Biosemiotics (2016) 9:227–246
DOI 10.1007/s12304-016-9266-3

The Application of the Acoustic Complexity Indices (ACI) to Ecoacoustic Event Detection and Identification (EEDI) Modeling

A. Farina[1,2] **· N. Pieretti**[1] **· P. Salutari**[2] **·**
E. Tognari[2] **· A. Lombardi**[2]

Received: 15 January 2016 / Accepted: 22 May 2016 / Published online: 6 June 2016

Abstract In programs of acoustic survey, the amount of data collected and the lack of automatic routines for their classification and interpretation can represent a serious obstacle to achieving quick results. To overcome these obstacles, we are proposing an ecosemiotic model of data mining, ecoacoustic event detection and identification (EEDI), that uses a combination of the acoustic complexity indices ($ACIt_f$, $ACIf_t$, and $ACIf_{te}$) and automatically extracts the ecoacoustic events of interest from the sound files. These events may be indicators of environmental functioning at the scale of individual vocal species (e.g., behavior, phenology, and dynamics), the acoustic community (e.g., dawn and dusk chorus), the sound marks (e.g., the flag species of a community), or the soundscape (e.g., sonotope types). The EEDI model is represented by three procedural steps: 1) selecting acoustic data according to environmental variables, 2) detecting the events by creating an ecoacoustic event space (EES) produced by plotting $ACIf_t$ and its evenness ($ACIf_{te}$), 3) identifying events according to the level of correlation between the acoustic signature ($ACIt_f$) of the detected events and an ad hoc library of previously identified events. The EEDI procedure can be extensively used in basic and applied research. In particular, EEDI may be used in long-term monitoring programs to assess the effect of climate change on individual vocal species behavior (fishes, frogs, birds, mammals, and arthropods), population, and acoustic community dynamics. The EEDI model can be also used to investigate acoustic human intrusion in natural systems and the effect in urban areas.

Electronic supplementary material The online version of this article (doi:10.1007/s12304-016-9266-3) contains supplementary material, which is available to authorized users.

✉ A. Farina
almo.farina@uniurb.it

[1] Department of Pure and Applied Sciences, University of Urbino, Urbino, Italy

[2] International Institute of Ecoacoustics, Fivizzano, Italy

Keywords Acoustic complexity index · Ecoacoustic events · Biosemiotics · Data mining · Acoustics soundscape explorer

Introduction

Soundscapes (Pijanowski et al. 2011), their functional sub-units, sonotopes (Farina 2014, p. 16–17), and acoustic communities (Farina and James 2016), are highly dynamic emergent patterns of the acoustic activity of physical (geophonic), biological (biophonic), and anthropogenic (technophonic) agents. These patterns respond to several environmental variables (Farina 2014), resulting in important indicators of the degree of ecosystem complexity and functioning. In particular, sound is used by many organisms as a carrier of meaning to assure intra- and interspecific communication, to memorize their acoustic umwelt (sensu von Uexküll 1982), and to navigate across their individual-based cognitive landscape (sensu Farina 2010, p. 19).

Ecoacoustics, a recent field of ecology, investigates the ecological role of sounds from individual to landscape scale using a passive noninvasive recording methodology and has been defined by Sueur and Farina (2015) as "a theoretical and applied discipline that studies the sounds emanating from natural systems along a broad range of spatial and temporal scales in order to tackle biodiversity and ecological questions."

Ecoacoustics offers a broad spectrum of theoretical and applied possibilities for ecological research. For instance, it may detect community diversity and daily dynamics of individual species, populations, and communities (Sueur et al. 2008a; Depraetere et al. 2012; Gasc et al. 2013). It represents an efficient tool to explore the relationship between environmental variables like temperature, humidity, light, and the acoustic activity of species, and it reports the functioning of animal aggregations under different disturbance regimes like climate change, land use change, or landscape degradation (Llusia et al. 2013; Krause and Farina 2016). The acoustic behavior that requires conspicuous energetic investment for individual species (Gillooly and Ophir 2010) is strictly related to the health status of ecosystems and for this it can be used as proxy for landscape assessment, planning and design (Joo et al. 2011; Bormpoudakis et al. 2013; Tucker et al. 2014), and long-term monitoring (Bardeli et al. 2010). In the conservation field, ecoacoustics can help detect the first stress signals of species as a consequence of human effects on ecosystems (Brandes 2008; Monacchi 2014; Harris et al. 2016).

To process the acoustic information according to an ecological perspective, new metrics have been successfully tested and applied in different environmental conditions (Gage et al. 2001; Sueur et al. 2008a; Gage and Axel 2014; Sueur et al. 2014; Towsey et al. 2014; Fuller et al. 2015).

However, the difficulty to assign appropriate meaning of the acoustic information when processed by current ecoacoustic metrics and the prohibitive time required to process big data remain problematic and unresolved topics. Unlike bioacoustics analysis, where the scale of investigation favors individual sounds and where investigators often do not pay attention to the sonic scene around an audio sensor, in ecoacoustic analysis, individual sounds are considered part of a sonic context, and the sources of sound are not analyzed in isolation but as part of emergent acoustic patterns that fulfill specific functions. These patterns, although partially intercepted by the ecoacoustic metrics, often remain difficult to interpret. To find a solution to this important aspect, we introduce the concept of the ecoacoustic event, an ecosemiotic tool to interpret the patterns emerging from sonic context.

Furthermore, in the ecoacoustic investigation, time is expanded, covering seasonal or yearly periods. The exigency to investigate for long periods of time causes a dramatic accumulation of acoustic data, which represents a challenge for researchers that intend to relate acoustic patterns to environmental processes. The processing of such big data requires a great amount of computational time that often forces investigators to adopt a sampling strategy instead of continuous surveys (Winner et al. 2013; Pieretti et al. 2015).

The aim of this paper is to face both the problems of introducing the concept of an ecoacoustic event as an agent of an ecosemiotic process (sensu Maran and Kull 2014) and to describe in detail the Acoustic Complexity Index (ACI) as a tool to detect and identify ecoacoustic events.

The ACI (Farina and Morri 2008; Pieretti et al. 2011), now renamed $ACIt_f$, is powered with the new index $ACIf_t$ (formally presented here for the first time), which includes the metrics proposed to process acoustic files and execute the ecoacoustic event detection and identification procedure (EEDI). At the same time, we propose a dedicated software (SoundscapeMeter 2.0) (Farina and Salutari 2016) to accelerate the computational processes.

Materials

To test and validate ACI metrics and describe the EEDI procedure with empirical cases, we have selected four recording stations located in the northern part of Tuscany (Italy): Carpaneta, Madonna Colli (1), Madonna Colli (2), and Agnino, characterized by sub-Mediterranean shrub lands. More details about the localities and recording sessions are reported in Table 1.

Four Soundscape Explorer (terrestrial) SET digital recorders (Lunilettronik, Fivizzano, Italy) were used to collect acoustic information at a sampling frequency of 48 kHz. On-board ACI metrics, applied in real time, were set with a background filter of 8 amplitude and a clumping of 1 s. The fast Fourier transform (FFT) window was fixed at 1024 points, obtaining 512 frequency bins. Acoustic files were collected from the 4th to the 16th of October 2015, for one minute during every five minutes (240 files a day), with a total of 8640 files processed (all localities included). An additional day

Table 1 Geographic position and altitude of the four localities and number of days of 240 daily recording sessions

Locality	Latitude	Longitude	Height a.s.l.	October 2015: Days
Carpaneta	44°13′33.94″N	10°07′09.56″E	284	4,5,6,7,8,9,11,12
Madonna Colli (1)	44°12′34.94″N	10°03′37.98″E	230	4,5,6,11,12,13,14,15,16
Madonna Colli (2)	44°12′47.77″N	10°03′26.82″E	250	4,5,6,12,13,14,15,16
Agnino	44°14′12.32″N	10°04′16.17”E	255	4,5,6,7,8,10,11,12,13,14,15, 21*

*December 21, 2015

from the Agnino location (December 21, 2015) has been used to present a further example of the EEDI procedure.

The beta release of the Soundscape Meter 2.0 (Farina and Salutari 2016) after the incorporation of the EEDI model has been applied to process the data.

