

# A new methodology to infer the singing activity of an avian community: The Acoustic Complexity Index (ACI)

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## ABSTRACT

The animal soundscape is a field of growing interest because of the implications it has for human–landscape interactions. Yet, it continues to be a difficult subject to investigate, due to the huge amount of information which it contains. In this contribution, the suitability of the Acoustic Complexity Index (ACI) is examined. It is an algorithm created to produce a direct quantification of the complex biotic songs by computing the variability of the intensities registered in audio-recordings, despite the presence of constant human-generated-noise. Twenty audio-recordings were made at equally spaced locations in a beech mountain forest in the Tuscan-Emilian Apennine National Park (Italy) between June and July 2008. The study area is characterized by the absence of recent human disturbance to forest assets but the presence of airplane routes does bring engine noise that overlaps and mixes with the natural soundscape, which resulted entirely composed by bird songs. The intensity values and frequency bin occurrences of soundscapes, the total number of bird vocalizations and the ACI were processed by using the Songscope v2.1 and Avisoft v4.40 software. The Spearman's rho calculation highlighted a significant correlation between the ACI values and the number of bird vocalizations, while the frequency bin occurrence and acoustic intensity were weaker correlated to bird singing activity because of the inclusion of all of the other geo/anthro-phonies composing the soundscape. The ACI tends to be efficient in filtering out anthroponies (such as airplane engine noise), and demonstrates the capacity to synthetically and efficiently describe the complexity of bird soundscapes. Finally, this index offers new opportunities for the monitoring of songbird communities faced with the challenge of human-induced disturbances and other proxies like climate and land use changes.

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## 1. Introduction

Animals acoustic cues are influenced by the physical and energetic context (see f. i. Richards and Wiley, 1980) in which organisms live and, consequently, probably reflect these circumstances. The possibility to measure the sounds produced by animals represents the obligatory route to approach the ecological dynamics of this informative structure (Derryberry, 2009; Farina et al., [accepted for publication](#)).

New tools for monitoring natural systems have been recently provided by technological advances such as the opportunity to automatically record sounds from animal communities (f. i. birds: Celis-Murillo et al., 2009; Haselmayer and Quinn, 2000; Rempel et al., 2005; Scott et al., 2005; mammals: Gedamke and Robinson, 2010; amphibia: Meek, 2010). Audio-recordings have many benefits, for instance the irrelevant disturbances caused by the operators during field surveys and the opportunity to remotely listen the

recorded sounds and post-process the collected acoustic information. The approach can also minimize observer errors by using a single interpreter, thus providing a potentially permanent record of surveys and solving the logistical problems that are often encountered in field studies, including the limited availability of expert ornithologists (Hobson et al., 2002).

Audio recordings are the basis of acoustic ecology, a recently developed ecological field of research that focuses on the relationship between the sounds of the environment (the soundscape) and the listener. The soundscape, defined as any acoustic environment, whether natural, urban, or rural, can be composed of three fundamental elements: the biophony (non-human biological sounds such as the vocalizations of birds, amphibians and other animals), the geophony (physical features of the environment such as the wind blowing through a forest or the burbling of water in a stream), and the anthrophony (human-induced noise from whatever source) (Krause et al., 2003; Pijanowsky et al., [accepted for publication](#)).

According to Schafer (1977), who was its initial promoter, the soundscape approach suggests that we should try to hear the natural acoustic environment as a musical symphony and, further,

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that we own responsibility for its composition and preservation from its bigger enemy: the pollution produced by noise. In recent years in particular, the increase in human mechanical noise (the anthropophony) has tended to mask the fine textures of the natural acoustic environment, forcing vocal creatures to displace or activate unusual adaptations (Dooling and Popper, 2007; Nemeth and Brumm, 2009; Rheindt, 2003; Slabbekoorn and Peet, 2003).

Nowadays, the study of the animal soundscape represents a field of growing interest because of the implications it has for the assessment of human–landscape interactions. Unfortunately, it continues to be a difficult subject to investigate, due to the wide variety of information available in each acoustic environment, and the difficulty that there is in identifying indices with which to quickly interpret the wide range of audio-registration data. Indeed, besides all the new technologies and software developed in recent years, the analysis of the natural sounds often remains a time-consuming process and this reduces the possibility to extract useful ecological data from this widely rich informative context. Several authors have successfully produced techniques based on bio-acoustic cues of a single species (e.g. Bardeli et al., 2010; Frommolt et al., 2008; Klinck et al., 2008; Wolf, 2009), while indices have been rarely calibrated for the monitoring of entire animals communities (e.g. Sueur et al., 2008a,b).

