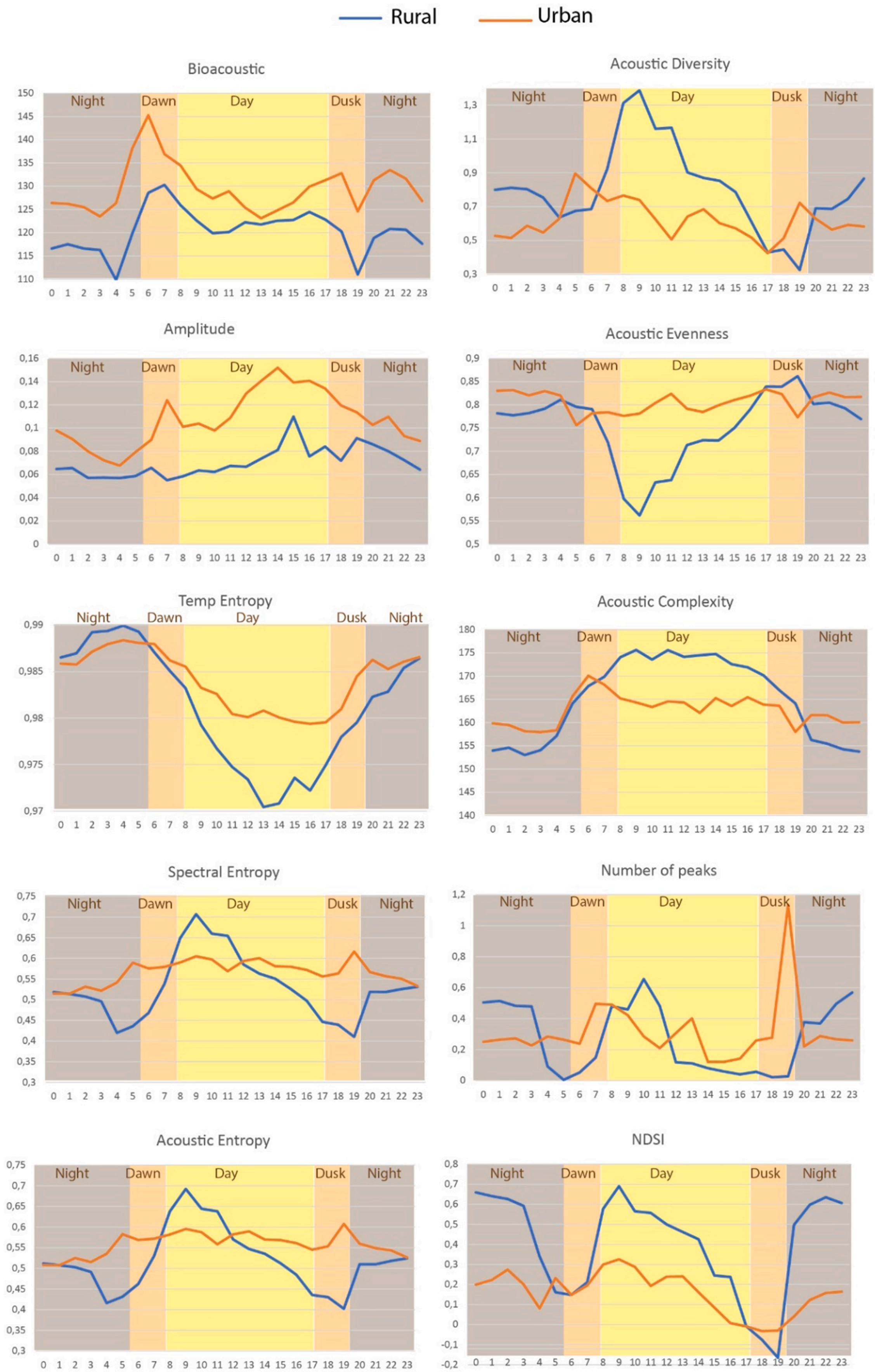

Fig. 2. Diel profiles of calculated sound indices for rural and urban sites.

Table 3
Night/day repartition of the clusters (in %).

Clusters	1	2	3	4	5	6	7	8	9	Total
NIGHT	45.4	18.7	44.1	6.5	**83.0**	**85.0**	30.2	39.0	35.1	49.5
DAY	54.6	**81.3**	55.9	**93.5**	17.0	15.0	69.8	61.0	64.9	50.5

function of the indices (Fig. 4), their distribution for each site (Fig. 5) and listening to samples with indices closest to the center of each cluster (spectrograms in Fig. 6), we grouped them into two categories (table 4). In the first are the five clusters that appear with the greatest frequency and represent 83.4% of samples. They constitute the regular sound environment of our sites. In the second are four clusters which are much less frequent and correspond to specific acoustic circumstances that happen only rarely, like rain.