The Ecoacoustic Events: Definition

Ecoacoustic events are emergent sonic patterns that are recognized by individual species during the completion of a specific function. Ecoacoustic events are incorporated into the eco-field theory (Farina and Belgrano 2004; Farina and Belgrano 2006). Their detection is a common practice in different fields of theoretical and applied acoustics (e.g., Mesaros et al. 2010; Zhuang et al. 2010; Heittola et al. 2011), although difficulties remain to complete the event identification due to the polyphonic nature of the signals present.

Definitively, categorizing acoustic events is not a simple *anatomy of sounds* or a descriptive exercise, but assuming that events have meaning not only for humans but also for other organisms, the detection and identification of functional units has become central in ecoacoustic analysis as well as a true challenge in ecosemiotic research. According to this perspective, acoustic events are not simply a description of some distinct characteristics that can be isolated and categorized from an indistinct background (Ma et al. 2006) but are functional agents actively used by organisms to fulfill specific functions. Therefore, in our narrative, we consider such events to be delimited by ecological roles and name them ecoacoustic events.

This vision is coincident with the ecosemiotic model of the (acoustic) eco-field (Farina and Belgrano 2004; Farina and Belgrano 2006), which has been effectively described by formally accepting the triadic mechanism of the Peirce semiosis. This model considers a sound collection (summation of individual sounds) as a spatial configuration carrier of meaning, the *representamen* that is used by a *representant* (the function, sensu Farina and Belgrano 2004; Farina and Belgrano 2006) to recognize the *object* that is requested to locate resources (e.g., territory, nesting site, roosting, presence of predators, and location of food resources) (Farina 2008).

According to this perspective, ecoacoustic events assume a central role inside the ecoacoustic narrative and justify the efforts to open a specific field of investigation inside ecoacoustics, providing a robust quantitative tool for developing ecosemiotic studies. Ecoacoustic events are scale dependent; they exist along a broad range of temporal scales. For instance, Ma et al. (2006) argued that a background noise is simply the summation of events that happen at finer temporal granularities.

Ecoacoustic events may be represented by broad categories of sounds, such as thunders, blasts, rifle shots, horns, different typologies of wind and rain, alarm calls of birds, morning and dusk animal choruses, silence, human voices, road traffic, or their combination, that result in some meaning for a listener and that produce an interruption or an invasion of the soundscape. The basic difference between the concept of events in social sciences and in ecological sciences consists of the typology of the sounds that are considered events, although some cases (e.g., the human voice), at least formally, are coincident to both epistemologies. The category to which we can assign an event depends on the goal of the classification. Consequently, the categories are variable and can change accordingly. In the ecological analysis of sounds, detection and identification of ecoacoustic events represent an important step forward.

The Acoustic Complexity Index

The ACI metrics, like other metrics operating in ecoacoustics, are based on the assumption that there is a strict relationship between the complexity of animal assemblages in the landscape or inside a community and the spectral and temporal complexity of a soundscape or, at a more detailed spatial scale, of an acoustic community. This means that more individuals and/or more species are present in a location and the acoustic information expressed by ACI metrics is greater (Farina et al. 2011).

The ACI algorithm was written in the 2008 by one of us (FA) and applied by Davide Morri a graduate student of Urbino University (Institute of Biomatematics) in a PhD project (Morri 2008; Farina and Morri 2008), later improved and tested by Pieretti et al. (2011) and successively applied both in terrestrial habitats (Farina et al. 2011; Farina et al. 2013; Pieretti and Farina 2013; Lozano et al. 2014; Bobryk et al. 2015; Duarte et al. 2015; Farina 2015) and in marine system (McWilliam and Hawkins 2013; Staaterman et al. 2013; Kaplan et al. 2015). Recently has been also applied in neurophysiological responses to musical stimuli (Jancke et al. 2015).

The ACI has been used to process data from different ecoregions: Madagascar (Farina in prep.), Brazil (Duarte et al. 2015; Pieretti et al. 2015), Mediterranean Europe (Farina et al. 2011; Farina et al. 2013), California (Krause and Farina 2016), Temperate Neartic (Bobryk et al. 2015), and Australia (Towsey et al. 2014).

The ACI has been included in WaveSurfer software (Sjolander and Beskow 2000) as SoundscapeMeter 1.0 plug-in (Farina et al. 2012) and later the ACI algorithm was included in the SeeWave software (Sueur et al. 2008b). More recently, it has been used for automated processing inside Soundscape Explorer [Terrestrial] (SET) (Lunilettronik), a new device that belongs to the category of low cost recorders (sensu Farina et al. 2014), that automatically analyzes soundscapes and acoustic communities powered by SoundscapeMeter 2.0 software (Farina and Salutari 2016).

The ACI that is applied without a logarithm conversion to the numerical expression of a FFT conversion that is utilized when the FFT output is expressed in decibels is a measure of the variation of the amplitude between the following:

a). a couple of pulses along a specific frequency bin (ACI, here named $ACIt_f$) and
b). a couple of pulses across frequencies along the same temporal interval ($ACIf_t$) (Fig. 1a).

Both measures are computed simultaneously along a temporal interval chosen according to the requirements of the research (e.g., 1 min, 5 min, and so on). The size of the frequency bin depends on the sampling frequency and the adopted FFT window.

The $ACIt_f$ is considered a reasonable proxy to assess the acoustic complexity/information embedded in an acoustic file (Pieretti et al. 2011) and $ACIf_t$ should a further important companion to describe the acoustic complexity (Fig. 1b). Definitively, when an acoustic sequence of pulses has low differences in amplitude, $ACIt_f$ and $ACIf_t$

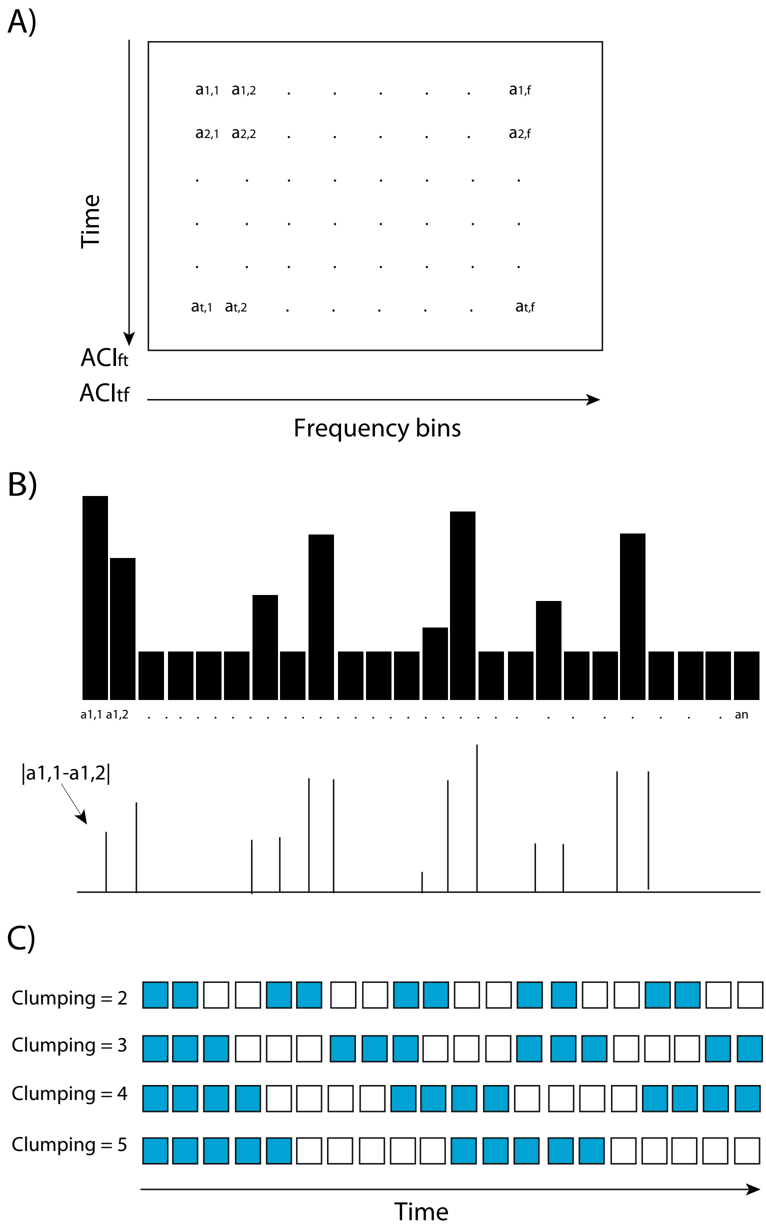

Fig. 1 **a** Numerical matrix as FFT output: *x*-axis frequency bins, *y*-axis time; **b** Confrontation between pulses along a frequency bin ($ACIt_f$); C) Clumping aggregation categories to calculate $ACIt_f$

are expected to be low (small information), reaching zero when adjacent pulses have the same amplitude.