In particular, an attempt to quickly measure the singing behaviour of a bird community was made by Farina and Morri (2008) who elaborated an index to rapidly quantify the typical complexity of the biotic songs of a soundscape, despite the presence of constant human-generated-noise. The aim of the present work is to further test this methodology by using the index, which we describe in this paper with the acronym ACI (Acoustic Complexity Index).

## 2. Materials and methods

### 2.1. Acoustic Complexity Index (ACI)

The Acoustic Complexity Index, elaborated by Farina and Morri (2008), was created in order to produce a direct and quick quantification of the birds vocalizations by processing the intensities registered in audio-files.

The hypothesis on which the ACI formula is based lays on the observation that many biotic sounds, such as bird songs, are characterized by an intrinsic variability of intensities, while some types of human generated noise (such as car passing or airplane transit) present very constant intensity values. Accordingly, the long term objective of the ACI is to develop an acoustic information extraction procedure of the natural soundscape, representing a useful tool to determine changes in behaviour and composition of a vocalizing community and, consequently, to better monitor animal dynamics in a quick way.

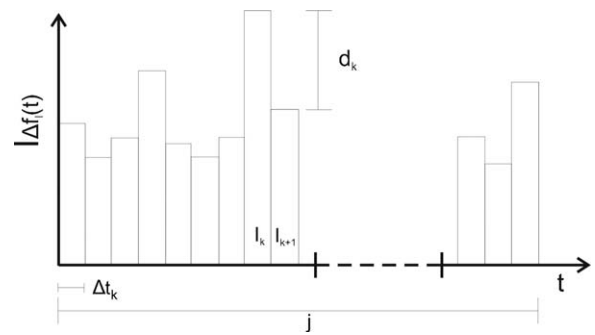
The ACI can be calculated according to a formula which involves only a few steps (see Fig. 1). On the basis of a matrix of the intensities extrapolated from the spectrogram (divided into temporal steps and frequency bins), the ACI calculates the absolute difference ( $d_k$ ) between two adjacent values of intensity ( $I_k$  and  $I_{(k+1)}$ ) in a single frequency bin ( $\Delta f_i$ ):

$$d_k = |I_k - I_{(k+1)}| \quad (1)$$

and then adds together all of the  $d_k$  encompassed in the first temporal step of the recording ( $j$ , e.g. 5 s, 30 s, 60 s, etc.):

$$D = \sum_{k=1}^n d_k \quad \text{for:} \quad j = \sum_{k=1}^n \Delta t_k; \quad n = \text{number of } \Delta t_k \text{ in } j \quad (2)$$

where  $D$  is the sum of all the  $d_k$  contained in  $j$ . In order to obtain the relative intensity and to reduce the effect of the distance of the



**Fig. 1.** Explanatory graph of the Acoustic Complexity Index ( $t$ : time;  $\Delta t_k$ : a single time fraction;  $\Delta f_i$ : a single frequency bin;  $I\Delta f_i(t)$ : intensity registered in a  $\Delta f_i$  frequency bin). For example, when the FFT size is set at 512 points, the output matrix will be composed by 310078  $\Delta t_k$ , ( $\Delta t_k = 0.02321$  s) and 256 frequency bins ( $\Delta f_i = c43$  Hz), with:  $j = c215$ ;  $\Delta t_k$ ;  $m = 310,078/215 = c1442$ ;  $q = 256$ ;  $n = 215$ .

birds from the recording microphone, this result is then divided by the total sum of the intensity values registered in  $j$ :

$$ACI = \frac{D}{\sum_{k=1}^n I_k} \quad (3)$$

where the ACI is calculated in a single temporal step ( $j$ ) and in a single frequency bin ( $\Delta f_i$ ). Thereafter, the ACI, which was worked out on all of the temporal steps encompassed in the recording, is calculated:

$$ACI_{(\Delta f_i)} = \sum_{j=1}^m ACI \quad \text{for:} \quad m = \text{number of } j \text{ in the entire recording} \quad (4)$$

where the  $ACI_{(\Delta f_i)}$  corresponds to the ACI of an entire frequency bin. Finally, the total ACI for all of the frequency bins is calculated:

$$ACI_{tot} = \sum_{l=1}^q ACI_{(\Delta f_l)} \quad \text{for:} \quad \Delta f = \sum_{l=1}^q \Delta f_l; \quad q = \text{number of } \Delta f_l \quad (5)$$

where the  $ACI_{(tot)}$  is the total value of the index for the entire recording.

