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RESEARCH ARTICLE

A primer of acoustic analysis for landscape ecologists

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Abstract In this paper we present an introduction to the physical characteristics of sound, basic recording principles as well as several ways to analyze digital sound files using spectrogram analysis. This paper is designed to be a "primer" which we hope will encourage landscape ecologists to study soundscapes. This primer uses data from a long-term study that are analyzed using common software tools. The paper presents these analyses as exercises. Spectrogram analyses are presented here introducing indices familiar to ecologists (e.g., Shannon's diversity, evenness, dominance) and GIS experts (patch analysis). A supplemental online tutorial provides detailed instructions with step by step directions for these exercises. We discuss specific terms when working with digital sound analysis, comment on the state of the art in acoustic analysis and present recommendations for future research.

Keywords Soundscapes · Acoustic analysis · Spectrograms · Entropy · Evenness · Sound patches

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Introduction

Microphones are the universal data collection instruments of bioacousticians (e.g., Marler and Slabbekoorn 2004; Sueur et al. 2008b) and will likely become the key data collection instrument for soundscape ecologists (e.g., Qi et al. 2008; Pijanowski et al. 2011a, b; Farina et al. 2011). Sound recording technology has advanced greatly in recent years mostly due to the commercial success of digital audio technology making it possible to record at multiple sites and long term (Brandes 2005), which is unprecedented. New tools and approaches to analyzing long-term data will be necessary as we move forward to address the myriad of questions related to the ecological significance of soundscape dynamics.

Because soundscape ecology is new, most landscape ecologists are not familiar with recording and analyzing acoustic data. In addition, the field of bioacoustics (cf. Fletcher 2007) are not likely to be fully aware of the approaches utilized by landscape ecologists (Turner et al. 2001; Farina 2006)—that is, our strong spatial perspective and the emphasis on the interplay of pattern and process. The purpose of this paper is to present a primer on sound and acoustic analysis so that landscape ecologists are aware of major concepts and principles of bioacoustics. Likewise, we present example acoustic analyses using the spatial toolkit of geographic information systems (GIS) showing at least one way that bioacoustics may benefit from a landscape ecology approach. We

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present these analyses in a novel format, as separate “exercises”, in an attempt to have this paper serve as an entry point into acoustics for landscape ecologists. Readers of this paper can download these data and tools and then follow step by step instructions in an online tutorial that supplements these exercises. Although they are not comprehensive, the exercises contained herein should provide a sufficient introduction to soundscape ecology to allow landscape ecologists to begin asking interesting questions about the soundscape. We conclude with a short discussion on further references that the learning soundscape ecologist can consult.

What is sound?

A simple sound emitted as a pure tone (Fig. 1) illustrates the features of an idealized sinusoidal wave signal as it travels over time. The length between the peaks of a wave is the wavelength (usually designated as λ), and the size of the wave its peak amplitude. Frequency (f) of the simple sound wave, measured as the number of waveform repetitions per unit time, usually expressed per second or Hertz (Hz), is derived from the wavelength and the speed of sound (v) in the medium (air = 343 m/s) as $f = v/\lambda$.

Intensity is expressed in decibels (or dB) in base 10 units (log), which is a convenient form as human ears can distinguish a billion-fold in intensity of sound (Everest and Pholmann 2009). The dB scale is expressed relative to a reference intensity, usually assigning a value of 0 to the minimum that a human can hear. Some example sounds and corresponding dB levels that they produce are (from Everest and Pholmann 2009): leaves rustling (20 dB), human conversation (60 dB), heavy traffic (80 dB), jet (160 dB), and Saturn rocket (190 dB). The amplitude of the sound wave decreases with the square of the distance from the source (Fig. 2).

Attenuation of sound waves is dependent on features in the landscape (e.g., buildings, trees) as well as their frequency. Sound waves at higher frequencies are absorbed more by leaves and other structures, whereas lower-frequency signals tend to be deflected around such obstacles. This limits the distance that higher-frequency signals can travel relative to lower-frequency signals. Experiments in forests have found that low frequency sounds are attenuated less and can therefore travel farther (Marten and Marler 1977; Marten et al. 1977).

Once a sound signal travels and is received, other factors may determine the accuracy and interpretation of the signal. The tympanum in animals has to be sensitive enough to detect the signal from the small random variations in pressure of the medium. The sensor has a range of acoustic frequencies it can detect, which is determined by the structure of the ear and therefore by the evolution of the organism (Greenfield 1994). Although the brain is extremely adept at separating overlapping signals, multiple sound signals can occasionally interfere with one another. Once the sound is detected, the brain processes the signals received. At this stage, specific signals may be rejected in favor of others (Henry and Lucas 2010) or some additional processing may take place to interpret the sound signal into its information contents (Keller and Hahnloser 2009). For humans, sound frequencies are perceived by the ear as “pitch”. Frequencies and pitch are not the same but are considered analogous (Everest and Pholmann 2009).

In reality, sounds in a landscape are often complex. Multiple sources located in different places in the landscape emit sounds at different times and intensities (Fig. 3). Here, several objects that produce

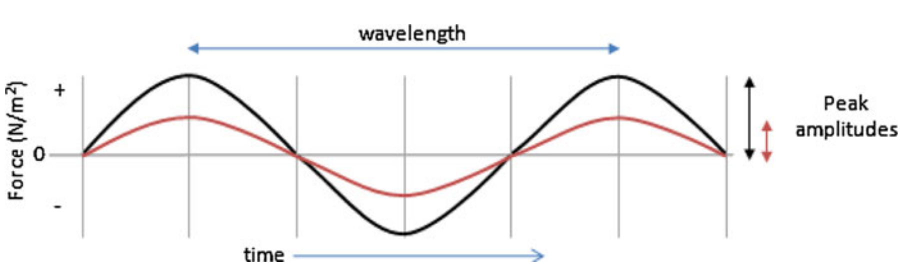

Fig. 1 A basic representation of a sound wave and the measurements taken to describe it. In this example, there are two waves represented by the *lines* of different color. Both waves have the same wavelength but different amplitude