To be applied in a more appropriate way (e.g., searching for patterns), $ACIt_f$ requires an aggregation of data (clumping). In fact, in the analysis of complex patterns of biological or ecological origin, often it is necessary to operate at a higher scale of temporal resolution

(O'Neill et al. 1986). More recurrent amplitudes will dominate in higher clumping. On the other hand, more singularities will emerge with smaller clumping. The temporal scaling of the clumping (Fig. 1c) consists of the repartition of an entire temporal sequence of pulses (e.g., 1 min), in temporal segments of equal length (e.g., 1 s). The $ACIt_f$ values are different according to the clumping size; $ACIt_f$ decreases with the increase of the clumping size (higher clump size and more data in the denominator lower the value of the $ACIt_f$). The complete (explicit) equation for $ACIt_f$ for each frequency bin *f*, where the clumping option is considered, can be represented as follows:

$$\mathrm{ACIt_f} = \sum_{k=1}^{c} \left(\frac{\sum_{i=1}^{\frac{t}{c}} \left| a_{i,j} - a_{i+1,j} \right|}{\sum_{i-1}^{\frac{t}{c}} a_{i,j}} \right)$$

where $a_{i,j}$ is the FFT numerical output, t is the number of temporal steps in which a file is subdivided after FFT, f is the frequency bin, c is the number of clumps in the recording, and t/c is the number of elements composing a clump.

The clumping has nonlinear behavior along the frequency spectrum because it is affected by the structure of the acoustic matrix. When the acoustic matrix has more zero values along the frequency bins, the variation of $ACIt_f$ due to a different clumping size is more modest (see Fig. 2a in which four clumping categories were confronted for the same spectrogram). In a real spectrogram, low frequencies, at least below 1 kHz, result in a more continuous distribution of pulses $\neq 0$ than the higher frequencies, which may result in several gaps due to a higher number of zero values inside a complex spectrum like the one created by biophonies. Consequently, the $ACIt_f$ value changes more at low frequencies for the different clumping sizes than at higher frequencies, where the clumping size is biased (buffered) by zero values that reduce the numerator and denominator as well.

The clumping operation is not mandatory for ACI metrics, but in our experience, it has demonstrated a more realistic approximation of the acoustic information. The comparison between two $ACIt_f$ calculated with a different clumping value may introduce important biases. To compare two $ACIt_f$ with a different temporal interval (e.g., 1 min versus 2 min), $ACIt_f$ must be averaged resulting in $ACIt_f/t$.

$ACIf_t$ a New Component of the ACI Metric

The $ACIf_t$ measures the information that occurs between two successive frequency bins inside the same temporal step t, such that:

$$\mathrm{ACIft} = \sum_{i=1}^{t} \sum_{j=1}^{f-1} \frac{\left| a_{i,j} - a_{i,j+1} \right|}{\left(a_{i,j} + a_{i,j+1} \right)}$$

where $a_{i,j}$ is the amplitude of each pulse, t is the number of temporal intervals, and f is the frequency bin. The $ACIf_t$ varies according to the temporal steps.

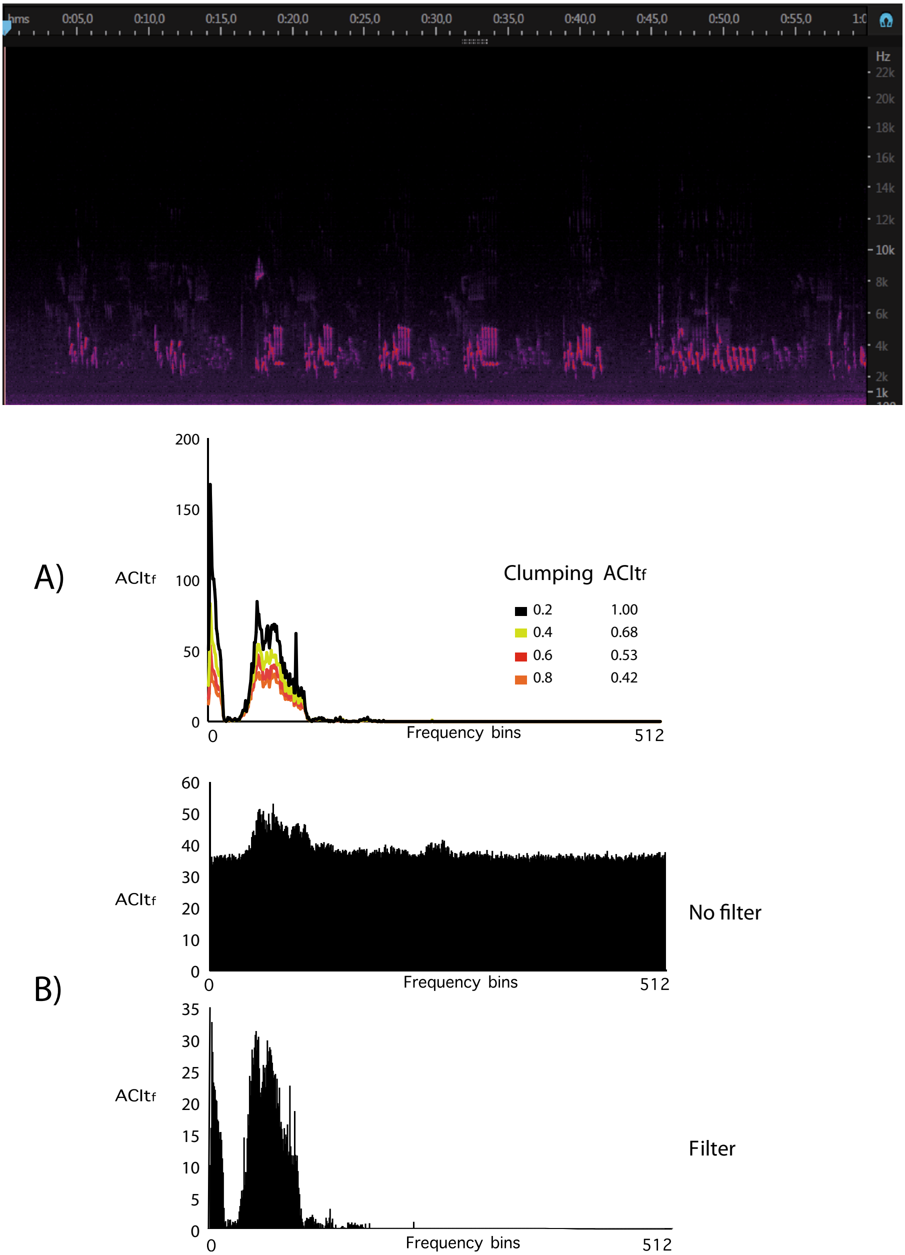

Fig. 2 The spectrogram obtained by one minute of recording (Blackcap (*Sylvia atricapilla*) song) at Carpaneta location on 0619 am of 12 April 2016 is used to illustrate the clumpling procedure and the filter effect. **a** The increase of clumping aggregation reduces the value of $ACIt_f$. This effect is particularly evident for the first frequencies that usually saturate the spectrogram. **b** The application of a filter during the ACIt process allows the elimination of every masking effect due to signal noise. The filter threshold must be selected empirically and is largely due to the quality of microphone capsules

The length of the temporal interval may be fixed equal to the clumping dimension of $ACIt_f$; however, this option is not mandatory. To compare two

$ACIf_t$ with a different temporal interval (e.g., 1 min versus 2 min), the $ACIf_t$ must be averaged, resulting in $ACIf_t/t$.