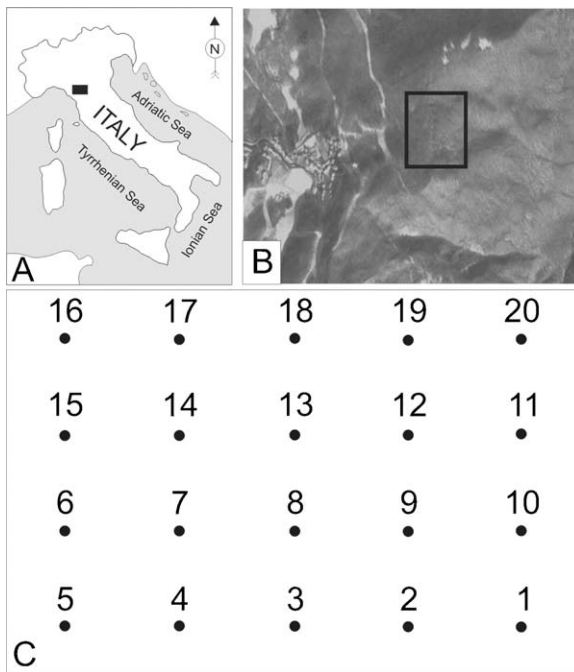
### 2.2. Study area

The study was carried out in the Tuscan-Emilian Apennine National Park, Northern-Italy (Fig. 2A). The park's territory (altitudinal range from 900 to 2000 m above sea level (a.s.l.)) is characterized by a complex sandstone morphology (deep valleys, mountain lakes, streams, and turbaries). The dense beech forest (*Fagus sylvatica*) is the dominant vegetation.

For the purposes of our research we chose a thick beechwood, located far from any human activity, on the Northern side of Mount La Nuda, at 1350 m a.s.l. (44° 17' 49.18" N; 10° 15' 25.80" E) (Fig. 2B). The homogeneity of the woody cover is interrupted by a few conifer plants located in a corner of the study area.

### 2.3. Audio-file recordings

The soundscape was investigated by positioning 20 digital recorders (Handy Recorder "H4", Zoom Corporation, Japan), located 100 m from each other according to a grid of four rows and five columns (Fig. 1C), for 190 min sessions. Such a distance was chosen with the aim of collecting a distinct soundscape at every station, thereby reducing the overlapping of sounds between two adjacent recording points and ensuring a good spatial sampling. The H4



**Fig. 2.** Location map showing: (A) the location of the Tuscan-Emilian Apennine National Park; (B) satellite map of the studied area; (C) distribution of the sampling stations.

recorders were set at 22.05 kHz/16 bit/stereo mode. Eleven recording sessions were conducted at dawn (6–9 a.m.) during the breeding season, and in optimal meteorological conditions. Only three of these (10–28<sup>th</sup> June and 19<sup>th</sup> July, 2008) are presented and discussed in this paper.

#### 2.4. Data analyses

In order to obtain a contemporary soundscape, which was subjected to the same environmental interferences, and to temporally compare the 20 stations, the 20 acoustic files were synchronized for each session using the Cool Edit Pro 2.1 software (Syntrillium Software Corp, 2002). Two hours of net usable files were consequently obtained.

The beech wood soundscape was characterized prevalently by bird's vocalizations, which were automatically recognized by Wildlife Acoustics, 2007 (Wildlife Acoustics Inc.). This software makes it possible to create a Recognizer, a model based on a sophisticated digital signal processing algorithm to extrapolate species-specific bird vocalizations. In particular, a general Recognizer model was constructed to return the vocalizations of all the species and filter out the noise produced by airplanes. Successively, every acoustic cue selected by the digital model was checked to identify the individual species and join together the bird syllables

that the Recognizer had distinguished into two or more separate records. Bird songs which did not reach the sound level of 20 db were isolated and classified as "Others" together with the false positive cues produced by wind, the flight of insects, or other accidental noises. The relative abundance and species richness of each recording session were also calculated.