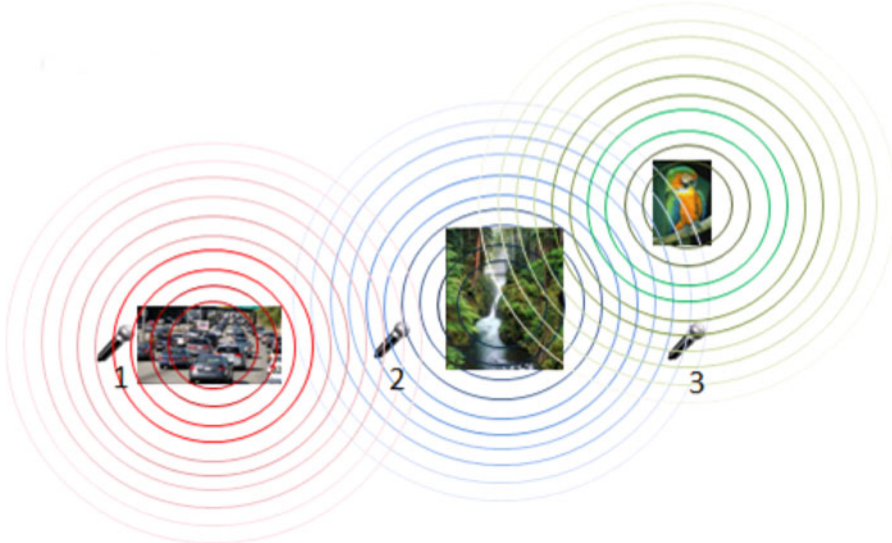

Fig. 2 Representation of a simple soundscape with three sound sources. Depending on the distance at which that each sound can be detected will affect which sensors, represented as numbered microphones, will record

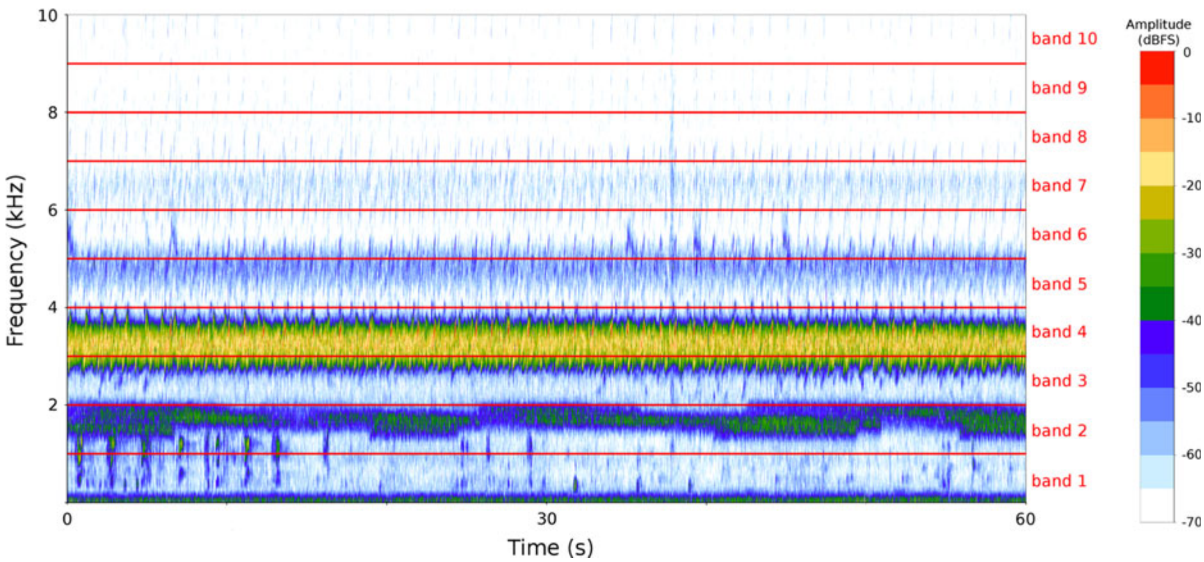

Fig. 3 Spectrogram showing 10 equal spaced frequency bands. Chorusing frogs in Band #4 dominate this recording as do toads in Band #2. Harmonic sounds produced by the chorusing frogs appear in Band #5 and then again in Band #7

sounds, a road, a bird and a stream, are scattered across the landscape, creating multiple sounds at different frequencies. The color shades of the sound waves represent the intensity of sound at that distance with darker (i.e., louder) sounds closer to the sound source. Using the terminology of soundscape ecology, the three main sources of sound (biophony, geophony and anthrophony) are present in this soundscape. Sensor #1 would record only anthrophony, sensor #2 would record sounds from the stream and road (a mixture of geophony and anthrophony), whereas sensor #3 would record the stream (faintly) and bird (hence both biophony and geophony).

How is sound recorded?

Although sound can be recorded in analog or digital formats, digital recorders have largely replaced analog recorders. A digital recorder stores discrete samples of the signal detected at the microphone at thousands of times per second. To properly record a signal requires at least a full cycle of the wave, which limits the maximum acoustic frequency recorded to half of the sampling rate, referred to as the Nyquist frequency. If the sound of interest has an acoustic frequency of 11 kHz, the sampling rate needs to be 22 kHz or greater to detect the high and low peaks of that wave. Since human hearing is limited to a maximum of approximately 20 kHz, most commercial equipment samples the sound at 44.1 kHz, for a Nyquist frequency of 22.05 kHz. Digital systems usually display amplitude as decibels relative to full scale (dBFS), where dBFS of 0 is the maximum amplitude in the digital file while amplitude levels less than the maximum are displayed as negative values.

Digital sound collections may require large storage facilities. As a general guideline, a sound file stored with CD quality (16 bit, 2 channels, at a sampling rate of 44.1 kHz) requires approximately 10 MB per minute of audio. Although compression of the sound file using algorithms like MP3 can reduce the disk space needed, these algorithms remove sounds humans cannot hear, therefore modifying the signal recorded and causing information to be lost. Some signals that are removed may be detected by other animals and the compression would be eliminating it from the file. For these reasons, sound recorded for analysis should be recorded in uncompressed formats, like Microsoft Wave (.wav), or lossless compression formats such as Free Lossless Audio Codec (.flac).