The $ACIf_t$ is the measure of information present inside an interval of time empirically chosen according to specific purposes. In our experience, 1 min is a good temporal interval to evaluate the instantaneous complexity of a terrestrial acoustic community of birds in a Mediterranean region (see Pieretti et al. 2015 for further discussion). In one minute, operating at a frequency of sampling of 48 kHz and applying a FFT window of 1024 points x 512 frequency bins (46.875 Hz each), there are 2812 elements (lasting 0.021337 s each) on which to make 512 confrontations of the amplitude from which $ACIf_t$ is extracted.

In every spectrogram, due to the low quality of the built-in microphone capsules used in commercial field digital recorders, the errors introduced in analog/digital conversion, and the electronic or electrical noise of circuits, the signal-to-noise ratio (SNR) may be quite low. To work appropriately, both metrics ($ACIt_f$, $ACIf_t$) require the application of a filter to exclude pulses below an empirically-fixed amplitude threshold attributed to non-environmental sounds. Such a filter is applied to the entire spectrogram, considering every pulse with an amplitude lower than a specific threshold to be zero. This amplitude threshold (represented by the real component of the FFT) corresponds to the $mVolt^2/Hz$ of the analogic device and is evaluated empirically by an experienced operator. Figures 2a, b illustrate an example of the application of ACI to wave files with and without the filter.

After the application of an amplitude filter to eliminate the background noise present in the FFT matrix, zero values will appear beside the zero values due to the absence of pulses in the unmodified file. Based on the difference between the two elements of the spectral matrix in the cases in which there is a pulse distribution such as … 0, 5, 0, 9, 0 … (where zero may be the absence of a signal or the presence of a value below the threshold) every difference from zero produces a ratio equal to one (e.g., $|(0–5)|/(0 + 5) = 1$, $|(0–9)|/(0 + 9) = 1$) that could be expressed as the max novelty, but this is extraneous to our goal, which is focused on the assessment of the difference of amplitude inside a signal structure and not between this structure and its background. To eliminate this possible unwanted information, the model automatically explores the FFT numerical matrix; it detects these cases in which the comparison between two pulses of which one has a value of zero and excludes them from the numerator of the algorithm. This means that in a sequence like this: … 2, 5, 0, 4, 0, 9, 0, 6, 8, 0… (for simplicity, we have used the value of a hypothetical amplitude from zero to nine without overlap between two successive clumps), after a clumping fixed equal to five, for the number of data to be considered in each of the two resulting clumps (… [2, 5, 0, 4, 0] [9, 0, 6, 8, 0]…), the algorithm will be $ACIt_f = [|2–5|/(2 + 5 + 4)] + [|6–8|/(9 + 6 + 8)]$, and at the numerator [4] (in the first clump) and [9] (in the second clump) values have not been considered at all because they have no value to be confronted on at least one of their sides.

$ACIt_f$ versus $ACIf_t$

The $ACIt_f$ and $ACIf_t$ are weakly correlated (Pearson's r) when sorted according to their values, and the correlation becomes dramatically weak with the decrease of the $ACIt_f$ or of the $ACIf_t$ values, for instance in $n = 8392$ cases of our data set, sorted by $ACIt_f$ (first quartile r = .91, $p < 0.05$; second quartile r = .12, $p < 0.05$; third quartile r = .02, ns; fourth quartile $r = -.03$, ns). This may be interpreted by a similar amount of information that $ACIt_f$ and $ACIf_t$ have in presence of saturated spectra (due to geophonies or technophonies), but these two indices diverge when the spectrum is less dense. This generally happens when there are biophonic signals that usually have different patterns according to time or frequency orientation. This confirms that the two indices extract different aspects of acoustic information. In this way, $ACIt_f$ and $ACIf_t$ are used with their specific explicit attributes (e.g., $ACIt_f$: distribution of frequencies to build the acoustic signature and $ACIf_t$: distribution of acoustic information along time).

The Evenness of ACI Metrics

Evenness, equidistribution, or equitability is a measure of the repartition of the number of animals, resources, or energy categories in a collection (Lloyd and Ghelardi 1964; Hill 1973; Whittaker 1975). Several metrics have calculated this index, which has an important application in population and community ecology (e.g., Levins 1968; Hill 1973; Heip 1974; Hurlbert 1978; Peet 1974; Alatalo 1981; Molinari 1989; Bulla 1994; Hill 1997). The application of the evenness metric to the ACI distribution allows evaluation of how frequency classes are distributed along a frequency set ($ACIt_f$) and how the acoustic information is distributed along a specific time lag ($ACIf_t$). The level of evenness of $ACIt_f$ and $ACIf_t$ has been calculated using the Levins evenness B (Levins 1968; Hurlbert 1978):

$$B = \frac{1}{\sum_{i-1}^{t} P_i^2}$$

where p_i is the importance of ACI in each frequency bin f ($ACIt_f$) or in each temporal Step t ($ACIf_t$). The standardized measure is

$$ACI_e = \frac{B-1}{t-1}$$

This measure ranges from zero to one. When information is equally distributed in all the classes of frequencies according to the FFT setting in which $ACIt_{fe}$ max is 1/512 (if the FFT window size is fixed at 1024), $ACIt_{fe}$ is one.

The $ACIf_{te}$ is low when only a few acoustic events are present along the temporal step considered (e.g., 1 min). The $ACIf_{te}$ is equal to one when $ACIf_t$ is equally distributed in all the temporal steps. For instance, operating at a sampling frequency of 48 kHz for 1 min with an FFT window of 1024 points, we obtain 2812 temporal steps. In this case, the ACIfte max is 1/2812.

The $ACIt_f$ is well correlated with $ACIt_{fe}$ (Pearson's $r = 0.90$, $p < 0.05$, $n = 7920$), but $ACIf_t$ and $ACIf_{te}$ show weak dependence (Pearson's $r = 0.25$, $p < 0.05$, $n = 7920$).

These last two metrics seem good candidates to be used for the detection of the acoustic events, as better explained in the next section.

Ecoacoustic Event Detection and Identification (EEDI)

The philosophy of the EEDI is based on the possibility of restricting the analysis of the acoustics files, excluding all the conditions about which we have no interest to investigate, reducing the computational effort by selecting the threshold to apply environmental variables, such as temperature, light, humidity, or daily time to ACI metrics.

The EEDI model is based on three steps. The first step selects the environmental variables (time, temperature, light, or humidity) according to an empirical threshold. The second step detects an event after the confrontation between $ACIf_t$ and $ACIf_{te}$ according an empirical threshold, and the third step identifies an event after the computation of the level of correlation/similarity between the detected event(s) and the acoustic signatures of the library (Fig. 3). The use of thresholds is necessary to filter out conditions from which it is difficult to extract meaningful information or simply when we decide to consider or exclude a specific category of events, such as geophonies (e.g., wind or rain) or technophonies (e.g., road traffic or airplanes).

After the selection of files associated with certain environmental conditions, such as temperature and light, the plot of $ACIf_t$ x $ACIf_{te}$ creates an ecoacoustic event space (EES). This space may be divided into four nominal quadrants or regions, where each quadrant is characterized by a different distribution of $ACIf_t$ and $ACIf_{te}$. To simplify, the quadrants have been indicated according to a geographical nomenclature: first quadrant (NW), second quadrant (NE), third quadrant (SE), and fourth quadrant (SW) (Table 2, Fig. 4).

The first quadrant (NW) is characterized by low $ACIf_t$ and high $ACIf_{te}$ (e.g., biophonies at low amplitude but at high evenness, such as a cricket song). The second quadrant (NE) is characterized by high $ACIf_t$ and high $ACIf_{te}$ (e.g., geophonies, such as strong wind and heavy rain that are distributed regularly along the time axis). The third quadrant (SE) is characterized by high $ACIf_t$ and low $ACIf_{te}$ (e.g., short technophonies at high amplitude, such as a jet at low altitude, or a geophony, such as thunder). The fourth quadrant (SW) is characterized by low $ACIf_t$ and low $ACIf_{te}$ (e.g., biophonies, such as isolated alarm calls). Each combination of $ACIf_t$ and $ACIf_{te}$ potentially corresponds to a real case of an ecoacoustic event.