By setting an Avisoft-SASLab Pro v4.40 (Specht, 2006) with a FFT size of 512 points, a database composed of 310078  $\Delta t_k$  (0.02321 s length) and 256 frequency bins ( $\Delta f_i$ , about 43 Hz) was extracted from each 2-h recording. For each intersection, the Avisoft software indicated the corresponding value of intensity registered ( $I_k$ ). Frequency occurrences, intensities and ACI values were calculated on the basis of these matrices.

Successively, in order to assess the reliability and sensitivity on different time scales of ACI, 10 samples of 5, 10, 15, and 30 s in length respectively, were randomly selected from any audio-file in the data-set and tested with this algorithm.

#### 2.5. Statistical analysis

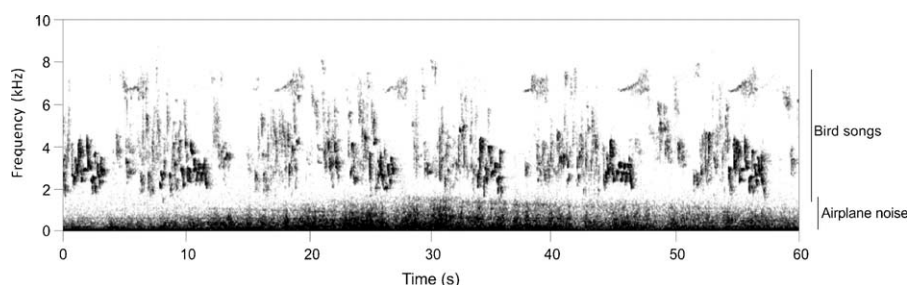
Since the probability distribution of the raw data fails the Kolmogorov-Smirnov test for normality, an additive logarithmic transformation  $\log(1+X)$  was performed prior to statistical analysis to remove the effects of orders of magnitude differences between variables, to avoid negative numbers (Manly, 1997), to normalize the data and increase the importance of smaller values. Despite this transformation, the data distribution of all of the variables could not be interpreted as normal. Accordingly, a non-parametric correlation analysis (Spearman's rho,  $p < 0.01$ ), processed by the Statistica v8.0 software (StatSoft, 2008), was chosen to investigate the relationship between variables and, consequently, to elucidate the strength of the ACI. The correlation matrix (Spearman's rho) was calculated for the transformed data of the total number of bird vocalizations (extracted by Songscope), the frequency bin occurrences, the intensities, and the values obtained from the ACI.

A second correlation matrix, in the form of a Spearman's rho correlation analysis between the number of bird vocalizations detected in the audio-fractions and the respective values of the ACI, was also performed on the values achieved in the study of the consistency of the ACI in different time scales (5–10–15–30 s lengths).

### 3. Results

#### 3.1. Acoustic environment at the study area

The soundscape of all of the 20 stations was dominated by bird song (biophony) and the anthropogenic noise from the airplane flight paths which crossed the study area (anthrophony). On average, 14 airplane transits for every 2 h of recording were registered. Fig. 3 sets out a spectrogram of an audio scene polluted by this kind of anthropogenic noise. Other typical audio-scenes are pro-