The type of microphone used will determine the quality, directionality, and frequency range of the recordings. Microphones detect subtle changes in air pressure, so more sensitive microphones will be able to detect fainter sounds. The design of the microphone determines whether it detects sound waves from all directions, omni-directional, or from a specific direction, referred to as shotgun microphones. All microphones have frequency–response curves that illustrate their sensitivity to particular ranges of frequencies. Common ranges are from 20 or 60 Hz at the lower end to 15 or 20 kHz at the upper frequencies. A pair of microphones can be used at the same time to provide a stereo recording that mimics human perception.

Sound data are stored as information expressed as a wave. To convert the sound data to a more useful format, a Fourier Transform (FT) is applied to the wave. Details of how FTs work is beyond the scope of this paper (cf. Hartmann 1997), but in general terms, the FT converts the wave signal to amplitude levels per frequency. These data, in turn, are used to obtain a plot of energy by frequency by time, called a spectrogram (Fig. 4). In a spectrogram time is displayed in the x-axis, frequency in the y-axis and energy (i.e., amplitude) on the z-axis, the latter usually represented as color intensity or shade. The spectrogram allows the researcher to have an overview of the sound intensities present in the file as a single figure. Frequency-amplitude plots are another common way researchers visualize sound files.

A number of excellent references provide in depth information about the physical properties of sound (Hartmann 1997; Truax 2001; Everest and Pholmann 2009), natural soundscape recording principles (Hopp et al. 1998; Krause 2002), acoustic data analysis (Charif et al. 2006; Sueur et al. 2008a, b), and the biological basis of sound production and hearing (Bradbury and Vehrencamp 1998; Ryan 2001; Gerhardt and Huber 2002; Marler and Slabbekoorn 2004; Kroodsma 2005; Fletcher 2007). Truax's (1999) *Handbook for Acoustic Ecology* contains an exhaustive list of acoustic communication and acoustic ecology technical terms that are excellent references for the new acoustician.

Sound analysis exercises

We use data from a long-term monitoring study being conducted west of the Purdue Campus in Tippecanoe County, Indiana to illustrate a few ways to analyze acoustic data for soundscape studies. For our Tippecanoe Soundscape Study, we deployed eight acoustic sensors in different habitats. One was located in a mature oak-hickory forest (Ross Reserve). Another was placed in a secondary forest (Martell Forest) of 20–30 year old hardwoods. The third sensor was located in a secondary forest stand approximately 5 m from the edge of a 3-ha wetland (called the Purdue Wildlife Area). Acoustic sensors were also placed in an abandoned orchard (called the FNR Farm) and a 5 ha forest stand (McCormick Woods) surrounded by apartment complexes. Two sensors were located in agricultural fields, one next to a corn crop (called Ag1) and the other along a soybean field (referred to here as Ag2). An eighth acoustic sensor was placed on the Purdue campus near a busy road intersection later in the year. All recorders were set to record for 15 min starting at the top of each hour

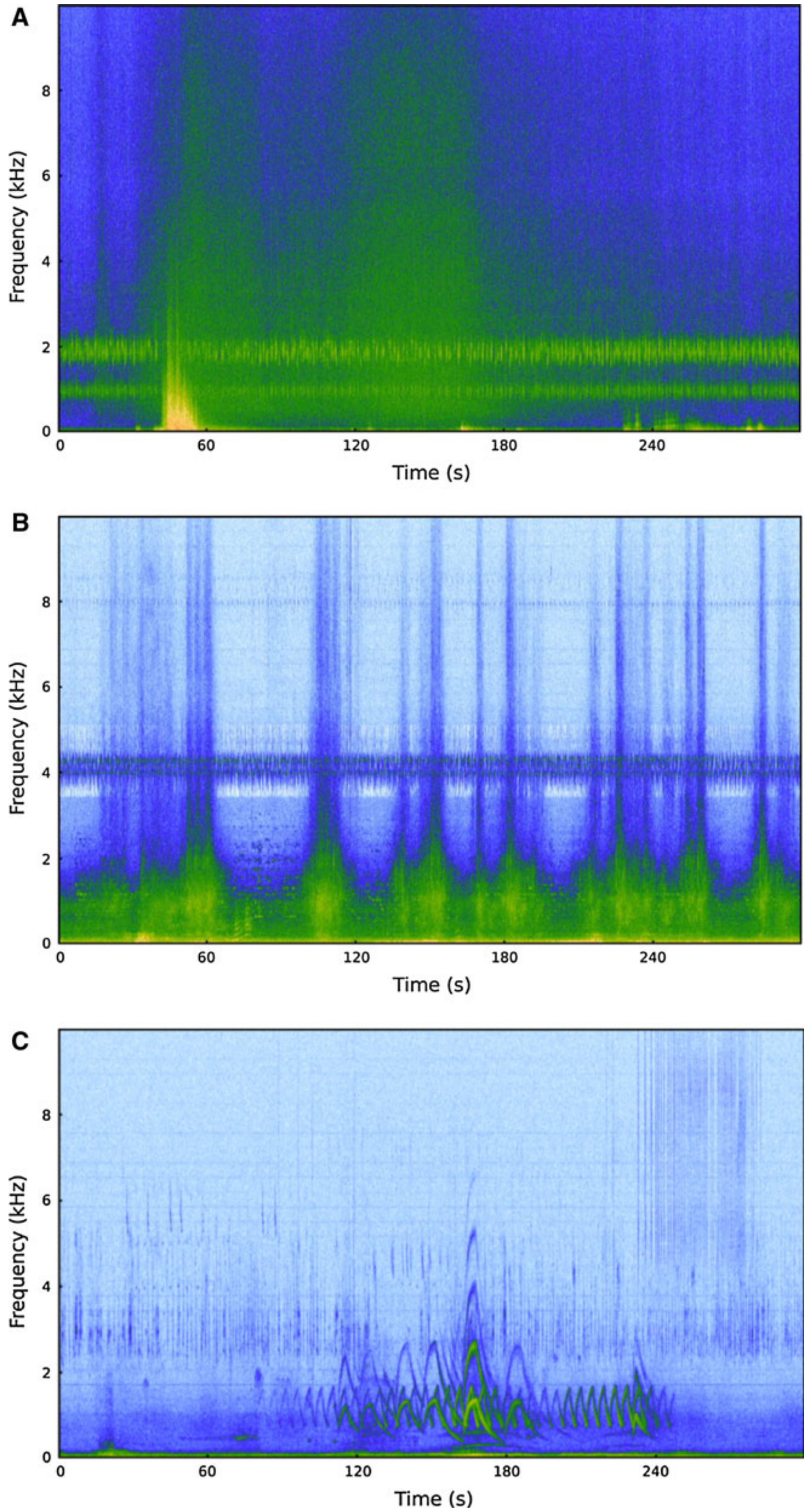

Fig. 4 Spectrograms of **a** example sound file #1, recorded at a forested wetland (Purdue Wildlife Area) at 01:00; **b** example sound file #2, recorded next to a major street at the Purdue University Campus at 22:00; and **c** example sound file #3, recorded at a forested plot (McCormick Woods) next to an urban area at 11:00