After the events have been detected according to an established threshold (in this case: ACIft >10 or ACIfte < 0.7), they must be identified. This further step requires the use of suitable libraries of known events. Such libraries are created from aural identifications of a specific event, and the acoustic signature ($ACIt_f$) of the event is compared with the acoustic signature of every detected event. The Pearson correlation, chord distance (Orloci 1967), and Whittaker's index of association (Whittaker 1952) are some of the possible metrics to test the relationship between the detected events and the library.

Figure 4 reports an example from the Agnino location collected on October 4, 2015. In this case, three events have been selected by way of example. The first corresponds to heavy rain, and a second event corresponds to the European robin (*Erithacus*

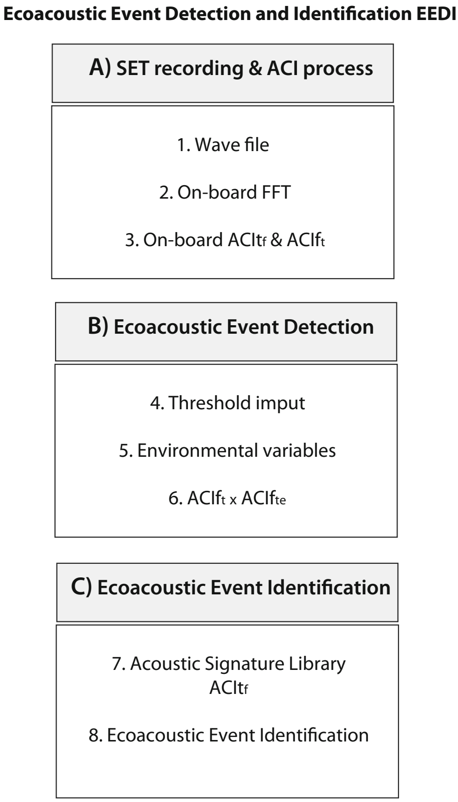

Fig. 3 The EEDI comprises three steps: **a** Recording and on-board FFT and ACI processing, **b** Ecoacoustic event detection, and **c** Ecoacoustic event identification

rubecula) call in the presence of light rain, while a third event is characterized by the European robin alarm calls without background noise. The acoustic signature shows very well the different distributions of $ACIt_f$ along the frequencies.

The identification of the selected patterns is made by comparing different groups of detected events with a library of selected events. In Fig. 5, examples show an aggregation of events of the NE and SW quadrants, which are identified as rain and the European robin call.

A second example from the same location is reported in Fig. 6. In this last case, few events are discriminated in the EES of which the two extremes are moderate rain (NE quadrant) and an isolated alarm call of the European blackbird (*Turdus merula*) (SW quadrant), respectively. The value of $ACIf_t$ is a quarter of the $ACIf_t$ found in October in

Table 2 Tentative distribution in the acoustic event space (EES) of the major categories of acoustic events

I	NW	High $ACIf_{te}$	Low $ACIf_t$	Several biophonies with low amplitude (far chorus)
II	NE	High $ACIf_{te}$	High $ACIf_t$	Geophonies with high amplitude (strong wind, heavy rain)
III	SW	Low $ACIf_{te}$	Low $ACIf_t$	Rare biophonies (individual species call or song) at low amplitude
IV	SE	Low $ACIf_{te}$	High $ACIf_t$	Biophonies at high amplitude (near chorus)

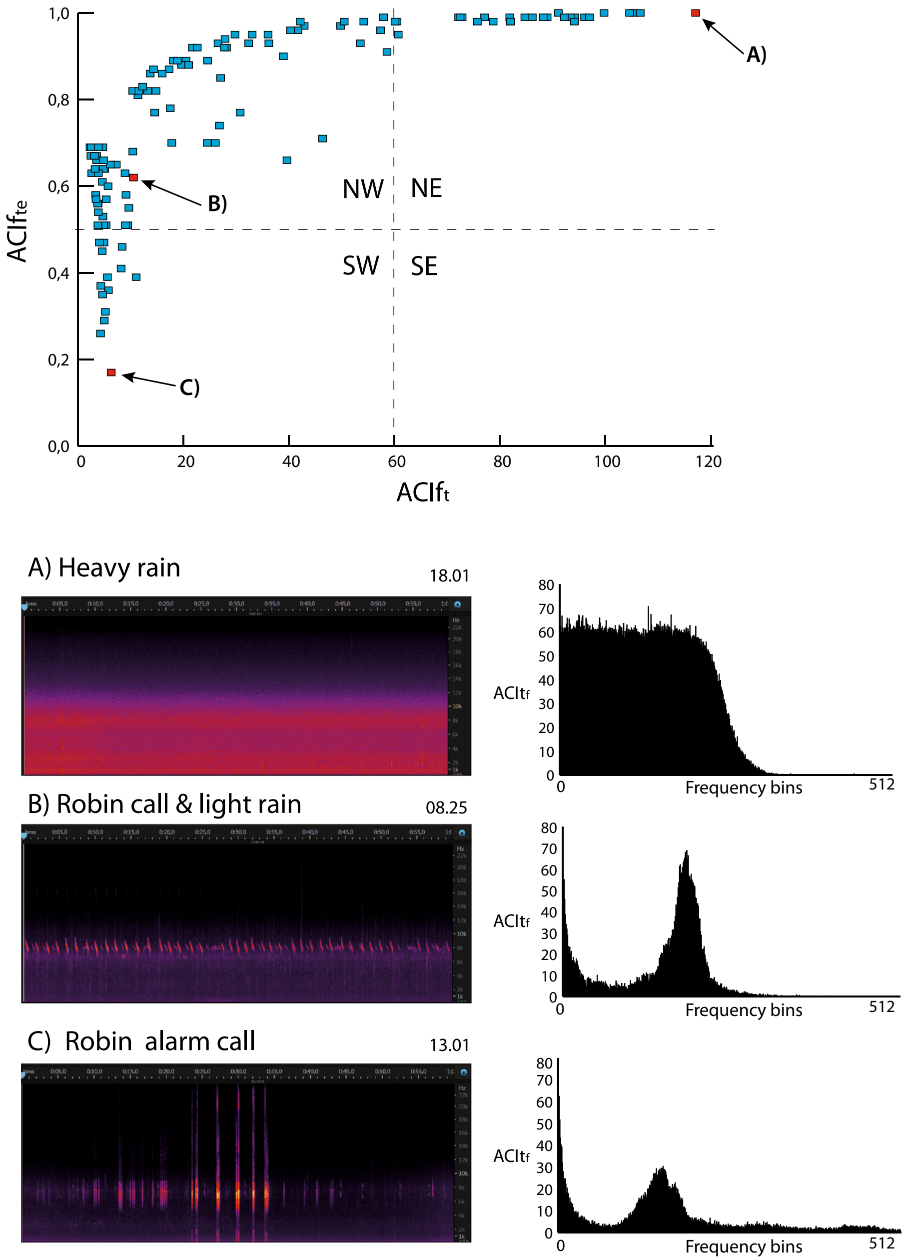

Fig. 4 Example of an EEDI applied on October 4, 2015 (Agnino, 44° 14′ 12.32″ N, 10° 0416.17″ E). The threshold of $ACIf_t$, fixed at >10, $ACIf_{te}$ < 0.7, has detected 127 cases on 240 when these conditions are respected separately. If the two thresholds are respected at the same time, only four cases are found. Three cases selected with the criterion to evaluate the two extremes (Heavy rain, robin alarm call) and an event in the middle (Robin call & light rain) are reported. At the side of each spectrogram the acoustic signature of each event is reported

the same location, and this is due to the reduction of biophonic activity of birds and less rain in December 2015.