3.3. Most frequent clusters – Usual sound environment

Starting with the category of most frequent clusters, and by order of importance, **cluster 3** stands out. It appears almost at any time in urban environments but is notably more frequent during the day. It appears much less in rural areas, where it is only present during the day. In terms of indices, it appears as quite balanced around low/medium values, except for the *NDSI*, which is low. On hearing, this cluster corresponds to a soundscape with low anthropophony (faint transit or A/C noise) and low biophony (some birds or insects). It thus seems to characterize quiet night or day in urban areas (where it is much more frequent since 84.3% of the samples in this cluster are urban), and quiet day in rural areas (where transit might be low during the day and almost nonexistent at night). Regarding sites, cluster 3 is very present in Tumamoc Hill (urban) and Patagonia Lake (rural), and to a lesser but still important extent in a mixed rural/urban subset of sites.

The second most frequent, **cluster 9**, shows slightly different dynamics between urban and rural areas. In the first, it appears strongly either in the middle of the night or during the day, being less frequent around dawn or dusk. Rural samples make up 45.4% of this cluster, whereas the proportion in our library is 37.5%. Thus, it represents the country, with sites like Biosphere 2 (almost 80%) and Proctor Road (>75%) which might suggest a relation with altitude (both sites are above 1150 m). It appears strongly during daylight, with a peak around 3–4 PM. As the previous one, this cluster exhibits median/low values for all the indices, with very low value of *temporal entropy* and *acoustic entropy*. It corresponds to quiet moments with low (but existing) levels of background human or animal sounds, with more events with a higher (but still moderate) sound intensity.

Cluster 5 is the third most common. The values of the indices are higher than for the former ones and the profile is balanced even if *amplitude* and *ACI* are low. Interestingly, this cluster is very well balanced between rural and urban samples (with a proportion corresponding to the average) and the diel distribution for both types of areas is almost the same, with a very strong predominance of night hours. This is the typical spring/summer Sonoran night soundscape, dominated by cricket (*Gryllus* spp.) stridulations. Cluster 5 is strongly present in *peri*-urban settings (Old Spanish Trail, Whispering Hills, La Cholla Hills) but can also appear in rural areas (Chuparosa Inn, Saguaro National Park). Interestingly this cluster almost disappears in sites with elevation over 1,200 m but appears strongly in the highest site, Chuparosa Inn.

Cluster 1 indices are higher than the previous ones, especially regarding ACI. Its diel distribution has the same profile for urban and rural areas. Contrary to the previous clusters, which were distributed across large windows during day and night, this cluster is particularly focused at dawn (and somewhat at dusk in urban areas). This cluster is influenced by bird choruses and is therefore strongly represented in the Audubon society site (>65% of the samples of this site) inside Tucson, where feeders attract lots of birds. It is not as present in the other sites, but appears in excess of 15% in several, with a mix of urban and rural areas concerned.

The final "regular soundscapes" cluster, **cluster 6**, has low indices scores except for *temporal entropy*. It appears predominantly at night and is more frequent in rural areas. It represents a globally silent environment with some incidental sound events (e.g., a car passing at some distance, voices from people passing, coyotes howling). It is typical of rather isolated places, like Gates Pass, the Desert Museum or Sylvester Springs).

3.4. Rarer clusters: Sound events

The next four clusters are infrequent and represent particular circumstances. **Cluster 7** is predominantly urban and sees an inverted diel distribution for urban and rural areas. It is present at night in rural zones and during the day, especially between 10 AM and 6 PM in urban locales. Interestingly, it is almost absent in both areas between 3 and 7 AM. Regarding the indices, the main feature is that its *bioacoustics index* is very low, as well as ACI. On the contrary, *H-index*, *ADI* and *NDSI* are relatively high. It corresponds to a soundscape dominated by transit noise or wind noise, with the presence of some biophony (birds, faint insects). It is predominantly found in urban or *peri*-urban areas located near roads (Rancho Feliz, Sweetwater Park), or in the middle of a rural locality, like the town of Patagonia (Paton Hummingbird site).

Cluster 4 is predominantly rural (75% of the samples against 37.5% in average) and appears almost exclusively during the day. It is characterized by very high indices for *H*, *ADI* and *ACI*. It corresponds to a soundscape dominated by constant biophony (like crickets) and low frequency human sounds (especially high-speed transit in nearby roads). Regarding the sites, cluster 4 is particularly present in Empire Ranch (rural) and Saguaro National Park (West side; rural). In urban areas, it appears in periurban settings such as Old Spanish Trail or Whispering Hills.