generating 24 fifteen-minute recordings per day at each site. We use data from a 1-week period, May 14, 2008 through May 20, 2008, for all sensors except urban, to demonstrate how metrics are sensitive to habitat type and time of day. All recordings were collected in stereo, although most analyses used only one channel, using a sampling rate of 44.1 kHz.

Three exercises are presented here that are designed to introduce ecologists to recording and acoustic data processing. The first exercise is a listening exercise where several recordings from our Tippecanoe Soundscape Study are presented and described using soundscape terminology and using the software packages Raven Lite (Charif et al. 2006) and Audacity (Audacity Development Team 2010). Raven is used by many bioacousticians to analyze single, or a small set, of recordings. Our second exercise focuses on spectrogram analysis using the R package Seewave (Sueur et al. 2008a). Finally, we show how a spectrogram can be discretized in vertical and horizontal directions to identify patches of sound that could represent unique signals with ArcGIS (ESRI 2010), tools traditionally used for spatial analysis. A supplement to these exercises, showing how to run the scripts, software and analyze these sound files can be found at: http://ltm.agriculture.purdue.edu/soundscapes/primer/.

Exercise 1. Listening to the soundscape

The sound file #1 was recorded during a rainy night at 01:00 in the Purdue Wildlife Area on May 14, 2008 (Fig. 4a). This rain represents one form of geophony (geo-physical sounds; Pijanowski et al. 2011a, b). Several species of frogs are the main contributors to this location's biophony (biological sounds). The recording starts with a chorus of Gray Treefrogs (*Hyla versicolor*), some Spring Peepers (*Pseudacris crucifer*) and a light rain. The Gray Treefrogs call around 2 kHz, while the Spring Peepers make a call that sounds like a whistle at around 3 kHz; both are typical soundmarks of a temperate pond. After approximately 40 s, loud thunder, another example of geophony, can be heard and the rain intensifies. Later in the file, the rain subsides while the frogs continue to call. At 4:18, a single faint "chuck" from a Bullfrog (*Rana catesbeiana*) is heard.

An urban soundscape (Fig. 4b, sound file #2) can contain many types of sounds, but this one is dominated by anthrophony (human sounds). This recording was made at 22:00 in the fall (October 10, 2008). During the entire recording, crickets stridulate between 3.9 and 4.4 kHz. After a few seconds, the bells of the Purdue Tower can be heard in the background playing several collegiate songs. The sound of the bells, an example of a keynote (Truax 1999) for this landscape, can be observed as discrete signals in the spectrogram that alternate their frequency. Each signal at particular frequencies corresponds to a different bell. Several cars and buses pass by—sounds produced include those from tire-pavement friction, air brakes, and music emitted from vehicles. Note that the sounds from the vehicles occupy a wide range of frequencies, particularly compared to the small range of the sounds emitted by the Purdue Tower bells.

Sound file #3 (Fig. 4c) was recorded on a summer day inside a forested plot near the Purdue University campus, on June 14, 2008; it has a mixture of animal and human sounds. During the duration of the sound, several species of birds are calling. A Red-eyed Vireo (*Vireo olivaceus*) sings constantly throughout the recording, occasional Red-winged Blackbirds (*Agelaius phoeniceus*) make a trill and squawk sound, and Eastern Chipmunks (*Tamias striatus*) emit their characteristic "chip" at the end of the recording. After time mark 1:30, a siren from an emergency vehicle can be heard for about 2 min. The sound of a siren on the spectrogram appears as frequencies alternating up and down, an example of frequency modulation created by a human object.

The accompanying hands-on tutorial to this exercise contains step-by-step instructions for how to obtain these files, load a sound file into Raven Lite or listen to these recordings online at the Purdue Soundscape Studies website. The skill level required to complete this exercise is elementary (e.g., requires very little expertise to understand the structure of acoustic files and run the computer software).

Exercise 2. Frequency band analysis

Seewave and associated packages are R software tools developed for sound analysis. In this example, we use Seewave to compute an index of frequency band diversity, evenness and dominance. An associated package, TuneR (Ligges 2009), is used to load a sound file in wav format as an object. Seewave can also save the data of the spectrogram as a numeric matrix with amplitude values by setting the value of *plot* in the function *spectro()* to false—saving the values as a matrix. We use this output matrix to calculate an acoustic diversity index using the script (*soundscape_band_diversity.R*) posted on the web site.

To demonstrate the value of this approach and tool, we use two sound files that were recorded in the Purdue Wildlife Area on 20 April 2008. The first sound file was recorded at night, at 00:00 (Fig. 5a), and the other one during the morning, at 07:00 (Fig. 5b). The night sound is dominated by frogs in the 1.3–3.8 kHz range while the sounds in the morning are from birds singing from approximately 0.2 to almost 8.0 kHz. Just by visually comparing the spectrograms of these sound files, we can see that there is a larger diversity of sounds in the morning than in the night. When we look at the distribution of the proportion of signals in each band in both sound files (Fig. 5c) the differences between the files are evident. The night recording has most of the signal in the bands corresponding to 1–4 kHz, while the signal for the morning has strong components from the 0 Hz up to the 6 kHz bands. The proportion of sound occurring in each frequency band can then be used to calculate a variety of metrics synonymous with those used in studies of species biodiversity. Allowing each band to represent a specific "species", the occupancy (i.e., the proportion of that band with sound) of each frequency band can be used to calculate Shannon's Index for a recording as:

$$\mathrm{H}' = \sum_{i=1}^{S} p_i \ln p_i \tag{1}$$

where p_i is the fraction of sound in each ith frequency band in s number of frequency bands.