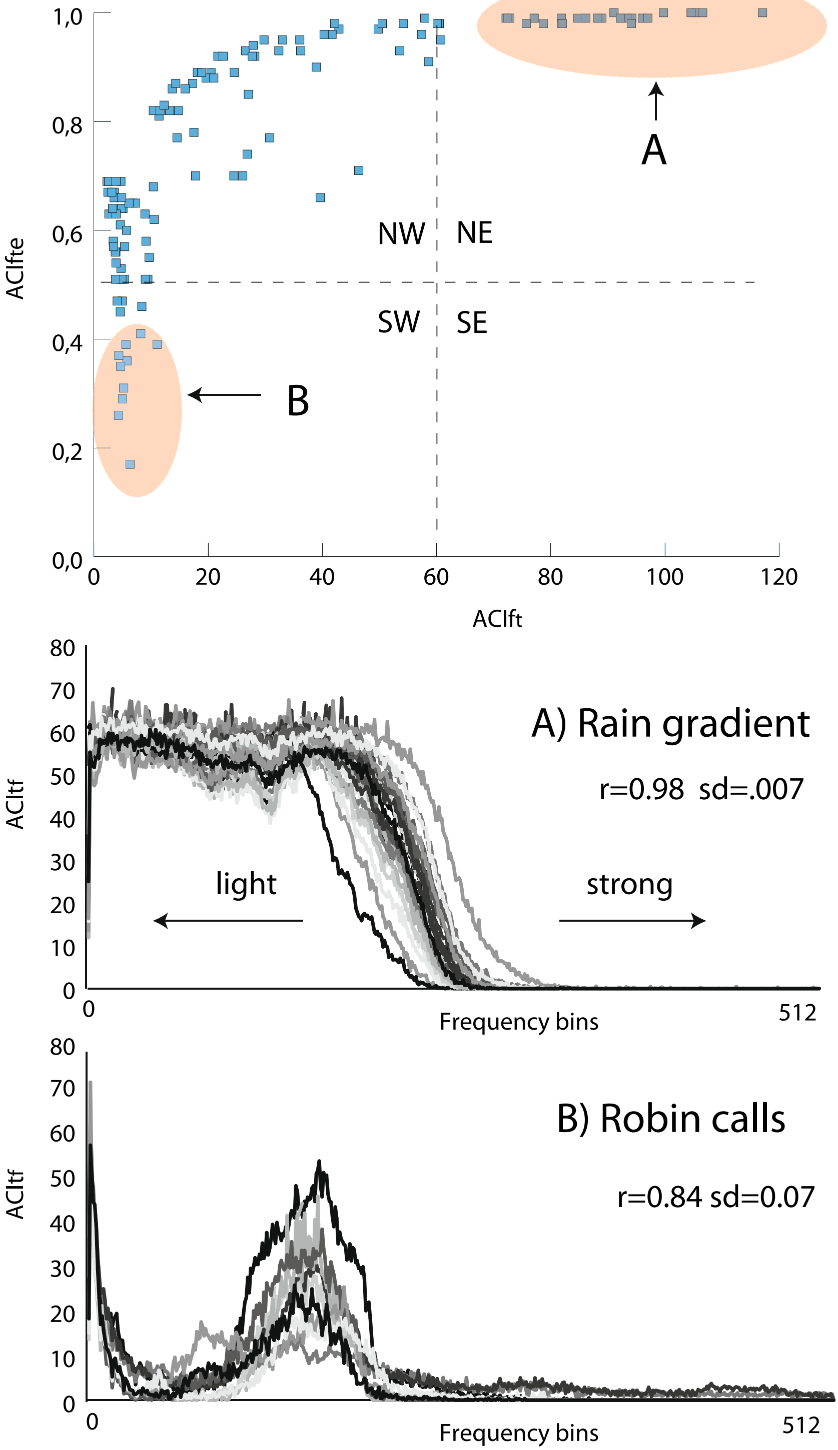
1,0
0,8
0,6
0,4
0,2
0,0
0
20
40
60
80
100
120
ACIfte
ACIft
NW
NE
SW
SE
A
B
80
70
60
50
40
30
20
10
0
ACItf
A) Rain gradient
r=0.98 sd=.007
light
strong
0
Frequency bins
512
80
70
60
50
40
30
20
10
0
ACItf
B) Robin calls
r=0.84 sd=0.07
0
Frequency bins
512

Fig. 5 From the example of Fig. 4, the acoustic signature of a group of events $ACIf_{te}$ values (rain gradient) **a** and with similar $ACIf_t$ (robin calls) **b** and the value of the *r* correlation inside each group are reported

We have applied the same conditions (ACIft >10 or ACIfte < 0.7) to the 36 days of total recording (all locations) obtaining 3000 (34 %) events in total of the possible 8640 events. The 36 EES obtained using these criteria are reported in the supplementary material for the four locations (Fig. 1 suppl.). From these data, it emerges that the majority of biophonies in this period of the year are confined below a value of $ACIf_t$ of 10. The highest value of $ACIf_t$ (100) has been obtained only during heavy rains. Rain or wind events range from 10 to 100 $ACIf_t$ according to intensity, but they are discriminated by a value of $ACIf_{te}$ close its max, which is one.

Discussion and Conclusions

The acoustic environment is rich in underexploited sources of information (Ma et al. 2006), and EEDI offers a new opportunity to model the acoustic information decoded by $ACIf_t$ and $ACIt_f$ metrics with the use of environmental parameters that are automatically associated with the acoustic data (e.g., light intensity, temperature, humidity, atmospheric pressure, and time of day). In this way, we can select the files according to one variable (e.g., light versus dark or cold versus warm) or according to a combination (e.g., warm morning, cold night, etc.) (Table 3).

After this selection, we can select $ACIf_t$ and $ACIf_{te}$ thresholds. The threshold applied to $ACIf_t$ may distinguish an EES, occupied by low or high information. The threshold applied to $ACIf_{te}$ may distinguish how $ACIf_t$ information is aggregated or evenly distributed along time (in this study, for one minute). Finally, the information expressed by $ACIt_f$ allows the production of the acoustic signature of a detected event.

The analysis can be conducted at the soundscape level or at the level of acoustic communities or individual species. At the soundscape level, we can detect geophonies, biophonies, technophonies, or their combinations. In this way, the analysis allows distinguishing the different typologies of sonotopes present around the recording site (Farina 2014, p. 17–18), although it remains problematic to produce good libraries of these components of a soundscape. At the level of acoustic community, the model may consider special events, such as the dawn or dusk chorus. To have a more precise idea of how active an acoustic community is, we can simply measure the number of events that the EEDI model detects as biophonies. At the level of single species, it is possible to investigate the daily dynamics or the presence of an isolated sound as in the example reported in Fig. 6.

The EEDI model enables the analysis of long-term monitoring data regarding biophonies produced by vocal animals (fishes, frogs, birds, mammals, and arthropods), but the possible applications of EEDI are several, and they are largely dependent on the target of the research. For instance, the EEDI model can detect the amount of ice calving and ice melting in the polar seas.

In the examples illustrated here, the application of a model, where $ACIf_t$ ranges from 10 to 100 and where $ACIf_{te}$ ranges from .7 to 1, makes it possible to find rainy or windy events that could be excluded in the case of a bioacoustics target. To search for acoustically rare species, we must select files with extremely low $ACIf_{te}$ associated with a very low $ACIf_t$.

If we want to discover how many civil aircrafts fly over the sampled area, we can select events characterized by low $ACIf_t$ (usually airplanes far from an airport have a low amplitude sound and a high $ACIf_{te}$ because the sound is constant along the interval of time considered, e.g., one minute). The EEDI model can be used to test the efficiency of soundscape categorization (classification) in different landscapes,