Cluster 8 is linked with rainfall, a rare event in the Sonoran Desert (it accounts for only 0.2% of the samples). It is characterized by a very high amplitude (due to saturation by the rain noise) and high *ACI* index, while all the other indices are low or very low. As it is linked with a weather event, it has little relationship to specific sites.

Last, **cluster 2** has a very high number of peaks in frequency and high *ADI* and *H-index*. It appears only during daylight, especially between 7 AM and 1 PM. It corresponds to very strong biophony where insect stridulation and bird choruses are major components and appears for this reason principally at dawn and during the first part of the morning. It appears almost exclusively in Empire Ranch and Saguaro National Park (West side) and to a lesser extent Paton Hummingbird.

4. Discussion

4.1. Beyond the rural/urban divide

The analysis of the acoustic indices yielded some surprises relative to the expectation that urban/rural division of the landscape would greatly influence soundscape (see also Fairbas *et al.*, 2017). Contrary to expectations, in our study *Bioacoustic index* values proved to be higher in urban than in rural areas. This can be due to the influence of specific situations, like the strong avian activity in the urban Sweetwater Park, but some *peri*-urban sites like Rancho Feliz also display a high biophony. Most probably, this fact points out a characteristic of the urban areas in the US West where urban sprawl creates a very sparse urbanization with lots of space where birds and other wildlife still manage to subsist,