**Fig. 3.** Spectrogram representing a typical scene of the airplane noise overlapping the natural soundscape.

**Table 1**  
Resume of the soundscape of three recording sessions.

	10th June		28 <sup>th</sup> June		19 <sup>th</sup> July		Total	
	Number of songs	%	Number of songs	%	Number of songs	%	Total	%
<i>Sylvia atricapilla</i>	1331	7.95	1604	14.62	705	8.28	3640	10.05
(alarm calls among songs)	4	0.02	2	0.02	7	0.08	13	0.04
<i>Parus major</i>	27	0.16	0	0.00	0	0.00	27	0.07
<i>Parus ater</i>	1132	6.76	817	7.44	474	5.57	2423	6.69
<i>Parus caeruleus</i>	200	1.19	90	0.82	214	2.51	504	1.39
<i>Regulus ignicapillus</i>	1037	6.19	482	4.39	148	1.74	1667	4.60
<i>Fringilla coelebs</i>	4113	24.56	2534	23.09	4175	49.06	10,822	29.87
(alarm calls among songs)	2015	12.03	496	4.52	649	7.63	3160	8.72
<i>Garrulus glandarius</i>	0	0.00	0	0.00	27	0.32	27	0.07
<i>Phyloscopus collybita</i>	196	1.17	277	2.52	1	0.01	474	1.31
<i>Pyrrhula pyrrhula</i>	0	0.00	1	0.01	4	0.05	5	0.01
<i>Erithacus rubecula</i>	4877	29.12	4117	37.52	2047	24.05	11,041	30.47
(alarm calls among songs)	780	4.66	17	0.15	619	7.27	1416	3.91
<i>Certhia brachydactyla</i>	3	0.02	0	0.00	1	0.01	4	0.01
<i>Turdus philomelos</i>	20	0.12	4	0.04	5	0.06	29	0.08
<i>Dendrocopos minor</i>	0	0.00	14	0.13	0	0.00	14	0.04
<i>Parus sp</i>	6	0.04	7	0.06	5	0.06	18	0.05
Not identified	50	0.30	8	0.07	5	0.06	63	0.17
Total songs	12,992	77.6	9955	90.7	7811	91.8	30,758	84.9
Others (rumors, songs <20 db)	3755	22.42	1019	9.29	699	8.21	5473	15.11
Total	16,747	100	10,974	100	8510	100	36,231	100

vided as Supplementary Content, together with their spectrogram representation (Wavesurfer v.1.8.5 Sjölander and Beskow, 2000).

Only a minimum presence of wind was noticed, and this played a crucial role since its impact on the quality of the recordings could not be avoided, leading to the appearance of false positives in the song extrapolation procedure. The occasional buzz of some insect flights was the only other kind of biogenic sound.

3.2. Avian community characterization

A total of 30,758 vocalizations (10th June: 12,992; 28<sup>th</sup> June: 9955; 19<sup>th</sup> July: 7811) pertaining to 13 species were counted during the three recording sessions, as shown in Table 1. The detailed descriptions of the birds' singing activity at each station is reported in Appendices A, B and C.

Recording sites three and eight were the most active in terms of songs during the 10th June recording session (2099 and 1604 songs, respectively), as were the seventh and fourth sites on 28th June (1678 and 1090 songs) and the eleventh and sixth sites on 19th July (988 and 971 songs).

3.3. Intensities, frequencies and ACI reliability

Recording site four on 10th June had the highest values of frequencies and intensities, while the lowest values were found at site three on 19th July, as reported in Appendix D.

A high correlation coefficient between the ACI values and the number of bird vocalizations ( $r = 0.94$ ;  $p < 0.01$ ) can be seen in the Spearman's rho correlation matrix (Table 2). The frequency bin occurrences and the decibels registered (intensities) were also significantly correlated with bird singing activity, albeit less strongly (respectively,  $r = 0.80$  and  $r = 0.67$ ) (Table 2). Frequencies and intensities were strongly and positively correlated (0.93) and these two

**Table 2**  
Spearman's rho correlation matrix ( $p < 0.01$ ;  $n = 60$ ).

	Songs	ACI	Frequencies	Intensities
Songs	1.00			
ACI	0.94	1.00		
Frequencies	0.80	0.89	1.00	
Intensities	0.67	0.73	0.93	1.00

variables were also significantly correlated with ACI (0.89 and 0.73, respectively).

The number of vocalizations counted by the operator in the 5, 10, 15 and 30 s long temporal windows were all significantly, and increasingly as the time periods lengthened, correlated with the ACI, as set out in Table 3.

4. Discussion and conclusions

Human activities are often the cause of dramatic changes to populations of wild animals, and we therefore need basic information about the extent of this impact if we are to make decisions about the most efficient ways of ensuring their conservation. Although methods and techniques are still a work in progress, the analysis of biotic sounds and their interrelations could produce new interpretations of community coalescence mechanisms and represent a new tool with which to monitor the complexity of the environment (Sueur et al., 2008b).

The bird song census outcomes revealed a community composed of only 13 species, which is less than was expected from such a habitat. Many studies have focused on the effect on wildlife of the noise caused by traffic and cities, demonstrating altered behaviour in different species (Dooling and Popper, 2007; Nemeth and Brumm, 2009; Rheindt, 2003; Slabbekoorn and Peet, 2003;). Specifically, Krause (1999) found that an infrequent fly-over of a military jet in the Amazon Basin caused a reduction of the number of creature vocalizations. In contrast, in our investigated area, and despite the intrusion of airplane noise, we found that the vocalizing species were not apparently influenced, with their singing being undisturbed.