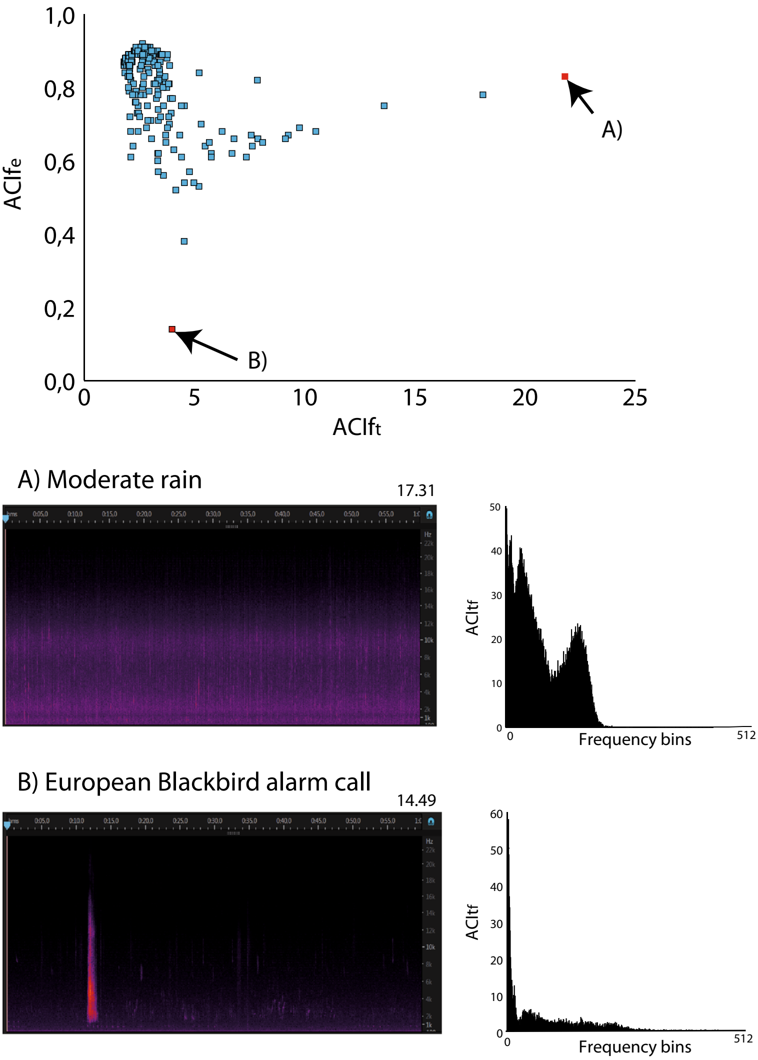

Fig. 6 Example of an EEDI applied on December 21, 2015 (Agnino, 44° 14′ 12.32″ N, 10° 0416.17″ E). The threshold of $ACIf_t$ was fixed at >10, $ACIf_{te}$ < 0.7, these conditions are respected separately. This day is characterized by low bird activity and light rain. In **a** moderate rain event) and in **b** European blackbird (*Turdus merula*) alarm call event. On their side the acoustic signature ($ACIt_f$)

Table 3 Possible applications of the EEDI procedure to ecological research, nature conservation, climate change, and human intrusion in natural environments. Small size, optional variables to put in the EEDI model

Event	Variables						Application
	Lux	C°	Hum	$ACIf_t$	$ACIf_{te}$	$ACIt_f$	
Geophonies	x	x	x	X	X	X	Soundscape analysis & climate change
Biophonies	x	x	x	X	X	X	Rare specie, endangered species, invasive species
	X	x	x	X	X	X	Acoustic community daily dynamics, individual species daily dynamics
		x	x	X	X	X	Climate change, individual species geographical shift, migration & stop-over dynamics
Extreme climate (e.g., heat waves)	x	X	x	X	X	X	Acoustic community activity, individual species dawn & dusk chorus
Technophonies	x	x	x	X	X	X	Soundscape analysis & social economic variables, individual species & community dynamics

exploring the event diversity as a proxy of the complexity of the land mosaic used by organisms and people.

The choice of the $ACIf_t$ and $ACIf_{te}$ thresholds depends on the geographic areas, the habitats, and the goals. The EEDI model integrates the information of the ACI metrics, moving from the crude data of $ACIt_f$ or $ACIf_t$ to the identification of the possible combinations with which these metrics can express meaningful information, and acts as a new and innovative tool of ecosemiotic investigation.

The model is simple, can be easily applied using a free open-access routine (SoundscapeMeter 2.0, Farina and Salutari 2016), and is particularly adept at analyzing a large amount of acoustic data. In fact, the model can concentrate on focal events, economizing work energy and processing time, excluding all the conditions that we have no interest to investigate. In the future, the entire procedure could be implemented by incorporating other ecoacoustic indices, like the evenness of $ACIt_f$, allowing a more discriminant analysis.

References

Alatalo, R. V. (1981). Problems in the measurement of evenness in ecology. *Oikos, 37*, 199–204.

Bardeli, R., Wolff, D., Kurth, F., Koch, M., & Frommolt, K. H. (2010). Detecting bird sounds in a complex acoustic environment and application to bioacoustic monitoring. *Pattern Recognition Letters, 31*, 1524–1534.

Bobryk, W. C., Rega, C. C., Bardhan, S., Farina, A., He, H. S., & Jose, S. (2015). Utility of soundscape assessment for understanding conservation benefits of temperate agroforestry systems. *Agroforestry Systems*. doi:10.1007/s10457-015-9879-6.

Bormpoudakis, D., Sueur, J., & Pantis, J. (2013). Spatial heterogeneity of ambient sound at the habitat type level: ecological implications and applications. *Landscape Ecology, 28*, 495–506.

Brandes, T. S. (2008). Automated sound recording and analysis techniques for bird surveys and conservation. *Bird Conservation International, 18*, S163–S173.

Bulla, L. (1994). An index of evenness and its associated diversity measure. *Oikos, 70*, 167–171.

Depraetere, M., Pavoine, S., Jiguet, F., Gasc, A., Duvail, S., & Sueur, J. (2012). Monitoring animal diversity using acoustic indices: implementation in a temperate woodland. *Ecological Indicators, 13*, 46–54.

Duarte, M. H. L., Sousa-Lima, R. S., Young, R. J., Farina, A., Vasconcelos, M., Rodrigues, M., & Pieretti, N. (2015). The impact of noise from open-cast mining on Atlantic forest biophony. *Biological Conservation, 191*, 623–631.

Farina, A. (2008). *Ecology, cognition and landscape. Linking natural and social systems*. Dordrecht, NL: Springer.

Farina, A. (2010). *Ecology, cognition and landscape*. Dordrecht, NL: Springer.

Farina, A. (2014). *Soundscape ecology: principles, patterns, methods and applications*. NL: Springer Dordrecht.

Farina, A. (2015). Animals in a noisy world. In R. Tønnessen & A. Oma (Eds.), *Thinking about animals in the age of anthropocene* (pp. 37–52). Rowan & Littlefield: Lexington Books, Lenham, MD, US.

Farina, A., & Belgrano, A. (2004). The eco-field: a new paradigm for landscape ecology. *Ecological Research, 19*(1), 107–110.

Farina, A., & Belgrano, A. (2006). The eco-field hypothesis: toward a cognitive landscape. *Landscape Ecology, 21*(1), 5–17.

Farina, A., & James, P. (2016). Acoustic community structure and dynamics: a fundamental component of acoustics. *Biosystems*. doi:10.1016/j.biosystems.2016.05.011.

Farina, A., & Morri, D. (2008). Source-sink e eco-field: ipotesi ed evidenze sperimentali. *Atti del X congresso nazionale della SIEP-IALE*. Ecologia e governance del paesaggio: esperienze e prospettive. Bari, 365–372.

Farina, A., & Salutari, P. (2016). Applying the ecoacoustic event detection and identification (EEDI) model to the analysis of acoustic complexity. *Journal of Mediterranean Ecology, 14*, 13–42.

Farina, A., Pieretti, N., & Piccioli, L. (2011). The soundscape methodology for long-term bird monitoring: a Mediterranean Europe case-study. *Ecological Informatics, 6*, 354–363.

Farina, A., Lattanzi, E., Piccioli, L., Pieretti, N. (2012). *The SoundscapeMeter*. http://www.disbef.uniurb.it/biomia/soundscapemeter.

Farina, A., Pieretti, N., & Morganti, N. (2013). Acoustic patterns of an invasive species: the red-billed Leiothrix (*Leiothrix lutea* Scopoli 1786) in a Mediterranean shrubland. *Bioacoustics, 22*(3), 175–194.

Farina, A., James, P., Bobryk, C., Pieretti, N., Lattanzi, E., & McWilliam, J. (2014). Low cost (audio) recording (LCR) for advancing soundscape ecology towards the conservation of sonic complexity and biodiversity in natural and urban landscapes. *Urban Ecosystems, 17*, 923–944.

Fuller, S., Axel, A. C., Tucker, D., & Gage, S. H. (2015). Connecting soundscape to landscape: which acoustic index best describe landscape configuration? *Ecological Indicators, 58*, 207–215.

Gage, S. H., & Axel, A. C. (2014). Visualization of temporal change in soundscape power of a Michigan lake habitat over a 4-year period. *Ecological Informatics, 21*, 100–109.

