UK Centre for Ecology & Hydrology

The potential use of acoustic indices for biodiversity monitoring at long-term ecological research (LTER) sites

A summary of current knowledge, equipment and methods.

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Summary

Passive acoustic monitoring (PAM) has been identified as a high priority research area by eLTER. This document provides background information and explores the potential for using acoustic indices as part of the suite of monitoring at UK Environmental Change Network (ECN) long-term ecological research (LTER) sites.

We explore some of the concepts around acoustic indices, their usefulness, and provide practical information on how to choose and use indices as part of PAM. A method is proposed for using acoustic indices as part of ECN / LTER site monitoring. Its aim is to open the discussion on how we proceed in developing a standardised method for use of acoustic indices in long-term monitoring. The method proposed is not intended as a fait-accompli.

1 Introduction

This report is written with the aim of reviewing acoustic monitoring within the environmental long-term monitoring network of the UK; the Environmental Change Network (http://www.ecn.ac.uk/) which is part funded by the UK-SCAPE project. The ECN network currently adhere to standard protocols allowing robust comparison between sites. In addition to the current standard protocols, agreed over 20 years ago, monitoring the soundscape has arisen as a relevant, cost efficient and feasible objective.

The ECN network is embedded in the European long-term monitoring community (eLTER) that is in the process of building a European infrastructure (https://www.lter-europe.net/elter-esfri). A major building block of the European infrastructure will be the eLTER Standard Observations (SO); a minimum set of variables and associated method protocols that can characterize adequately the state and future trends of the Earth's systems (Zacharias et al 2021). The SO's developed by the eLTER community will be selected to have high impact, high feasibility, relatively low cost of implementation and sufficient spatiotemporal coverage (Masó et al., 2020; Reyers et al., 2017).

This review is timely as the eLTER have identified as a high priority terrestrial monitoring of birds, bats, frogs, some insects (e.g., grasshoppers) using acoustic recording (Zacharias et al., 2021). In addition, Dick et al (2019, 2020) concluded that the soundscape was the least studied of the societal challenges identified by policy makers following a systematic literature review of nature-based solutions and human wellbeing linkages.

Some definitions used in this report

Soundscape	The acoustic perception of an environment. It is created by all the sounds comprising the biophony, geophony and anthrophony.
Bioacoustic	The sounds of an animal, its vocalizations etc…
Ecoacoustic	Natural and anthropogenic sounds and their relationship with the environment
Anthrophony	Sounds associated with human activities (e.g. people, vehicles etc..)
Geophony	Sounds associated with non-biological ambient sounds (e.g. wind and rain)
Biophony	Sounds generated by non-human biotic organisms (e.g. bird song, bat calls etc…)

2 Background to acoustic diversity indices

2.1 What is an acoustic diversity index?

All bio- and ecoacoustic analysis starts with the recording of the soundscape. The soundscape was defined by Pijanowski et al. (2011) as the "biological, geophysical and anthropogenic sounds that emanate from a landscape and which vary over space and time reflecting important ecosystem processes and human activities"

Soundscapes can provide information on the spatial and temporal distribution of biodiversity, population density, the richness and composition of the community, and the acoustic activity of taxonomic groups or individual species. However, difficulties remain in extracting reliable species level data, which can be expensive in time and effort.

An acoustic diversity index is a quantitative measure of acoustic heterogeneity (complexity) of a sound sample using temporal and/or spectral analysis. An acoustic diversity index provides a measure of the local biodiversity at the community level without any species identification, and utilises the assumption that the more species that are present, then the more diverse the soundscape could be expected to be (Sueur et al., 2008a). This is rooted in the idea of acoustic niche partitioning, where vocalising animals partition temporal and frequency domains across the soundscape in order to be heard (Marín-Gómez et al., 2020).

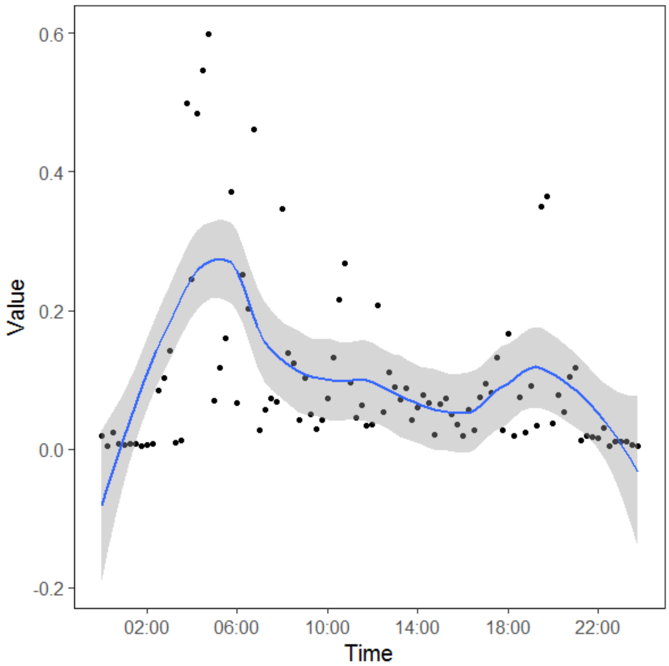

Figure 1. *Example of diurnal variation in an acoustic diversity index (Bioacoustic Index (BI, see section 2.3.1)), generated from soundscapes of 1 minute duration recorded as 1 minute in every 15 minutes over a 24 hour period. Note the peaks correspond with the dawn and dusk periods when birds are particularly vocal, and the consistently low values through the night hours. Loess smoothing with 95 % confidence interval shown.*

Acoustic diversity indices have a wide range of uses in the ecological context. They have been demonstrated for use in exploring the spatial heterogeneity of the soundscape (Bormpoudakis et al., 2013); species richness across habitats (Eldridge et al., 2018); community differences following disturbance (Gasc et al., 2018); monitoring long-term change (e.g. Phillips et al., 2018); mapping relationships between community and landscape features (e.g. Pekin et al., 2012); and mapping anthropogenic and ecological value of wilderness areas (Carruthers-Jones et al., 2019).

It is important to note some limitations of using acoustic indices. As they make no assumptions on what a sound is, the researcher needs to understand potential sources of sounds within their recordings. Anthropogenic and geophonic sounds have been found to correlate strongly with several indices, and as such need to be taken into consideration. For example, Fairbrass et al. (2017) found several popular indices were not always suitable for measuring biodiversity in urban environments without first removing biasing anthropogenic and geophonic sounds. Whilst geophonic sounds such as wind (e.g. Towsey et al., 2014; Pieretti et al., 2015) and rain (e.g. Towsey et al., 2014; Pieretti et al., 2015; Sánchez-Giraldo, 2020) are known to affect the estimation of indices.