Species evenness can be calculated in a variety of ways by ecologists. We used the *Gini()* function of the R package Ineq (Zeileis 2009) to calculate the Gini coefficient with occupancy at each frequency band as inputs per recording. We also calculate frequency band dominance by determining the frequency band that has the greatest occupancy per recording. Acoustic diversity (using Shannon's index), evenness and dominance can be compared between sites and over different time periods.

We calculated average values of acoustic diversity for each site for the week as well as averages for each hour of the day from the weekly recordings at the six sites. Acoustic diversity for Martell and Wildlife sites are greatest, followed by Ross and McCormick. FNR Farm, Ag1 and Ag2 contain the least amount of acoustic diversity (Fig. 6). The average acoustic diversity by time of day shows that Martell, Ross, FNR Farm, Wildlife and McCormick have high diversity values during the morning and evening time periods, coinciding with the dawn and dusk chorus. Nearly all of these sites also have a period prior to the dawn chorus that appears to exhibit a "rest" after a relatively diverse array of sounds occurring at night. The diversity of sounds during the evening is as great as those during the dawn chorus. The two agricultural sites reflect a "flat lining" of acoustic diversity throughout the day and night with almost no dawn and dusk chorus peaks in acoustic diversity occurring at either of these sites.

The weekly average Gini coefficient values (Fig. 7) are greatest for the two agricultural sites and the FNR Farm site, reflecting less evenness across frequency bands. The greatest weekly average evenness occurred at the Martell site. Gini coefficient weekly averages by hour are greatest for the agricultural sites with very little variation across the day and night. Evenness changed greatly over the day at the Martell and Wildlife sites with the most evenness occurring during the dawn and dusk chorus periods.

The proportion that each frequency band was dominant in each recording is illustrated in Fig. 8. Note that the lowest frequency band dominated nearly all recordings; this frequency band was removed from the analysis to assess the variation in the other bands. For the remaining frequency bands, band 2 (1–2 kHz) was the most common frequency band in all sites. The forested sites (Ross, FNR Farm, and McCormick) had times where band 3 was common, being dominant about 20% of the time. Wildlife had band 4 dominate 28% of the time, likely due to the numerous amphibians that were located there. In both agricultural sites, band 2 dominated nearly all of the recording periods, as much as 97% of all recordings in Ag1.

In short, the Seewave tool can be used to subset a sound file into frequency bands which can then be used as inputs to traditional ecological metrics of biodiversity. The metrics plotted over space and over time (some plotted with ggplot2 by Wickham (2009)) provide a useful means to understand the patterns of

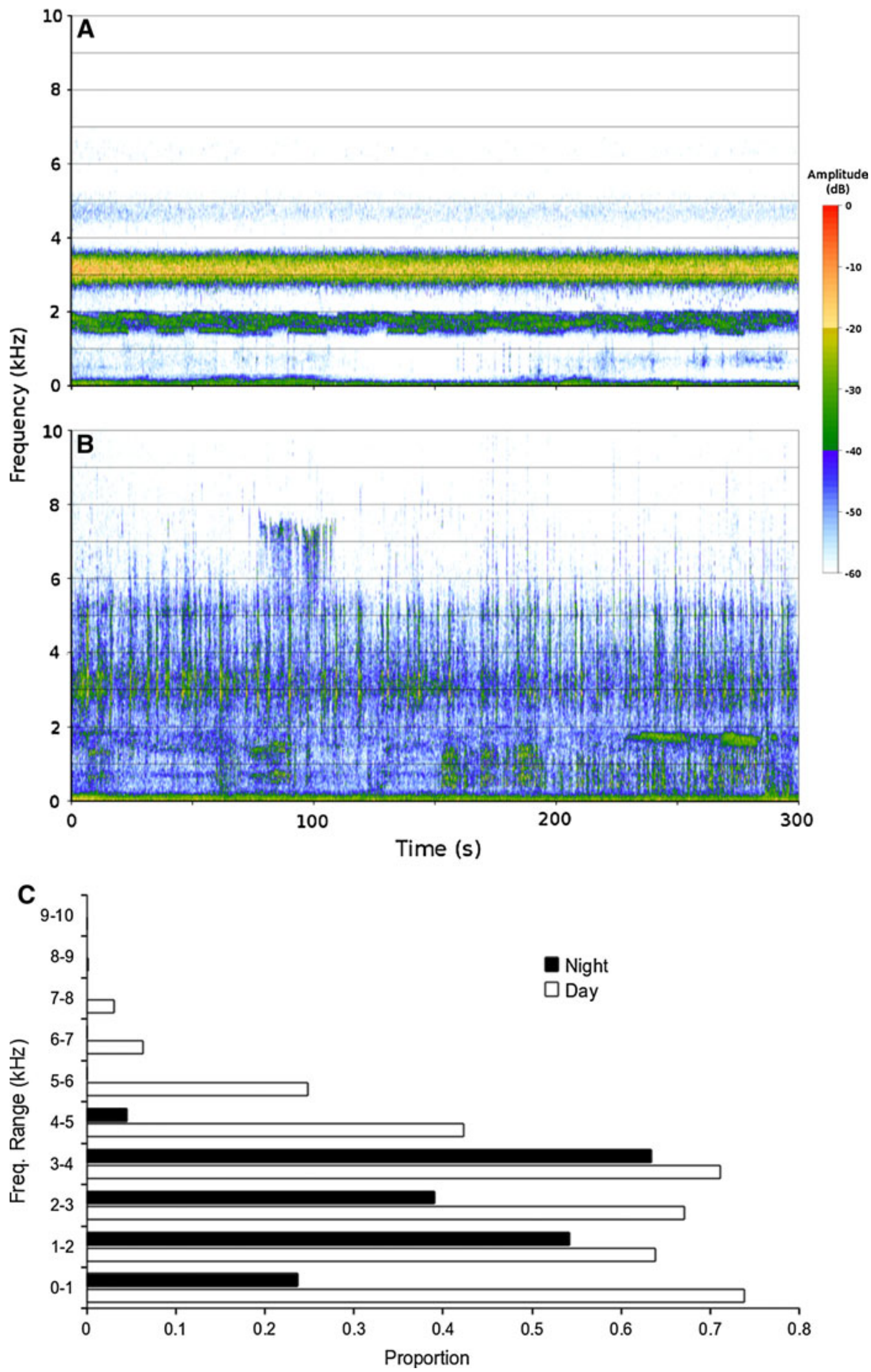

Fig. 5 Spectrograms of two sound files recorded at a forested wetland at two times: **a** recorded at 00:00, **b** recorded at 07:00 and **c** proportion of each frequency range band with a signal above a −50 dBFS threshold for the night (*filled bars*) and day (*empty bars*) recordings

sound in landscapes. Users familiar with R could modify inputs to examine more frequency bands or use the frequency bands as inputs to other metrics.