Gage, S. H., Napoletano, B. M., & Cooper, M. C. (2001). Assessment of ecosystem biodiversity by acoustic diversity indices. *The Journal of the Acoustical Society of America, 109*, 2430.

Gasc, A., Sueur, J., Jiguet, F., Devictor, V., Grandcolas, P., Burrow, C., et al. (2013). Assessing biodiversity with sound: do acoustic diversity indices reflect phylogenetic and functional diversities of bird communities? *Ecological Indicators, 25*, 279–287.

Gillooly, J.F., Ophir, A.G., (2010). The energetic basis of acoustic communication. *Proceedings of the Royal Society*, B, 277, 1325–1331.

Harris, S., Shears N. T., & Radford, C. A. (2016). Ecoacoustic indices as proxies for biodiversity on temperate reefs. *Methods in Ecology and Evolution*. doi:10.1111/2041-210X.12527

Heip, C. (1974). A new index measuring evenness. *Journal of the Marine Biological Association of the UK, 54*, 555–557.

Heittola, T., Mesaros, A., Virtanen, T., Eronen, A. (2011). *Sound event detection and context recognition.* CHiME 2011 Workshop on Machine Listening in Multisource Environments.

Hill, M. O. (1973). Diversity and evenness: a unifying notation and its consequences. *Ecology, 54*(2), 427–432.

Hill, M. O. (1997). An evenness statistics based on the abundance-weighted variance of species proportions. *Oikos, 79*, 413–416.

Hurlbert, S. H. (1978). The measurement of niche overlap and some relatives. *Ecology, 59*(1), 66–77.

Jancke, L., Kuhnis, J., Rogenmoser, L., Elmer, S. (2015). Time course of EEG oscillations during repeated listening of a well-known aria. *Frontiers in Human Neuroscience, 9*. doi:10.3389/fnhum.2015.00401.

Joo, W., Gage, S. H., & Kasten, E. P. (2011). Analysis and interpretation of variability in soundscapes along an urban–rural gradient. *Landscape and Urban Planning, 103*, 259–276.

Kaplan, M. B., Mooney, T. A., Partan, J., & Solow, A. R. (2015). Coral reef species assemblages are associated with ambient soundscape. *Marine Ecology Progress Series, 533*, 93–107.

Krause, B., & Farina, A. (2016). Using ecoacoustic methods to survey the impacts of climate change on biodiversity. *Biological Conservation, 195*, 245–253.

Levins, R. (1968). *Evolution in changing environments*. Some theoretical explorations: Princeton University Press, Princeton, New Jersey.

Lloyd, M., & Ghelardi, R. J. (1964). A table for calculating the "equitability" component of species diversity. *Journal of Animal Ecology, 33*, 217–225.

Llusia, D., Marquez, R., Beltran, J. F., Benitez, M., & Do Amara, J. (2013). Calling behaviour under climatic change: geographical and seasonal variation of calling temperatures in ectotherms. *Global Change Biology, 19*, 2655–2674.

Lozano, A., Farina, A., & Márquez, R. (2014). ACI (acoustic complexity index): Nueva herramienta Para el estudio del canto de anuros ACI (acoustic complexity index): a new tool to study anuran calls. *Quehacer Científico en Chiapas, 9*(2), 2014.

Ma, L., Milner, B., & Smith, D. (2006). Acoustic environment classification. *ACM Trans. Speech Language Processing, 3*(2), 1–22.

Maran, T., & Kull, K. (2014). Ecosemiotics: main principles and current developments. *Geografiska Annaler: Series B, Human Geography, 96*, 41–50.

McWilliam, J. N., & Hawkins, A. D. (2013). A comparison of inshore marine soundscapes. *Journal of Experimental Marine Biology and Ecology, 446*, 166–176.

Mesaros, A., Heittola, T., Eronen, A., Virtanen, T. (2010). Acoustic event detection in real-life recordings. *18th European Signal Processing Conference* (*EUSIPCO* 2010), Aalborg, Denmark, Aug. 2010, pp. 1267–1271.

Molinari, J. (1989). A calibrated index for the measurement of evenness. *Oikos, 56*, 319–326.
Monacchi, D. (2014). Fragments of extinction. In *Leonardo Music Journal, 23*. Cambridge, MA: MIT Press.
Morri, D. (2008). *Ecosemiotica e paesaggi sonori*: *nuove teorie e metodologie per l'ecologia*. Unpl. PhD thesis, Università degli Studi di Urbino "Carlo Bo".
O'Neill, R. V., DeAngelis, L., Waide, J. B., & Allen, T. F. H. (1986). *A hierarchical concept of ecosystems*. Princeton, NJ, US: Princeton University Press.
Orloci, L. (1967). An agglomerative method for classification of plant communities. *Journal of Ecology, 55*, 193–205.
Peet, R. K. (1974). The measurements of species diversity. *Annual Review of Ecology, Evolution, and Systematics, 5*, 285–307.
Pieretti, N., & Farina, A. (2013). Application of a recently introduced index for acoustic complexity to an avian soundscape with traffic noise. *The Journal of the Acoustical Society of America, 134*(1), 891–900.
Pieretti, N., Farina, A., & Morri, D. (2011). A new methodology to infer the singing activity of an avian community: the acoustic complexity index (ACI). *Ecological Indicators, 11*, 868–873.
Pieretti, N., Duarte, M. H. L., Sousa-Lima, R. S., Rodrigues, M., Young, R. J., & Farina, A. (2015). Determining temporal sampling schemes for passive acoustic studies in different tropical ecosystems. *Tropical Conservation Science, 8*, 215–234.
Pijanowski, B. C., Villanueva-Rivera, L. J., Dumyahn, S. L., Farin, A., Krause, B. L., Napoletano, B. M., et al. (2011). Soundscape ecology: the science of sound in the landscape. *Bioscience, 61*, 203–216.
Sjolander, K., & Beskow, J. (2000). *WaveSurfer—An open source speech tool*. *Proceedings of the ICSLP, 2000*(4), 464–467.
Staaterman, E., Rice, A. N., Mann, D. A., & Paris, C. B. (2013). Soundscapes from a tropical eastern Pacific reef and a Caribbean Sea reef. *Coral Reefs, 32*, 553–557.
Sueur, J., & Farina, A. (2015). Acoustics: the ecological investigation and interpretation of environmental sound. *Biosemiotics, 8*, 493–502. doi:10.1007/s12304-015-9248-x.
Sueur, J., Pavoine, S., Hamerlynck, O., & Duvail, S. (2008a). Rapid acoustic survey for biodiversity appraisal. *PLoS ONE, 3*, 1–9.
Sueur, J., Aubin, T., & Simonis, C. (2008b). Seewave: a free modular tool for sound analysis and synthesis. *Bioacoustics, 18*, 213–226.
Sueur, J., Farina, A., Gasc, A., Pieretti, N., & Pavoine, S. (2014). Acoustic indices for biodiversity assessment and landscape investigation. *Acta Acustica united with Acustica, 100*, 772–781.
Towsey, M., Wimmer, J., Williamson, I., & Roe, P. (2014). The use of acoustic indices to determine avian species richness in audio-recordings of the environment. *Ecological Informatics, 21*, 110–119.
Tucker, D., Gag, S., Williamson, I., & Fuller, S. (2014). Linking ecological condition and the soundscape in fragmented Australian forests. *Landscape Ecology, 29*, 745–758.
von Uexküll, J. (1982). The theory of meaning. *Semiotica, 42*(1), 25–82.
Whittaker, R. H. (1952). A study of the summer foliage insect communities in the great Smoky Mountains. *Ecological Monographs, 22*, 1–44.
Whittaker, R. H. (1975). *Communities and ecosystems* (Second ed.). Inc. New York: MacMillan Publishing Co..
Winner, J., Towsey, M., Roe, P., & Williamson, I. (2013). Sampling environmental acoustic recordings to determine bird species richness. *Ecological Applications, 23*(6), 1419–1428.
Zhuang, X., Zhiu, X., Hasegawa-Johnson, M. A., & Huang, T. S. (2010). Real-world acoustic event detection. *Pattern Recognition Letters, 31*, 1543–1551.