2.2 How to record a soundscape

Recording of the soundscape can be done in several ways, so long as it has the ability to output sound files. The simplest method could be to use a cheap recording microphone left in a place of interest. However, this is likely to lose valuable information required by most researchers, including crucially, a time stamp for recordings. It would further lack control over recording variables such as frequency ranges and time-periods of interest, and may suffer from short deployment periods.

Passive acoustic monitoring generally requires specialist autonomous recording units (ARUs) left in-situ for a set period. These recorders can be expensive to buy, but provide all the control and data required for long-term soundscape recording. They can be acoustic and/or ultrasonic to record different elements of the soundscape, and are designed for outdoor use over long periods. When connected with external batteries and solar panels, they can record indefinitely (within the limits of installed memory that is usually expandable).

There are several makers of ARUs on the open market. Wildlife Acoustics Song Meters (https://www.wildlifeacoustics.com/) and Frontier Labs (https://frontierlabs.com.au/) are available in the UK and are 'off-the-shelf' ready, but which are relatively expensive to buy (>£700 depending on model) (Beason et al., 2018; Rhinehart et al., 2020). The Soundscape Explorer Terrestrial (SET - http://www.lunilettronik.it/soundscape_explorer/), is a slightly cheaper option (c£500) and includes several environmental sensors and automatic ACI computation (see section 2.3.1). Several cheaper alternatives exist which may be more suitable if recording at multiple sites, but require varying amounts of user construction or further development to be field ready. These include the open-source AudioMoth (https://www.openacousticdevices.info/audiomoth; Hill et al., 2017) and several Raspberry Pi based devices (see Darras et al., 2019 for a summary) such as the SOLO (Whytock & Christie, 2017) and AURITA (Beason et al., 2018).

The ideal duration of a recording varies depending on research needs. Typically, one minute recordings have been used for calculating indices (e.g. Abrahams et al, 2021; Wimmer et al., 2013, Rodriguez et al., 2014; Farina & Pieretti, 2014; Towsey et al., 2014; Piretti et al., 2015); but whether the soundscape is recorded continuously and split into shorter files, or recorded on an intermittent schedule (e.g. recording one minute in every five) depends on numerous factors. These include the memory and battery capacities of the ARU, availability of archiving space, computer processing power/time, and most importantly the research questions being addressed.

Bradfer-Lawrence et al. (2019) advocated for continuous recording for a minimum of 120 hours to generate accurate indices for a given site. They demonstrated that scheduled recording can lead to delays in capturing the site variability, and as a result that it might become difficult to distinguish between short-term stochasticity and longer term variability such as seasonal changes. Pieretti et al. (2015) however, demonstrated that much of the detail of continuous recording could be captured using a relatively conservative one minute in five recording schedule, but that this varied between habitats and time of day, and mixed scheduling could be appropriate. The intensity of recording schedule generally needs to be greater where acoustic emissions are occasional or intermittent and difficult to predict (Pieretti et al., 2015). These decisions are important because a one minute every five amounts to an 80% saving on battery and memory compared to continuous monitoring.

2.3 What indices are currently available?

The development of acoustic indices has accelerated rapidly in recent years. In a 2014 review of indices, Sueur et al. identified 21 α-indices and 7 β-indices that had been developed in the preceding six years. A more recent review by Buxton et al. (2018), identified over 60 different indices that had been developed for use in studying various elements of ecoacoustics. Acoustic indices, like traditional measures of community diversity, can sample the acoustic complexity of a single recording (α indices), or calculate the acoustic complexity between two or more recordings (β diversity).

The following lists cover some of the more popular α and β indices currently in use, but many others are available to suit specific needs.

2.3.1 α Indices

Five popular α indices currently in use are the Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Bioacoustic Index (BI), Number of frequency peaks (NP) and Normalized Difference Sounds Index (NDSI). Each provide a single value for each recording which on its own is of little value, but can be used with multiple recordings to compare for example temporal changes, and/or sites (e.g. habitat, land-use, ecological differences). A useful review of some of the indices below can be found in Eldridge et al. (2016, 2018).

Bioacoustic Index (BI). BI was proposed by Boelman et al. (2007), and was one of the first published acoustic complexity indices. The index works by calculating the area between the mean spectrum curve and a threshold value (the minimum value of the curve). The higher the given BI value the greater the acoustic diversity. BI has since been found to be quite sensitive to geo- and anthrophonic 'background' noise, and has recently lost some favour (Harris et al., 2016).

Acoustic entropy (H). Developed by Sueur et al. (2008a). Is a normalised index (returning a value between 1 and 0), which increases in value when there is an increased evenness of amplitude between frequency bands and/or time steps. As it is based on spectral entropy, it is likely susceptible background (e.g. traffic) and broadband signals (e.g. rain) (Eldridge et al., 2016).

Acoustic Diversity Index (ADI) and Acoustic Evenness Index (AEI). Acoustic Diversity Index is a measure of spectral entropy which is analogous with the traditionally used Shannon's Diversity Index. It was developed by Villanueva-Rivera et al. (2011), and calculates the complexity of the sound spectrum. The same authors also proposed methods for acoustic evenness (using Gini coefficient) and richness, essentially providing a similar suite of diversity indices familiar with ecologists.

Acoustic Complexity Index (ACI). ACI was proposed by Pieretti et al. (2011), and is possibly the most commonly used index. The aim is to capture the variation in call frequency over time within a soundscape, whilst being less sensitive to background noise (persistent sounds of constant intensity). Where there is greater variation in sound frequencies, this results in a higher ACI value. The calculation is based on splitting the frequency and temporal range of the soundscape into bins and comparing the difference in amplitude between consecutive bins. For recordings with multiple phases which are very different, then it is possible to split using a temporal step. The ACI of each step is then added together.

Normalized Difference Sounds Index (NDSI). NDSI was proposed by Kasten et al. (2012). It is a simple calculation that compares the relationship of the biophony and the anthrophony on a normalised index (-1 to +1), where -1 is a soundscape dominated by the anthrophony, and +1 dominated by the biophony. It is potentially useful for observing long-term interactions between wildlife and human populations. Separate scores are provided for the anthrophony ($NDSI_{Anthro}$) and biophony ($NDSI_{Bio}$), which are combined for the overall NDSI. Lower frequency sounds are considered the anthrophony, but the value is user defined depending on the site used for recording. Typically, a value of around 0.2-2 kHz is used, but a higher value can be needed in urban areas. There can be some overlap between sounds of the upper anthrophony and lower biophony (typically 2-8 kHz), and it is up the researcher to establish a sensible threshold frequency. Problems can also exist with sounds of the geophony (wind etc…) which are often low frequency overlapping with the anthrophony.