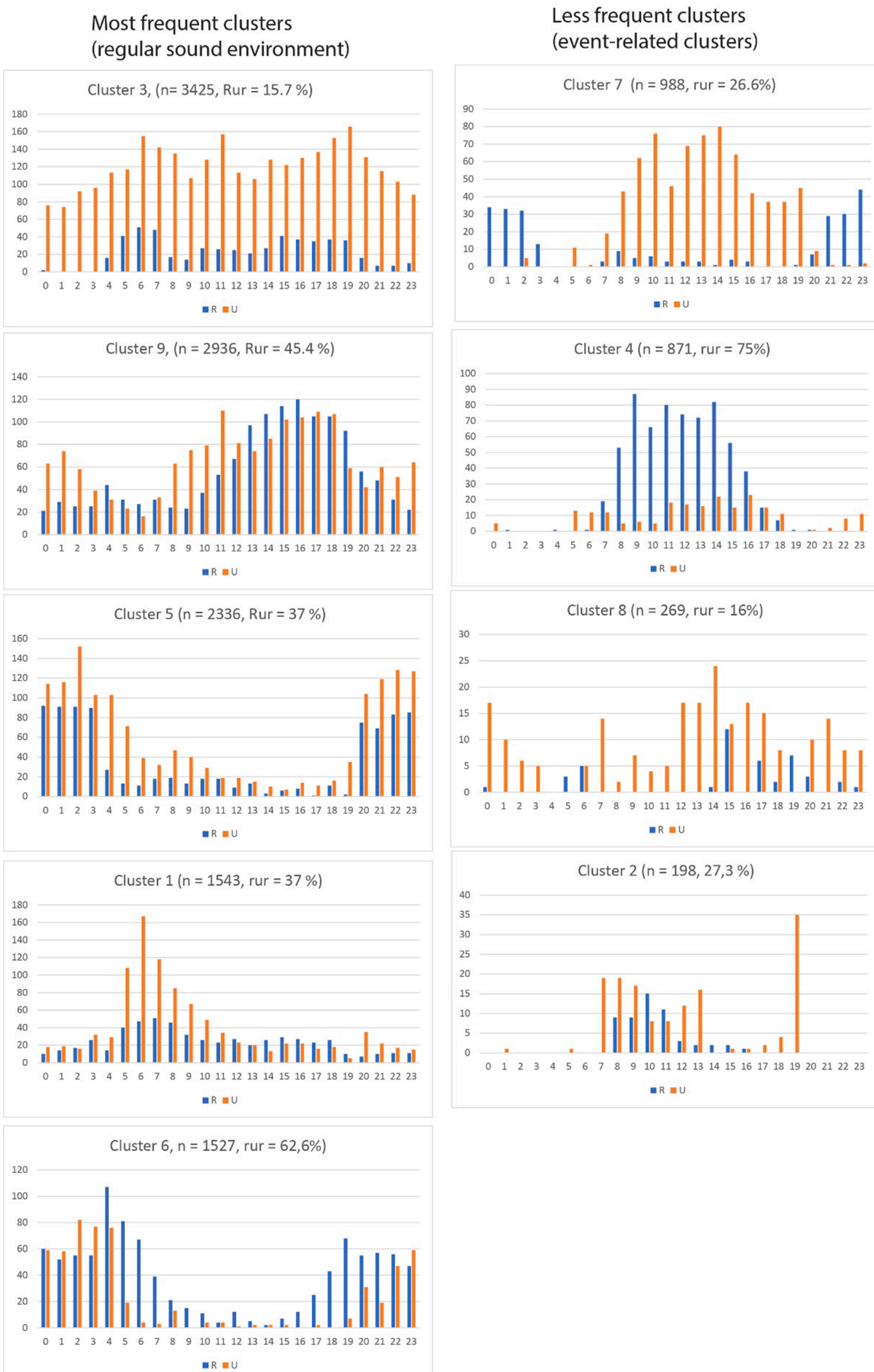

Fig. 3. Diel distribution of the clusters.

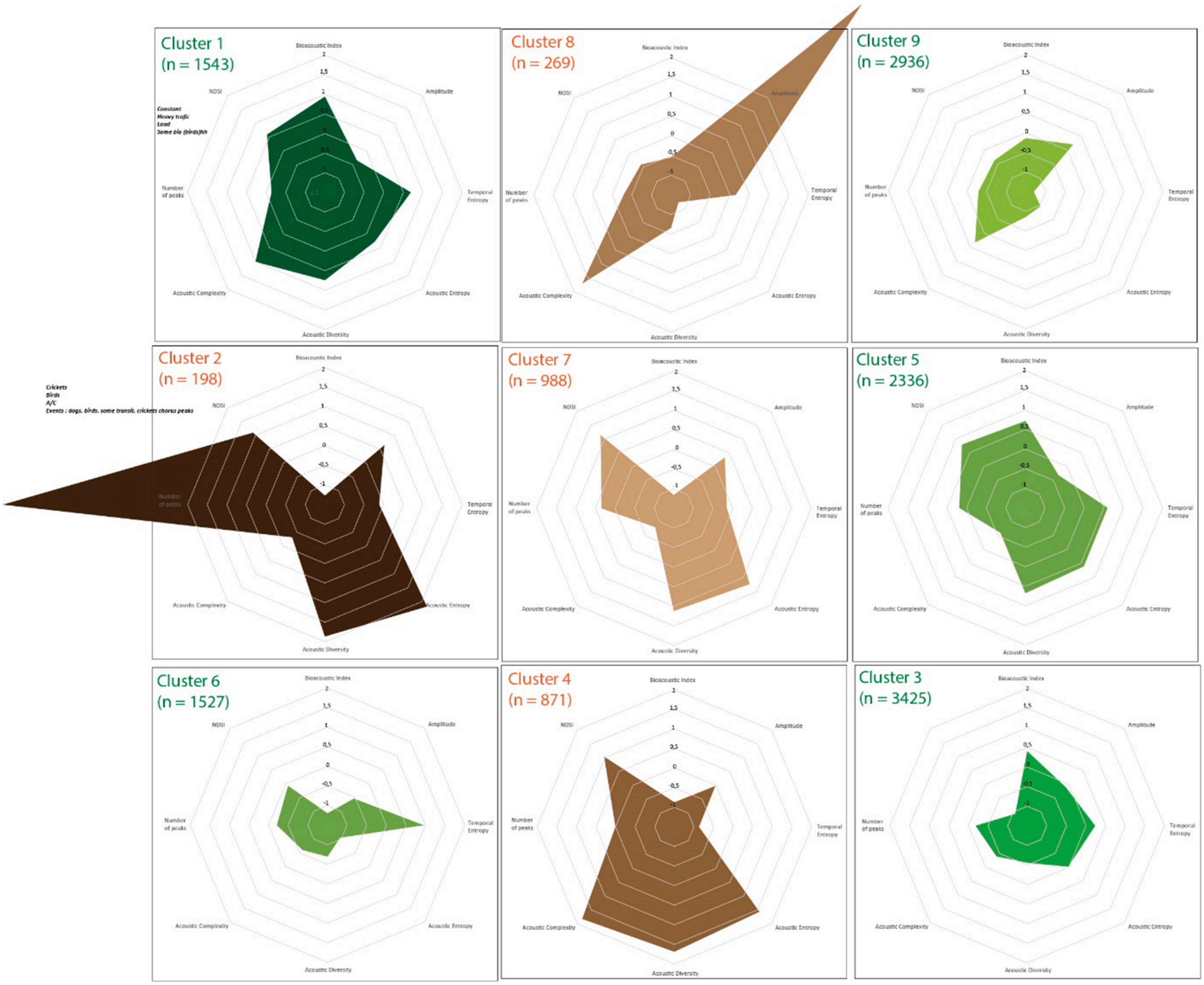

Fig. 4. Profiles of the clusters as a function of the 8 indices.

sometimes faring better than in rural areas because of the presence of alternative food and water sources. Conversely, rural areas do not seem to be totally spared by technophony, as peaks in the *amplitude index* show. These peaks indicate the existence of daily commutes to and from work or transit by visitors. All in all, the difference between rural and urban areas seems blurred, which reflects the discussion in geography about suburbanization, exurbanization or even counter-urbanization (Löffler and Steinicke, 2006; Travis, 2007).