Our census of bird vocalizations provided exact information about the distribution of the singing activities of singular species, but this form of empirical analysis cannot be extended to the mon-

**Table 3**  
Spearman's rho correlation matrix ( $p < 0.01$ ;  $n = 600$ ).

	ACI
Songs 5 s	0.77
Songs 10 s	0.79
Songs 15 s	0.80
Songs 30 s	0.82

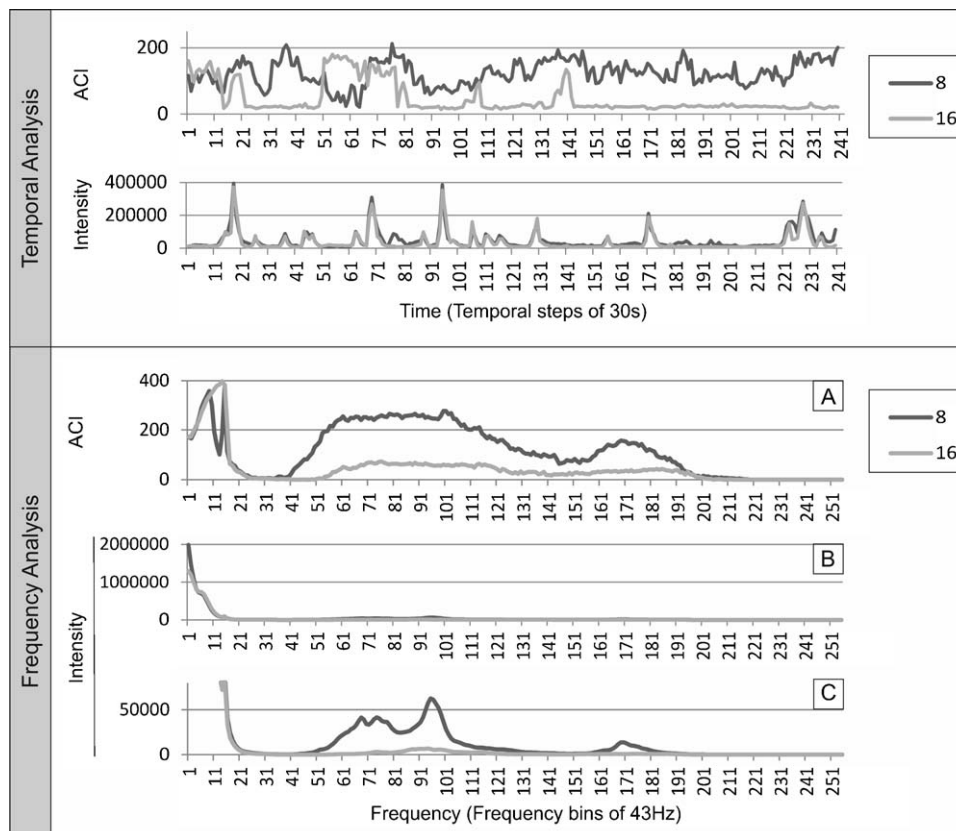
itoring of repeated recording sessions because it is extremely time consuming. Frequency bin occurrence and intensity counts can be used in general investigations, since they also include other sounds (e.g. wind, insects, airplanes) and, consequently, tend to lose their efficiency in studies of the singing activity of birds. Accordingly, as shown in Table 2, both the frequency bin occurrence and intensity counts were significantly correlated with the number of bird songs (respectively,  $r=0.80$ ,  $0.67$ ;  $n=60$ ;  $p<0.01$ ) but less so than in the case of the ACI, which revealed a very strong and positive correlation with the birds' singing activity ( $r=0.94$ ;  $n=60$ ;  $p<0.01$ ).

When our attention was later focused on the behaviour of this index in brief recording intervals, the ACI provided a corroboration of its validity since it was significantly and positively correlated with the number of bird songs in 5, 10, 15, and 30 s long samples. The increase of the correlation from the 5 to the 30 s long recordings is attributed to the logistical procedure that is the outcome when the bird song does not fall entirely within the sample, which was particularly common in the 5 s samples, but was less significant in the longer intervals. In these cases, the fragment of song was noted by the operator as an entire manifestation, while the ACI only measured the intensities of that fragment, causing a discrepancy between the two survey methods.