Number of Frequency Peaks (NP). NP was proposed by Gasc et al. (2013). It was developed as a means to remove some of the background effects (e.g. wind, water etc…) which can effect BI values. It basically provides a value on the number of frequency peaks within a mean spectrum, rather than the area under the curve.

2.3.2 β Indices

A number of dissimilarity indices exist for analysing β diversity between two acoustic communities, however they appear less widely reported than those developed for α diversity. The most popular is the Acoustic Dissimilarity Index (D).

Acoustic dissimilarity index (D). D is a beta index which works on the mean spectrum. It was proposed by Sueur et al. (2008a). As it is a beta index it looks at differences between different recordings, comparing each part of each curve. It is a normalised index (0-1), where 0 means there is no difference between the curves, and 1 is complete difference. It is computed as the product of both temporal (Dt) and spectral (Df) dissimilarities.

3 Tools to calculate acoustic indices

There are numerous acoustic indices in use in the literature and others are in development (see section 2.3). General practice is to use several indices on the same data, as with standard community indices. The calculation of similar indices does however vary, so once selected, it is important to use the same indices throughout an analysis. Many of the available analysis software use multiple published acoustic indices.

There are three options for calculating acoustic diversity indices for a set of recordings

i. Specific free/open software e.g.
    a. Analysis Programs (https://ap.qut.ecoacoustics.info; Towsey et al., 2018)
    b. RFCx Arbimon (https://arbimon.rfcx.org; Aide et al., 2013).
    c. Ecosounds Acoustic Workbench (https://www.ecosounds.org, Truskinger et al., 2014)

ii. Commercial sound file processing and analysis software e.g.
    a. Wildlife Acoustics Kaleidoscope (https://www.wildlifeacoustics.com/products/kaleidoscope-pro)

iii. Open source programmes running in R or Python.
    a. R using the seewave (Sueur et al., 2008b) and soundecology (Villanueva-Rivera & Pijanowski, 2018) packages
    b. Python using the Acoustic_Indices github repository by Patrice Guyot (https://github.com/patriceguyot/Acoustic_Indices).

All of the methods above allow for calculating various indices, however they differ in terms of the number and method, ability to visualise data, and how they store or process sound files. They also vary greatly in how ‘user-friendly’ they are. R is the most versatile option, but requires coding knowledge so it not universally user friendly. Kaleidoscope is the most user-friendly and can also process (and cloud store) sound files. However it is not free (c£300 pa), and cannot visualise the data natively (but exports data in .csv format for use elsewhere).

4 Developing protocol for acoustic monitoring at LTER sites

4.1 Monitoring in a LTER context

The need to standardise the type/make/model of equipment, measurement protocol and form of analysis in an LTER context requires network consensus either at national (e.g. ECN) or international (e.g. eLTER or INTERACT) level, and depends to some extent on the question asked.

The eLTER community have recently published a discussion document of standard observations (Zacharias et al., 2021). They prioritise monitoring birds, bats, frogs, some insects (e.g., grasshoppers) using acoustic recording but do not yet provide any guidance on protocol.

There are a range of considerations necessary to develop a standardised protocol for long-term acoustic monitoring at LTER sites, and the following sections are written as a starting point for such discussions, rather than a fait accompli.

At the beginning of this process there are several key decisions that need to be made dependant on what the monitoring intends to record and why. Once these decisions are made it is possible to select the correct hardware and analyses to meet the needs of the project.

i. The most important is to make sure any audio recordings can provide robust data to meet the aims and objectives of the research. Therefore an understanding of the what and why of the intended research is needed prior to establishing a protocol.
ii. Temporal resolution. How to 'characterise' a site depends on the research question being asked, but for long-term monitoring of LTER's it is likely of interest to record both the long-term temporal and within-year seasonal variation. Over time, such data should provide a measure of any phenological change within the soundscape, and help distinguish between variation and change. For some studies, an understanding of the diurnal pattern may also be useful to fully characterise a site.
iii. What constitutes a site? LTER sites vary in size and habitat complexity. Depending on funding, it would seem preferential to record soundscapes from each key habitat type within the LTER. However, where the site is large and homogenous, or funding prohibits multiple samples, then recording from a targeted or most representative habitat type would suffice. Within sites there may be interest in boundary or landscape feature effects, so recording at increasing distances from boundaries/feature may be useful.
iv. Frequency range. Bats, and some invertebrates, make up the majority of high frequency or ultrasonic recording. They are crucial parts of the biodiversity of many sites, but pose additional logistical challenges for sound recording due to the higher sample rate required. It is feasibly possible to focus on lower frequency acoustic diversity only, but this will likely under represent diversity at sites where bats in particular form a larger part of the biodiversity present.

v. Storage capacity. Storage capacity is linked to the temporal and frequency ranges as they determine the number and size of the files generated. The biggest decision is the frequency range. Setting a sample rate of 192 KHz as would be required to capture sounds from all frequencies up to and including those by most UK bat species (< 96 KHz), results in files that are 23 MB per minute of recording (using an AM acoustic recorder). Alternatively, if focusing on audible frequencies below 16 KHz, then a sample rate of only 32 KHz would be required which generates files that are 3.8 MB per minute of recording. This is 6x smaller than when including ultrasonic recording. The number of recordings is also important here, recording 1 min in every 5 or 15 amounts to an 80 or 96% storage saving respectively compared to continuous recording.

For this proposed protocol, we will assume there are no barriers to logistics, but will still take a pragmatic approach to balance the scientific needs with logistical demands. We are further assuming that ultrasonic frequencies are an important part of a sites soundscape, and that understanding daily, seasonal and annual variation are important to the site researcher.

4.2 Equipment

Choosing the correct acoustic logger will depend on a number of factors including the aims of the study, the costs (and quantity required), and the degree of autonomy required.

If the aim is to use multiple loggers for comparing soundscapes within and across sites, then it is highly recommended that the same hardware and software is used across the entire study. A small study comparing two different co-located loggers (AudioMoth and Song Meter Micro) is available in the supplementary information. This study found clear differences in the values of several acoustic indices generated using the sound files from the two different loggers, whilst differences between co-located loggers of the same type were minimal.

Although technology is always improving and the availability changing, the AudioMoth (AM; v1.2.0 or later) from Open Acoustic Devices (https://www.openacousticdevices.info/audiomoth) currently appears to be a cost-effective solution for long-term soundscape recording. There are a number of reasons for this, but the ability to record at ultrasonic frequencies, the low cost (c £90 including a waterproof case) and the open source nature of the product allowing for customisation if preferred are key. The AM utilises expandable micro SD storage, and works best with a UHS Speed Class 3 (U3) or greater micro SDXC card. If fitted with a suitably large memory card, then the maximum deployment time will be dependent only on the battery capacity. Energy consumption is strongly dependant on sample rate and recording frequency (see section 4.1), but good quality AA lithium batteries typically have a near 40 % higher capacity than equivalent alkaline batteries, as well as weighing 25 % less, and as such are the practical choice.