Other indices, however, still point to more usual differences between rural and urban sites. If a*coustic complexity* is in general higher in urban than in rural areas, it remains high in the latter during the whole day. Also, the *number of peaks index* curves are very different between urban and rural areas. In the former, the curve oscillates between median values but has a very sharp peak at dusk, possibly linked with intense but discontinued insect stridulation at this time of the day. In the latter, two peaks appear around 10 am and during the night, with sharp drops in between.

Some indices confirm that the urban areas are very noisy environments, which is a recognized hindrance to wildlife (Farina, 2014). Thus, urban areas show flatter curves for *temporal* and *spectral entropy*, probably because the average sound level is much more constant during the day. Urban activities do emit noise continuously and they rarely leave periods of silence. On the contrary, in the country, animal choruses in the morning offer a very high contrast with the rest of the day, resulting in a higher entropy. The dawn and dusk peaks are present in urban areas as well, but to a lesser level. They also seem to present a shift in time compared with rural areas, happening somewhat sooner or later. It is possible that this represents an adaptation by animal communities to the urban environment: in rural areas they are not competing with urban noises and their choruses happen later in the morning; in urban areas, they favor pre-dawn and late-dusk moments because those are before and after the urban transit rush that creates important sound perturbation. The fact that bird choruses adapt to transit and other city noises would be consistent with Derryberry et al.'s (2020) observations of the recent lockdown in San Francisco.

Globally, the fact that clusters vary as a function of time of the day or represent certain events like rain correspond to Farina et al.'s (2018) results concerning acoustic complexity indices, with some urban-specific events appearing in our sample which were not present in theirs.

As with the indices, the detailed analysis of the clusters also does not show a clear urban–rural divide. While clusters 4 and 6 appear predominantly rural and clusters 3 and 8 predominantly urban, the others do not align with this dichotomy. Furthermore, even the most unbalanced clusters have at least 15% of the samples from rural sites (compared with 37.5% rural samples overall) or 25% of urban sites (62.5% overall). Thus, we can conclude that we are not faced, in the Sonoran Desert, with typical and easily distinguishable urban or rural environments as far as sound is concerned. Urban soundscapes in Tucson