The tutorial that accompanies this exercise provides step-by-step instructions for downloading and installing R and the associated packages used here (Seewave, TuneR and Ineq), executing the scripts, understand the data format and import data into MS Excel. It explains the calculation of the Gini coefficient in more detail. We believe that readers familiar

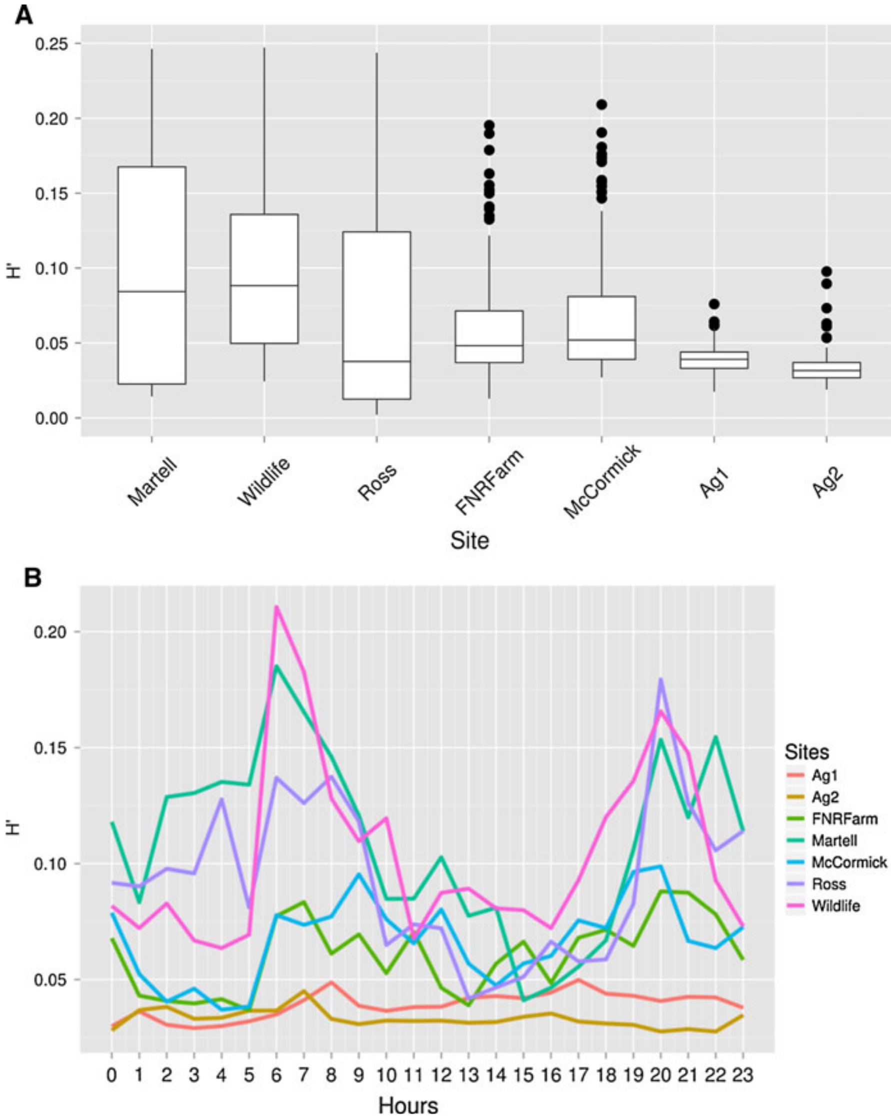

Fig. 6 Boxplot of **a** diversity values by site and **b** hourly averages. Values were calculated over a 7 day period in May 2008

with R or command line environment will be able to complete this exercise. Notes are provided that describe how a user can process a large number of files. The skill level required is moderate and considered advanced for those interested in processing a large number of files.

Exercise 3. Spectrograms as raster files

Seewave allows users to easily export that spectrogram as a raster file for analysis in a GIS. The resultant raster map allows users to treat specific signals as patches in a landscape. Patch and landscape statistics may help in quantifying the diversity of sounds and their relationships in a way that is more intuitive for landscape ecologists. The accompanying tutorial explains in detail how to extract a spectrogram from a sound file using Seewave and analyze it with ArcGIS. Briefly, patch metrics (e.g., size, perimeter) are generated and summary statistics (e.g., mean, standard deviation) reported for an entire recording.

Summary statistics for the signal patches are plotted by site and time of day for the weeklong recordings at seven sites in Fig. 9a. Note that the number of signals is greatest in the morning (07:00–08:00) and evening (21:00 and 22:00), corresponding to the dawn and dusk chorus, respectively.