As is standard in many studies involving recording environmental/biological sound, loggers should be installed 1.5m above ground level where possible, facing into the habitat under investigation.

4.3 Measurement protocol

How to 'characterise' a site depends on the research question being asked, but for long-term monitoring of LTER's it is likely of interest to record both the long-term temporal and within-year seasonal variation. Over time, such data should provide a measure of any phenological change within the soundscape.

It has been proposed that continuous recording is required to accurately characterise a site (Bradfer-Lawrence et al., 2019). However, for practical purposes around battery life, data storage, and data processing, this is not likely to be optimal for long-term recording. Pieretti et al. (2015) demonstrated that a greater sampling effort is required for habitats/sites with lower acoustic activity, whilst richer habitats or those with continuous present of sound could have less intense schedules. Where there is large variation in the temporal soundscape (either seasonally or diurnally), then targeted scheduling may be most appropriate to capture the complexity of the soundscape.

Within the UK where we have strong diurnal and seasonal variation in the soundscape, a good compromise might be to record 1 minute in every 10, which Pieretti et al. (2015) found to be a good compromise between the data generated by, and the energy and storage requirements of continuous recording.

As bats are an important part of the night-time biodiversity at many locations within the UK, it would seem reasonable to include their vocalisations within any analysis. Therefore, suitable settings for recording could be as described in table 1.

Table 1. *Proposed recording settings for broad frequency acoustic monitoring*

Parameters	Settings
Sample rate	192 KHz
Recording Bandwidth	0 – 96 KHz
Gain	Medium (15 dB)
Sleep duration	540 seconds
Recording duration	60 seconds
Recording period	00:00 – 24:00

It needs to be explored whether the AM can be programmed to run different sample rates during the day and night. As AM uses open-source firmware this should be possible, but requires a background in coding to implement. This would make a large difference to data storage and energy usage as the higher sample rates required to record ultrasonic sounds draw more power and create larger file sizes. Other partial solutions to this could be to utilise the development version of the AM (AudioMoth Dev) in conjunction with external power sources (e.g. solar/battery), or for additional cost, to run two AMs side-by-side with one set for day and the other night.

4.4 Data processing and storage

It is imperative that the audio files produced are suitably documented and archived. This means that files can be retrieved for analysis both immediately but also as new and/or improved analytical methods become available in the future. Files generated by AM are currently named in YYYYMMDD_hhmmss format, and the recording metadata is encoded into each file, including, the filename, recording date/time, sample rate and gain, the unique ID of the device, and the battery level. Full details can be found in the AudioMoth operations Manual here https://www.openacousticdevices.info/open-source. Although the unique logger code is recorded within the metadata, this may not be immediately obvious within a folder structure when archiving the generated sound files. As such, it seems sensible to prefix a site/sub-site code into each file name. This can be done in bulk using freely available third party software such as Bulk Rename Utility (https://www.bulkrenameutility.co.uk/).

In order for acoustic indices values to accurately reflect the biodiversity of a habitat/site, it is important to remove some of the potential forms of bias that can occur. A major element of this comes from the geophony, and particularly to rainfall. Rainfall generates high intensity background noise which has variable effects on the values of acoustic indices (Sánchez-Giraldo et al., 2020). The standard practice is to remove sound files that contain rainfall, but it is first necessary to identify them. The simplest solution may be to cross-reference sound files with known periods of rainfall from co-located weather stations, and remove them on en mass. However, this would undoubtedly lead to unnecessary loss of some sound files that contain useful data. There have been several solutions to automate rain identification in sound files in recent years including machine learning (Brown et al., 2019) and signal to noise ratios of the frequency of rain falling through foliage (Bedoya et al., 2017). The most practical approach appears to use the r package hardRain (Metlcalf et al., 2020) which is an adaption of the work by Bedoya. A drawback is that in temperate regions this may only remove 40-50 % of files containing rain, although the false-positive rate is very low, and most disruptive heavy rain events should be removed. This is important, because although heavy rain is disruptive, many species will continue to vocalise during lighter rain events. To use hardRain however, a site-specific training dataset is still required to establish thresholds for classification of rain, so it would be necessary to specifically record, or manually sift, for 200 sound files of 15 seconds duration containing rain for a training dataset.

4.5 Analysis and indices

Once sound files are suitably archived, there are several options available for bio- and/or ecoacoustic analysis, the selection of which would be dependent on site and network requirements.

At the network level, it would appear important to select indices that reflect both the richness, diversity and dynamic changes of the soundscape at a given site/habitat, and thus provide a measure of long-term change in such metrics. Although not applicable to all sites, measuring the changing relationship of human and wildlife sounds may also be beneficial. We would therefore suggest a suite of indices that capture these including, ACI, ADI, AEI and NDSI. If background and broadband signals are well managed (i.e. through removal) then it would also seem sensible to use indices such as BI and H. All such indices can easily be applied using the seewave and soundecology packages in R, providing a suite of scores which reflect multiple elements of the acoustic space at a given site over multiple time points.

It is important to remember that the soundscape research field is currently undergoing rapid evolution, and new and improved methods for extracting valuable data from soundscapes are published frequently. As such, the focus should possibly be on the best methods for recording and archiving sound files so that they are available for use as new methods become available. Already, alternate and potentially more accurate measures to acoustic indices have been proposed, such as those utilising deep learning techniques as described by Sethi et al. (2020).

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Supplementary information 1

Comparison of the Song Meter Micro and AudioMoth sound recorders for use with acoustic indices.

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Summary

This short report details the outcomes from comparing acoustic indices derived from sound files produces by two co-located AudioMoth (AM) and a co-located AM and Song Meter Micro (SMM) audio recorder. It was not designed as a rigorous test, but as an aid to decision making when it comes to utilising multiple loggers in field experiments. The interpretation is limited by the small number of loggers available for testing at the time (2 x AM; 1 x SMM).

The overall recommendation based on this analysis is that using multiple AM loggers common settings should provide sound files that reflect differences in the local soundscape. However, mixing logger types, even when running very similar settings, should be avoided.

Method

Two audio recording devices were tested for suitability for long-term monitoring and generating acoustic diversity indices. The Song Meter Micro (SMM) by Wildlife Acoustics and the AudioMoth (AM) by Open Acoustic Devices (figure 1, table 1).