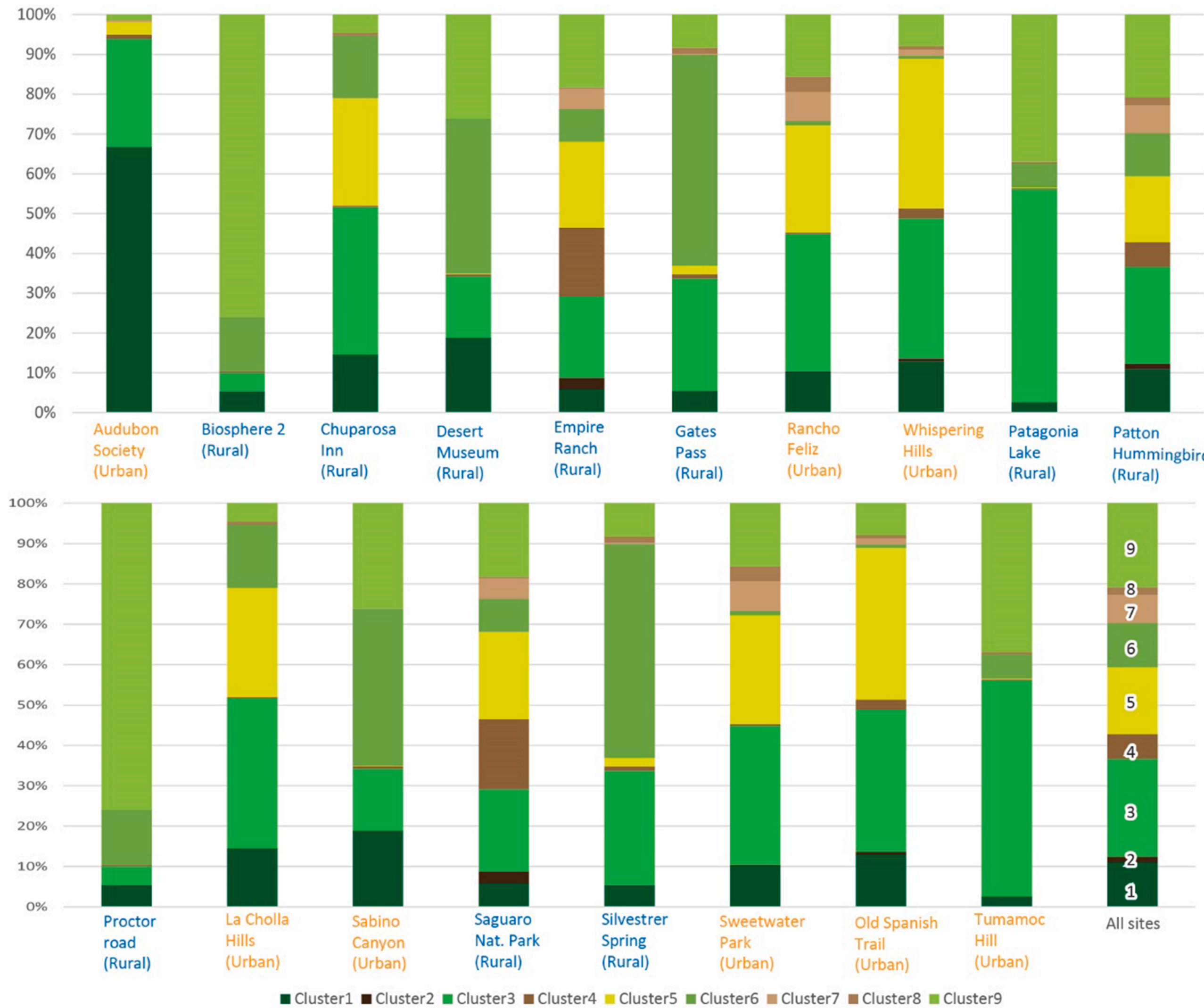

Fig. 5. Distribution of the clusters for each site in %.

include a relatively high biophony along with a stronger technophony which varies by time of day. In the country, anthropophonic sounds also exist (e.g., planes and cars passing by), even if they are lower and less frequent. In both types of areas, geophony, and especially rain and wind, create very similar soundscapes in which all other sounds are dimmed.

4.2. Temporal and spatial dimensions of soundscapes: Towards a new geography?

In the word landscape, the -scape desinence indicates a general quality of the land (etymologically, this –scape is the same as –ship and serves to generalize). Scientifically, two definitions of landscape can be pointed out to. In Landscape ecology, following a tradition set up by Carl Troll in the 1930 s, "*Landscape is considered mainly a mosaic of geographical entities in which organisms deal with the spatial arrangement of these entities determined by complex dynamics*" (Farina et al., 2005: 36). Based on the concepts of ecotope and ecotone, Farina suggested the concepts of soundtope and sonotone to label the sonic environment (Farina, 2014; Farina and Fuller, 2017). In geography, the definition of landscape will be considered as carrying less objectively quantifiable elements and more cultural elements. It is seen as a meta- or integrating category that sums up different distinct elements, forming a recognizable (but culturally situated) unit when combined (Antrop, 2000). As several authors pointed out (Farina, 2014; Mennitt et al., 2014; Farina and Fuller, 2017; Mullet, 2017), the relationship between landscape and soundscape are complex.

The starting point of our study was to see in which way the calculation of a battery of diverse acoustic indices, representing most of the sound characteristics, and an automatic classification of the result would align or not with the visual landscape. We expected this to point out some generic patterns (the –scape) that are present in recordings, much as landscape types are recognizable in a picture even if details may vary. However, the results of our clustering, where samples recorded in places with different 'landscape' labels (e.g., urban or rural) were put in the same cluster, seem to prove that the differences are not obvious from an acoustic point of view. Urban areas can exhibit typically rural soundscapes. This is, for instance, the case for the Audubon Society garden in Tucson, which records very high levels of biophony, often stronger than the ones recorded in "wild" areas. Conversely, anthropophonics sounds can be strongly present in places which are otherwise preserved, such as Saguaro National Park.