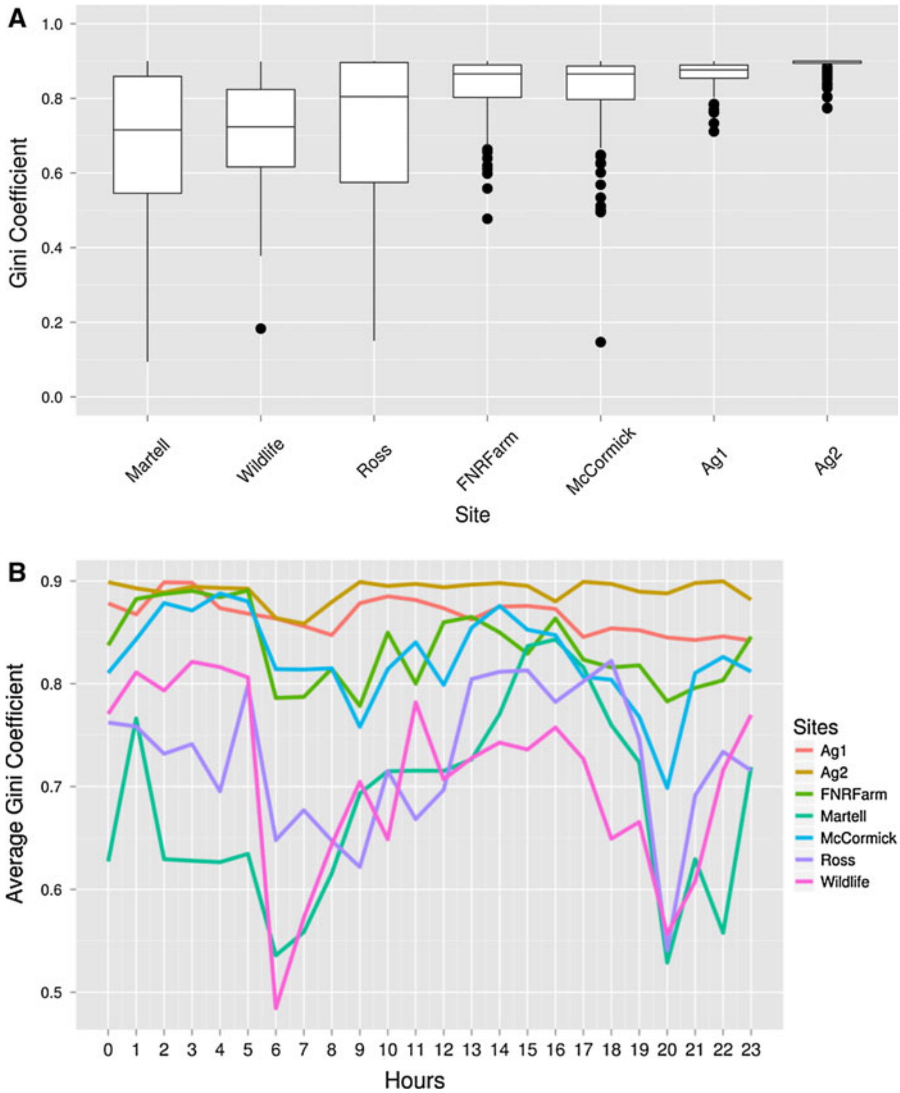

Fig. 7 Boxplot of **a** band evenness (i.e., Gini coefficient) calculated over a 7 day period in May 2008 by site; **b** average by time of day. Values close to 1.0 reflect perfect inequality (sounds occur mostly in one band) and values close to 0.0 reflect perfect equality (sounds occur equally across all bands)

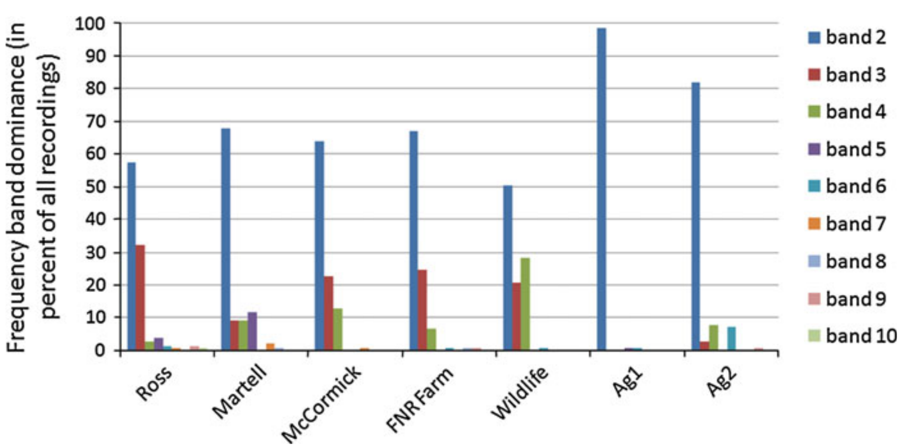

Fig. 8 Frequency band dominance for bands 2 through 10. The percentage of time that each band dominated in a 15 min recording over the week of recordings

The fewest number of signals occur during the day for the forested sites. There are very few signals at the two agricultural sites, where sounds are limited to wind and rain (geophony) and some occasional traffic (anthrophony).

The size of signals present in these sound raster maps differed greatly (Fig. 9b); both agricultural sites have very large sound patches, probably as a result of constant wind and traffic noise from the rural roads near the sites. Non-agricultural sites do not exhibit a temporal pattern to the patch size although it is slightly larger in the morning for some sites. When size distribution is examined across sites (Fig. 9c), all sites have about 15% of the sound patches are 4 pixels. Signals of size 5–9 pixels make up about 40% of all signals, another 40% of the signals are 10–49 pixels and less than 5% of patches are greater than 50 pixels. Patches larger than 10,000 pixels are rare, which makes sense since few real signals can have such a large footprint, either by duration or by acoustic frequency.

The tutorial describes how to run Python scripts and examine the output in a spreadsheet. Users familiar with data formats common to GIS and running scripts in ArcGIS can modify the scripts to create custom applications. This exercise requires some advanced knowledge although step-by-step instructions are provided for the novice ArcGIS Python user. Suggestions for further reading about these advanced tools are contained in this tutorial as well.

Discussion

We have presented an overview of sound and how ecologists can work with soundscape data from the field. Instead of limiting sound research to particular questions at the species level, we can study the soundscape at the landscape scale. Several tools familiar to many landscape ecologists (e.g., R and GIS) have been used and the exercises presented range from basic (listening to soundscape recordings) to advanced (running Python scripts in ArcGIS).

The best way to start studying the soundscape is to become acquainted with the sounds present in it and their spatial and temporal patterns. A purely descriptive approach will yield an interesting depth to any soundscape. Quiet soundscapes can have a constant component from the wind and leaves rustling. Urban soundscapes, usually described plainly as noisy, can have an overwhelming diversity of sounds and sources as demonstrated by exercise 1. Forested areas with a high diversity or occupancy of species will have a great variety of sounds, both from their vocalizations and their movements than those utilized by humans as demonstrated by the greater number of sound patches in forested versus agricultural plots in exercise 3.