Figure 1. *External image of two differing acoustic recorders discussed in this report. The Song Meter Micro (SMM) by Wildlife Acoustics and the AudioMoth (AM) by Open Acoustic Devices.*

Recordings for the AM/AM and the AM/SMM comparisons were run on consecutive nights (29/30th July and 30/31st July) in an urban garden in Fife, Scotland. Audio recorders were located side-by-side, orientated in the same direction, and set to record for 1 minute in every 15 minutes over a 12 hour period (20:45 to 08:45) at a sample rate of 32 KHz. This produced 49 one-minute audio files for use in each for each comparison. Individual file sizes were 3.66 MB for the AM and 2.75 MB for the SMM.

Table 1. *Details of acoustic recorders used in this study. The given device weights were as measured by the author. The Song Meter Micro (SMM) by Wildlife Acoustics and the AudioMoth (AM) by Open Acoustic Devices.*

	SMM	**AM**
Recording Format	16-bit WAV	16-bit WAV
Recording Bandwidth	20 - 48,000 Hz	20 - 192000 Hz
Maximum sample rate	96 kHz	384 kHz
Programming Method	App	App / software
Adjustable Gain	Yes	Yes
Battery Type	3 AA alkaline or NiMH (lithium ion)	3 AA alkaline or NiMH (lithium ion)
Memory Storage	microSD card	microSD card
Weight	118 g (with batteries / case)	130 g (with batteries / case)
Dimensions	101 x 74 x 28 mm	58 x 48 x 15 mm

As far as was possible both recorder types were set to record identical parameters (table 2), and were triggered to commence recording using their respective dedicated apps (Song Meter Configurator v1.5; AudioMoth App v1.1.0) on the same mobile phone (iPhone SE (2020), IOS 14.7.0). This ensured their internal clocks, and thus the recording periods, should be identical. Such a setup was entirely possible for comparing two AM's, but slight differences existed between the AM and SMM setup (see table of parametrisation). Although both recorders used the default microphone gain, on the AM this is 'medium' (15 dB), whilst on the SMM this is 18 dB. As the choices for gain are fixed, it was not possible to set this identically.

Table 2. *Acoustic recorder configuration used during this trial for two different devices. The Song Meter Micro (SMM) by Wildlife Acoustics and the AudioMoth (AM) by Open Acoustic Devices.*

Parameters	**SMM**	**AM**
Sample rate	32 KHz	32 KHz
Recording Bandwidth	20 – 16,000 Hz	20 – 16,000 Hz
Gain (default)	18 dB	15 dB
Sleep duration	840 seconds	840 seconds
Recording duration	60 seconds	60 seconds
Run length	12 hours	12 hours

Seven well used acoustic indices were derived from the resulting sound files for the purposes of the comparison. There was no scientific merit for choosing particular indices beyond covering a wide breadth of differences indices. The indices (ACI, BI, H, NDSI, NP, ADI and AEI) were calculated using the Seewave and Soundecology packages in R. Index values were checked for correlation between loggers using the Spearman Rank order correlation due to non-normally distributed data. The mean value of each index was then tested for differences between loggers using the Wilcoxon rank sum test. All analyses were undertaken and plots drawn using R and the ggpubr package.

Comparison of AM v AM

Visual inspection of a randomly selected spectrogram (fig 1) showed only a 0.1 second mismatch between the recordings of the two AM loggers. In practice, this means that when using multiple AMs triggered using a common device, we can reasonably expect the resulting recordings to occupy the same temporal period.

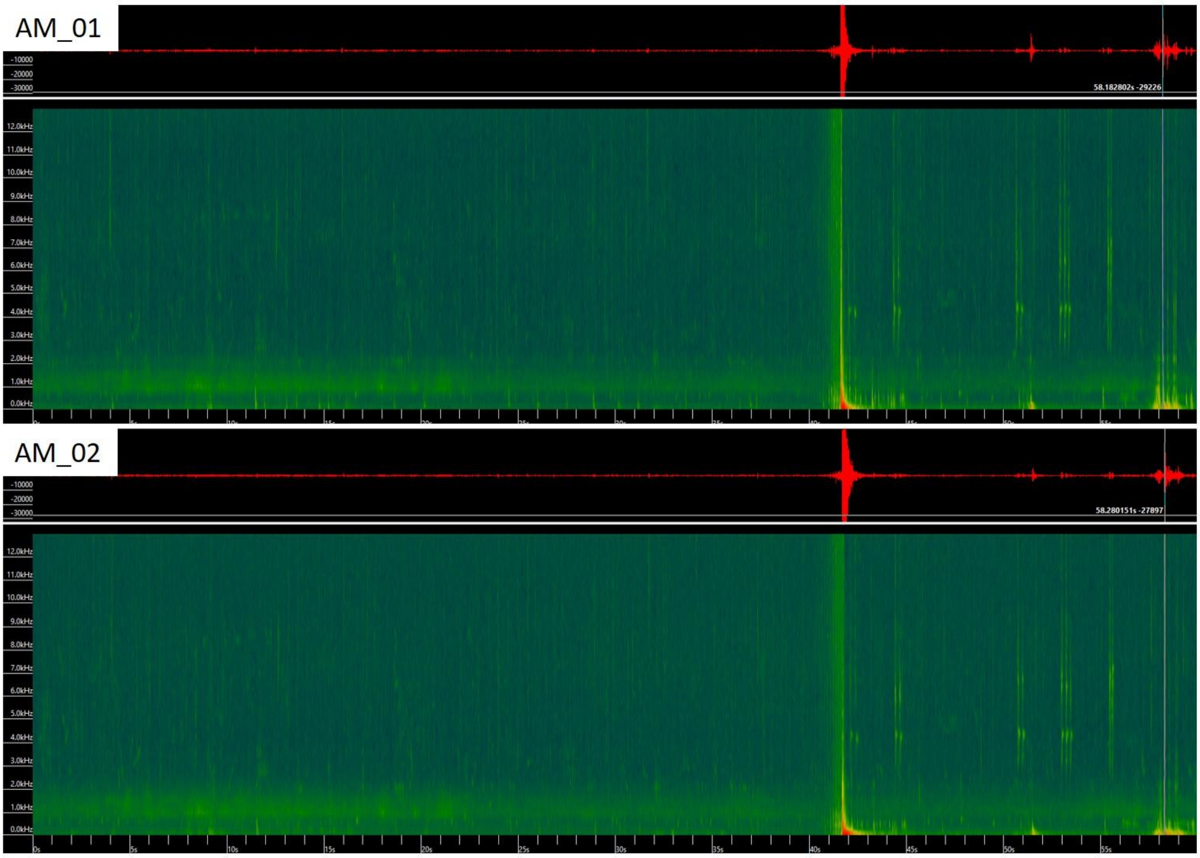

Figure 1. *Example 1 minute spectrograms recorded on two different co-located AudioMoth (AM) sound recorders running identical programmes.*

A comparison of the seven acoustic index values derived from the two AM loggers found that each acoustic index was significantly correlated with its counterpart, with r^2

values of greater than 90 % for all metrics other than NP (number of frequency peaks) which had an r^2 value of 72 % (fig 2). Furthermore, no significant differences were found between the mean values for each acoustic index between the two loggers (fig 3).