Furthermore, what we see in most of our locations is not just one soundscape, but a series of quite different sound environments with diel variations. Soundscapes thus appear not to be constant across time or only marked by seasonal variations. Some of the diel variations, like the appearing of bird or insect choruses at specific times of the day are well known, but our results suggest that recorded soundscapes are a mosaic of several different sonic environments both across space (which

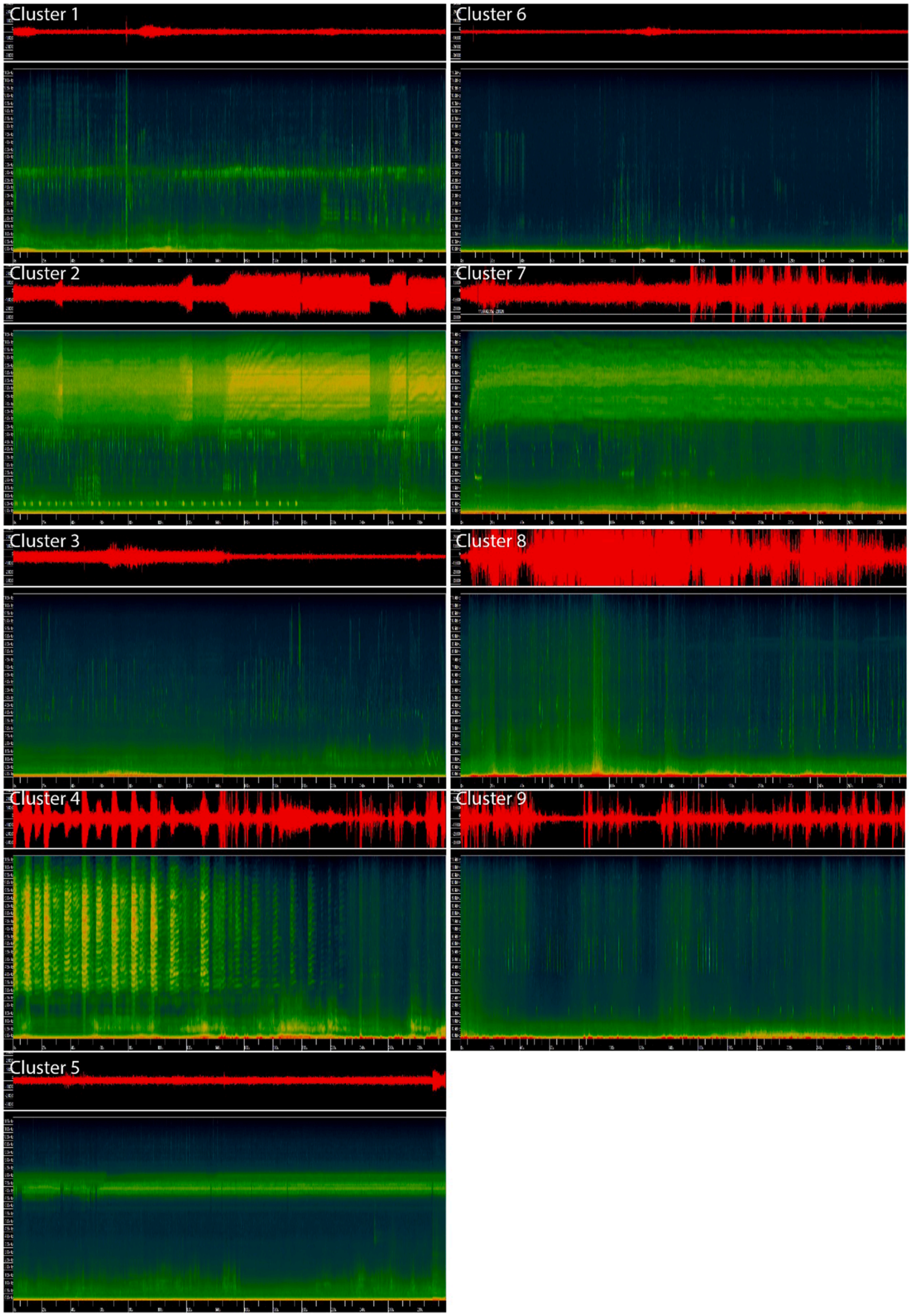

Fig. 6. Spectrograms of the samples closest to the clusters' centers.

Farina's sonotone concept already introduced) but also across time. The relative frequency of multiple sub-soundscapes across time could thus be another defining characteristics of more global soundscapes. These sub-soundscapes are not necessarily linked to specific locations but can appear in similar forms across all the geographical categories.

In clear language, a typical *peri*-urban soundscape in Tucson is not exactly defined by the mixture of background transit noise and persistent biophony (cricket stridulation, bird choruses), but by the succession of several soundscapes like "deep night" (insect stridulation, low background transit), "biophony near dawn chorus" (bird chorus anticipating

Table 4
Summary of the 9 clusters.