A simple measure of the sound diversity in a spectrogram summarizes the complex acoustical data in an effective way. Sueur et al. (2008a) developed a similar diversity index within Seewave that uses a different algorithm but is similar conceptually (it was not used here due to the very complex nature of its calculation). In exercise 2, we used a measurement of the diversity of signals according to their frequency in a single sound file to obtain statistics for that sound file that can be compared to others. This approach can yield objective comparisons between sites (e.g. across a human disturbance gradient) or across time (e.g. the sound patterns across seasons). For example, the band analysis and diversity metrics utilized in our analysis showed that the soundscape is less diverse in the evening compared to the morning.

Future soundscape ecology research should focus on the spatial–temporal patterns of sound from different sources. However, for this to be accomplished, signals in soundscape recordings need to be extracted with signal classifiers into major sources like biophony, geophony and anthrophony. Our analyses here examined spectrograms with all sounds present.

Signal classifiers vary in the way they work, but in general, the classifiers are trained to recognize particular signals. This is often accomplished by first selecting a sample of sounds which are labeled by the researcher. An algorithm is then employed that uses features of the sound within the class. Then, once it has learned to identify these sounds, the classifier identifies the signals in the rest of the recording. Many bioacousticians have successfully used statistical (i.e., hidden Markov models) and machine learning (e.g., neural networks, support vector machines) approaches to identify sounds (Acevedo et al. 2009; Kasten et al. 2010). Same-source signals could then be recombined to create partial spectrograms, one each for biophony, geophony, and anthrophony. Metrics (e.g. entropy) of these partial spectrograms could be compared across

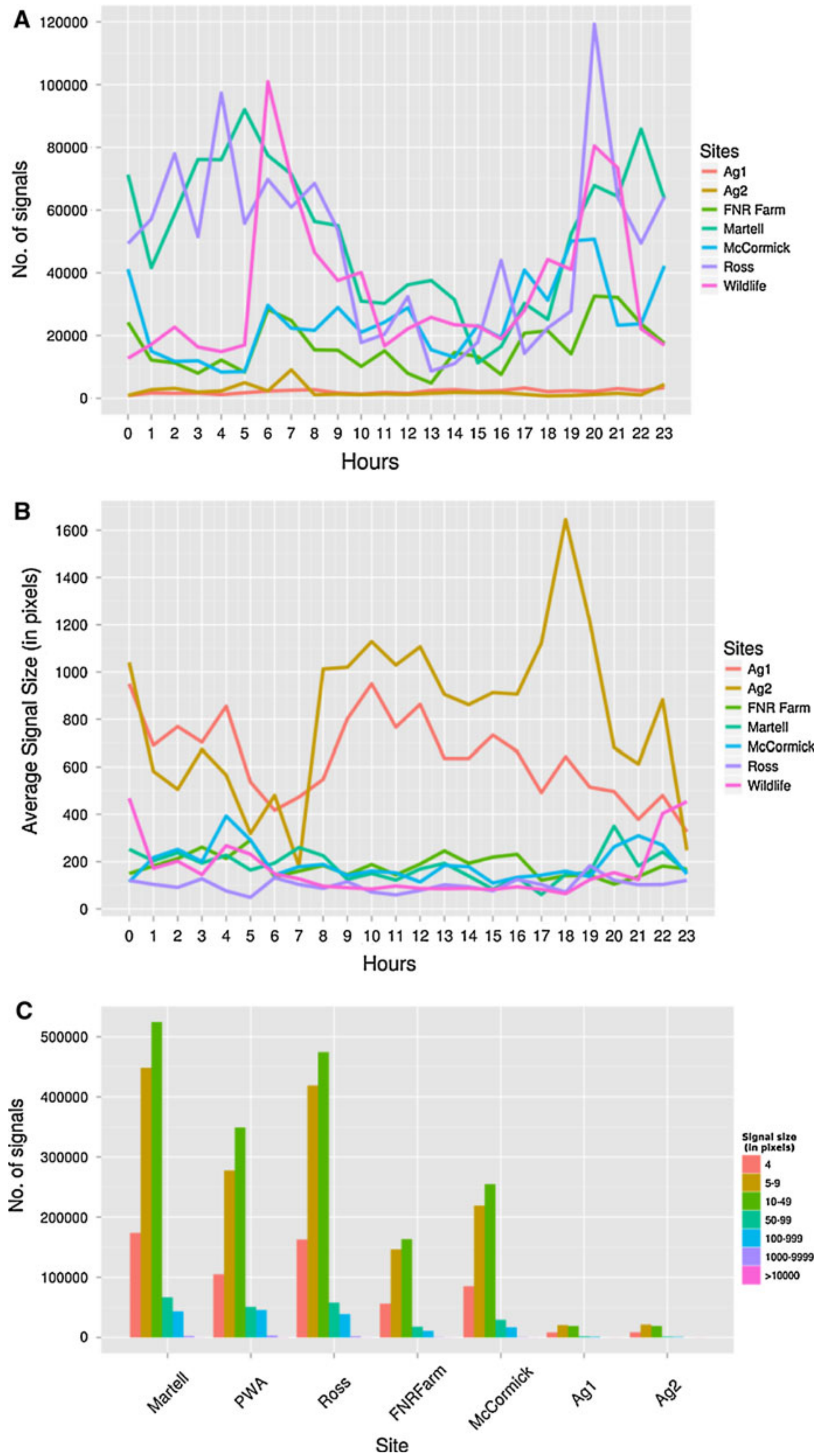

Fig. 9 Signals extracted from sound files recorded over a 7 day period in May 2008 by site: **a** number of signals per hour; **b** average size of signals per hour; **c** distribution of signal size

different landscapes, possibly varying in the human disturbance, and over a variety of time frames (hours, days, months, seasons, years), as we did here.

Other approaches to studying soundscapes are presented in this special issue. The ACI metric of Farina et al. (2011) uses a complex signal extraction approach to analyzing a sound recording. Studies that compare different levels of noise and their impact on the behavior, physiology and reproductive success of animals are conducted across human disturbance gradients (Francis et al. 2011). Future work needs to focus on comparing different methods with an assessment of how they differ across space and time.

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