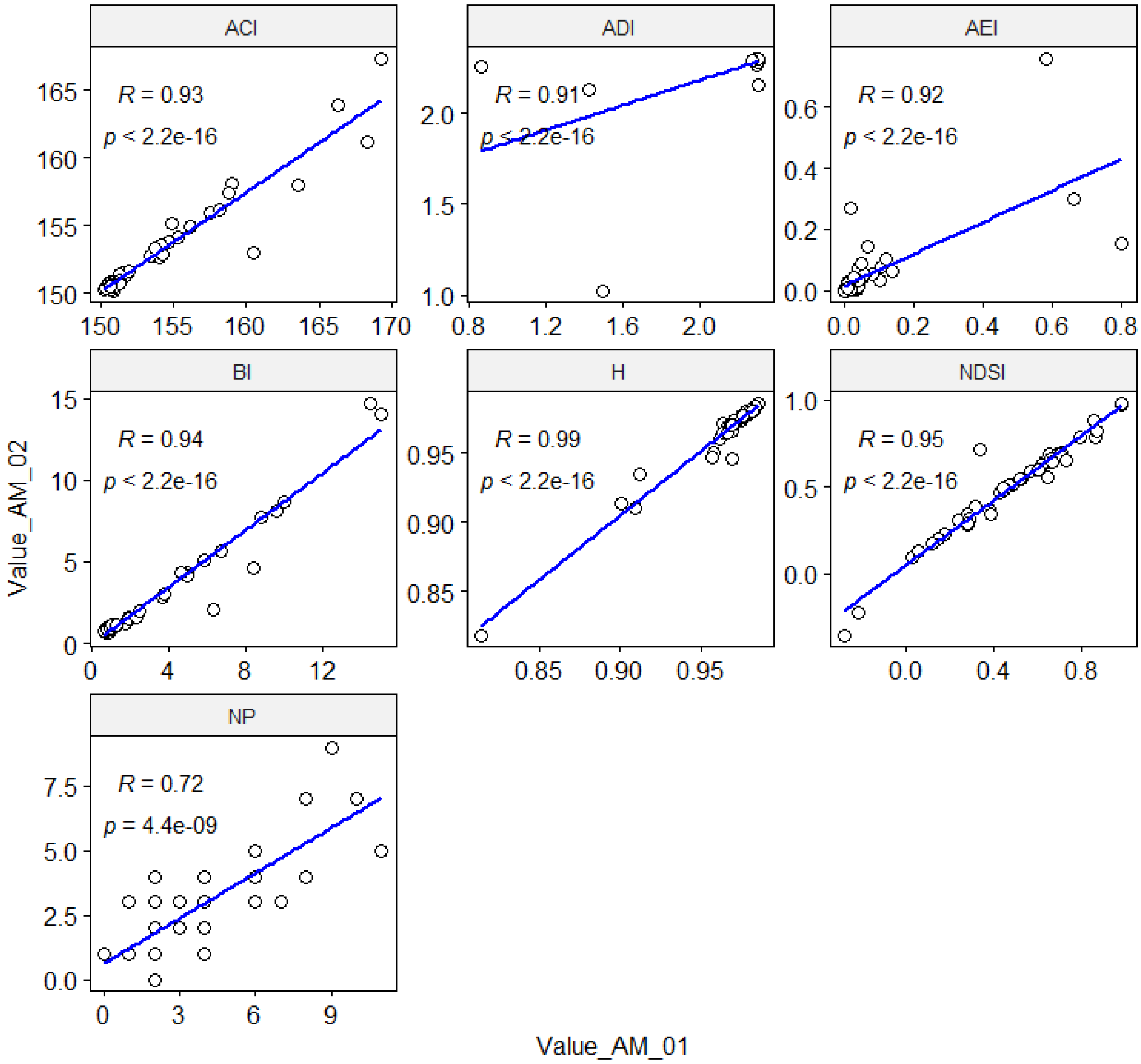

Figure 2. *Comparison of acoustic indices values for 49 one-minute sound files derived from two co-located AudioMoth (AM) sound recorders. Regression line is shown along with r^2 and significance value for Spearman correlation coefficient.*

In practice, with strong correlations between the paired acoustic indices generated by co-located AM loggers, and no difference between the actual values, we can assume that variations arising during the use of multiple AM loggers, reflects localised variations in a soundscape, rather than a manufactured difference between loggers.