Cluster	Number of samples	Nature
3	**3425**	Night or day quiet soundscape with low anthropophony background
9	2936	Globally quiet mostly day soundscape with some middle intensity events.
5	2336	Night soundscapes with insect chorus
1	1543	Dawn bird choruses
6	1527	Silent night soundscape with incidental sound events
7	988	Rush hour or windy day
4	871	Rural biophony dominated with transit noise background
8	269	Rain
2	198	Very strong biophony combining bird choruses and insect stridulation

the morning anthropophony peak), “rush hour” (high level of transit noise), “rising heat” (decreasing biophony, low transit), and so on. And sometimes all of those are changed in a “rain soundscape”, which is not an event outside the regular soundscape but a genuine component of it. None of these is unique to this geographical environment and they can appear with very similar characteristics in neighboring urban areas as well as in more remote rural zones. The proportion of each of these elements, however, could be a defining factor for a specific location.

This suggests that our approach of soundscapes may be reevaluated. Many times, the geographical environment guides the location of the recorders or the analysis, with the ambition to retrieve elements of this classification into the sound. Mullet et al. (2017) did just this by comparing a number of geographically distributed information layers with their soundscape characteristics to find which one is better correlated to the sonic pattern they detected. But while there are important influences of the geographical environment on sound propagation (Farina, 2014), since sound is a different phenomenon in nature, it is logical that the boundaries and geographical categories that it points out are different from the visual ones.

4.3. Scaling up: Using clustering for continuous recording and monitoring

Today’s technology allows for multiplying recording points so that dozens if not hundreds of recording devices can be deployed across a region to monitor soundscapes continuously. The enormous amount of data that this can potentially create suggests the need for immediate processing and the production of synthetic indices which can capture most of the information in a highly condensed form. In this line, Farina et al. (2016, 2021) pointed out the utility of a small set of indices based on acoustic complexity, and they proposed a device that was capable of on-board sound processing to extract acoustic events.

The consequent and defining questions center around which synthetic indices will be selected, and whether those indices are sufficiently representative of the information in a given soundscape sample. In this study, we have shown that the calculation of eight different indices provided an interesting alternative to raw sound storage. The pattern constituted by the indices in a 8-dimension space creates a signature for each sample of the database that can be compared to the others and grouped into families. This method allowed us to adequately describe diel variation while at the same time proposing unusual proximity between otherwise different places at certain time, leading to the idea that the temporal *variation* in soundscapes is probably as much an element of their definition as the components that appear at a given time.

Such a method also allows for the monitoring in time of the transformation of soundscapes. Deviation in comparison to the initial clusters’ silhouette can be very easily spotted, providing one more tool to gauge the transformation of the environment.

5. Conclusion

As Sugai et al. (2019) showed, soundscapes studies are often characterized by the search for specific clues (presence/absence of given species) and the use of automatic methods of interpretation, while rising, is not generalized. However, faced with massive amount of data potentially produced by more accessible recorders, the processing of acoustic recordings will be more and more crucial for long-term continuous monitoring of the environment. The difficulty here is that the processing of the data should guarantee that the information contained in the recordings is adequately represented. Several methods have been proposed based on indices with specific purposes (like the *biophony index* to gauge the overall activity of the fauna, especially birds and insects) or on specific acoustic characteristics, like the different acoustic complexity indices proposed by Farina et al. (2018), Farina et al. (2021). In this paper, we presented an automatic method based on two steps. First, we calculated eight different acoustic indices, which cover each different characteristics or type of information contained in acoustic recordings. Next, we performed an unsupervised classification on a database which grouped all the samples (reduced to 8 indices) recorded in different sites.

This analysis showed that diel variation in soundscapes appears to be more important than location and leads to the idea that soundscapes could be more adequately described as the succession of multiple different sonic environments rather than as one. These different soundscapes suggest a different geography than the one we are accustomed to. Comparable sound environments can be found, for instance, in urban or rural areas. The difference between both types is therefore not a matter of nature, but a matter of variations in the proportion of each subtype which appears in them across time. This should not be a surprise. After all, admitting that hearing leads to different perceptions and classifications than seeing is somewhat logical, but rarely pointed out in soundscapes studies.

CRediT authorship contribution statement

Colton Flowers: Conceptualization, Data curation, Formal analysis, Resources, Writing - original draft. **François-Michel Le Tourneau:** Conceptualization, Data curation, Formal analysis, Writing - original draft, Funding acquisition. **Nirav Merchant:** Conceptualization, Supervision, Validation. **Brian Heidorn:** Conceptualization, Supervision, Validation, Writing - review & editing. **Régis Ferriere:** Conceptualization, Supervision, Validation, Funding acquisition. **Jake Harwood:** Validation, 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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