The strong correlation between the ACI and the singing activity of the avian community is related to the capacity of this index to successfully highlight rapid variations of intensity in each single frequency bin, a feature that is typical of bird song. In contrast, others flat-like sounds, such as insects buzz or other anthropogenic noise (i.e. cars, airplanes, etc.), are characterized by approximately constant levels of intensity, which produce very small ACI values.

In our study site, the biotic part of the soundscape was almost entirely composed by bird vocalizations but the ACI ability to highlight the sounds characterized by different intensity modulations could produce similar results by analysing other species sounds. Our preliminary studies have shown that the human voice and the sounds produced by other organisms (e.g. cicadas) are detected by our index as well. Moreover, strong intensity modulations can be generated even by humans in cities or in any lo-fi soundscape. The horn of a car, a ringing bell, any intermitting anthropic sound as the one of the industries could cause a rapid variation of intensities, and the ACI will register it. Accordingly, the described index should be used preferably in hi-fi soundscapes (*sensu* Schafer, 1977) since, if these sources of noise are present, the ACI analyses would not bring a reliable result. On the other hand, it could be perfect in analyses like the one presented in the paper, where the anthropic noise present in the soundscape is characterized by constant intensities, as the one generated from airplanes or car transits.

In addition, the ACI algorithm computes the relative intensity [the sum of all the  $d_k$  values (differences in intensities) is divided for the total sum of intensities], reducing the variability introduced by the singing organisms being different distances from the recording microphones. Despite this standardization, the index remains moderately sensible at the proximity/remoteness of the sound source and a close sound will result in a higher ACI value than an identical sound emitted in a more distant location. This particular behaviour of the ACI is to refer to the obvious differences of shape, intensity and modularity of the structure of a sound emitted near/distant the microphone. In this way it is possible to evaluate the complexity of the community also pondering its effective proximity at the recording site.



**Fig. 4.** Temporal and frequency analyses (June, 10th 2008, 2 h-length recording n. 8 and 16). Temporal analysis: the ACI immediately highlights the bird singing activity (higher in station n. 8) while the evaluation of the intensities remains strictly connected to the airplane transits. Frequency analysis: the ACI reflects the frequency footprint of the community (A) while the intensities are mostly influenced by airplane noise (B); when cutting the influence of the first noisy frequency bins (C), the intensity investigation shows a discrepancy with the ACI results, since the latter ponders the remoteness/proximity distance to the microphone of the singing birds.

To directly and quickly measure the acoustic complexity of biotic sounds could be helpful to determine changes in behaviour and composition of a community and, consequently, to better monitor animal dynamics and their interaction with their living environment. Accordingly, the ACI could be very effective for any preliminary investigation of the recorded sites in every kind of animal study since the resulting overall picture of the singing community could also be regarded as a useful starting point, which permits a general view of the songs distribution in the investigated territory and allows the examination of only the audio-files in which the ACI highlights significant values. Consequently, it would facilitate finding the best sampling territory and reducing work in the file-processing phase.

The outcomes of the ACI could also be useful to notice the daily dynamics of the biotic community looking at its changes among the different temporal steps of a recording, or to give the frequency footprint of the community when observing its variation in the different frequency bins. In particular, the latter could permit to compare the acoustic niche breath of different communities and to immediately comprehend the presence of certain species with a very specific singing niche (Farina, pers. comm.). Typical examples of both temporal and frequency analyses, compared with the very different results obtained with the simple intensity measures, are shown in Fig. 4.

On the basis of these first results, it can be inferred that this new methodology could be efficiently used in hi-fi soundscape investigations to provide an indirect and immediate measure of avian vocalization dynamics, both in time and space, even when conducted by observers with limited skills in identifying bird song. To test our index with other biotic sounds, to investigate its relationship with different kinds of human noise disturbance and to document if the ACI is able to reduce other kinds of acoustic influences is planned for future research.

We can, therefore, conclude that the ACI could make a useful contribution to bird surveys, providing the researcher with a suitable tool for avian investigations. This index could also provide new possibilities for the monitoring of landscape transformations under the challenges of human development and other actual issues, such as climate and land use changes.

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## Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ecolind.2010.11.005.

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