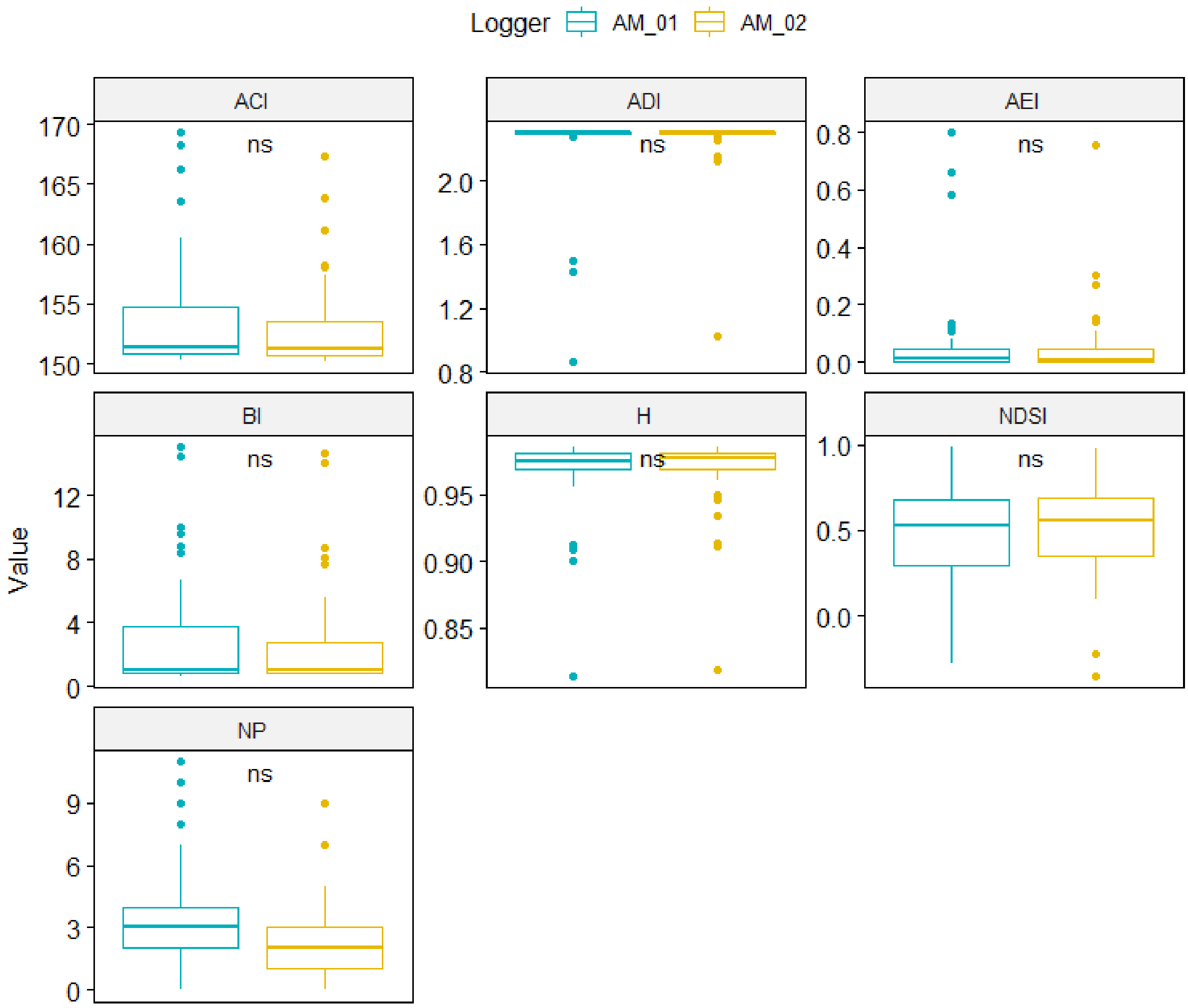

Figure 3. *Mean index value for seven different acoustic indices. Data is derived from two co-located AudioMoth (AM) sound recorders. Means were compared using the Wilcoxon rank sum test, and the significance value is shown. ns = no significant difference.*

Comparison of AM v SMM

Despite being set using the same device to trigger the recording period, comparison of the spectrograms found a 1.1 second mismatch between the two (fig 4). This means that nearly 2% of the recording occurred in a different temporal space to the co-located logger, and could potentially alter acoustic index values when sound occurs at the very end of the recording. Compared to the SMM, the AM logger also appeared to have more background microphone/preamp noise.

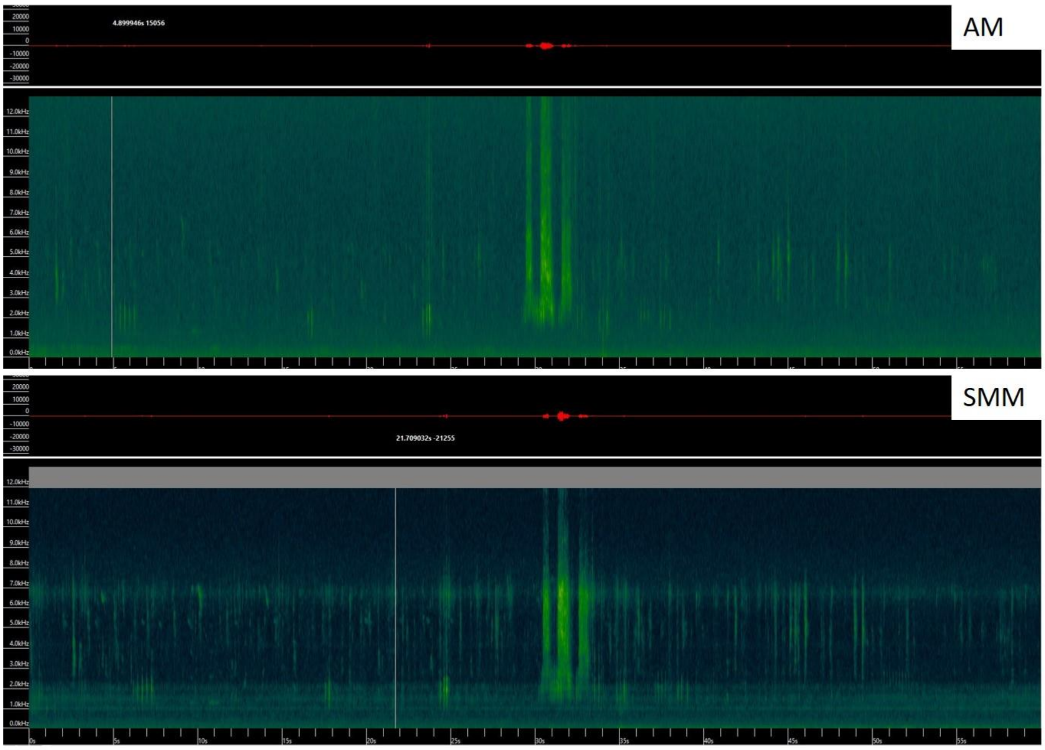

Figure 4. *Example 1 minute spectrograms recorded on AudioMoth (AM) and Song Meter Micro (SMM) sound recorders running near-identical programmes*

Although each acoustic index was significantly correlated between the two loggers (fig 5), the relationships were much weaker than those between the two AM loggers. Mean acoustic index values also varied significantly between the two logger types (fig 6), with the exception of ACI which was not significantly different between loggers.

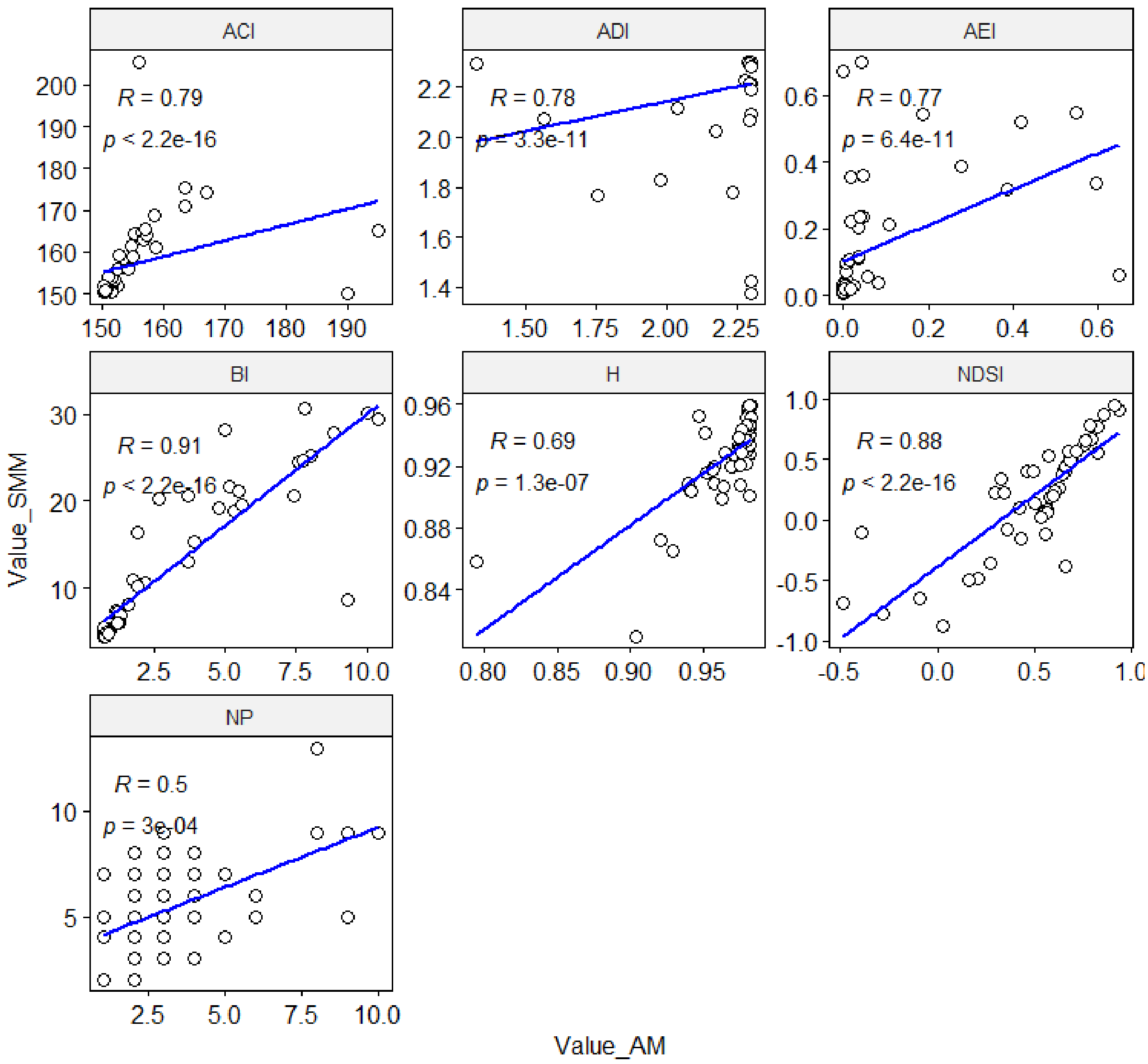

Figure 5. *Comparison of acoustic indices values for 49 one-minute sound files derived from two co-located AudioMoth (AM) sound recorders. Regression line is shown along with* r^2 *and significance value for Spearman correlation coefficient.*

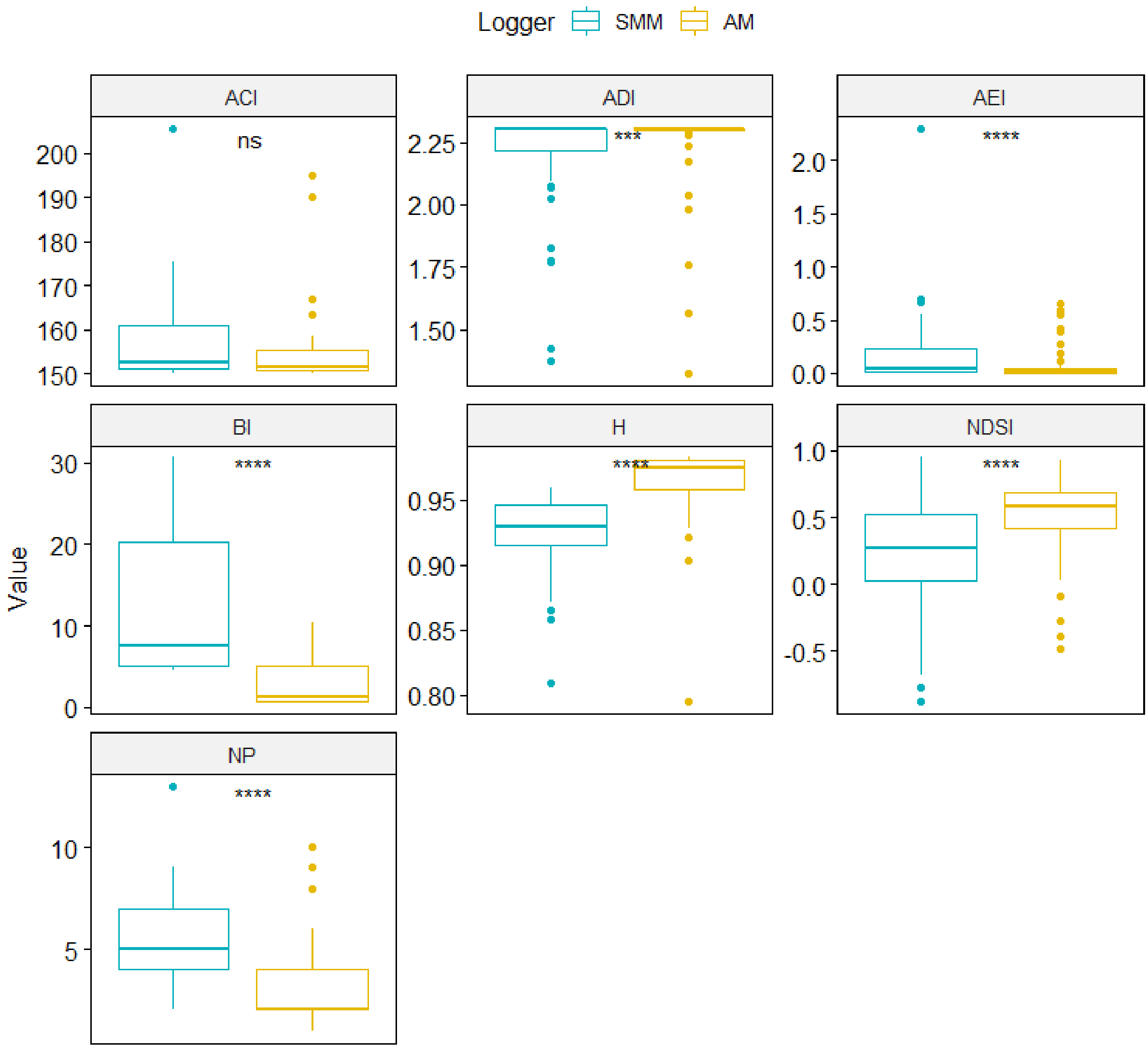

Figure 6. *Mean index value for seven different acoustic indices. Data is derived from two co-located AudioMoth (AM) sound recorders. Means were compared using the Wilcoxon rank sum test, and the significance value is shown. ns = no significant difference.*

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