



The Acoustic Index User's Guide: A practical manual for defining, generating and understanding current and future acoustic indices

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Abstract

1. Ecoacoustics, the study of environmental sound, is a rapidly growing discipline offering ecological insights at scales ranging from individual organisms to whole ecosystems. Substantial methodological developments over the last 15 years have streamlined extraction of ecological information from audio recordings. One widely used set of methods are acoustic indices, which offer numerical summaries of the spectral, temporal and amplitude patterns in audio recordings.
2. Currently, the specifics of each index's background, methodology and the soundscape patterns they are designed to summarise, are spread across multiple sources. Critically, details of index calculation are sometimes scarce, making it challenging for users to understand how index values are generated. Discrepancies in understanding can lead to misuse of acoustic indices or reporting of spurious results. This hinders ecological inference, replicability and discourages adoption of these tools for conservation and ecosystem monitoring, where they might otherwise provide useful insight.
3. Here we present the Acoustic Index User's Guide—an interactive RShiny web app that defines and deconstructs eight of the most commonly used acoustic indices to facilitate consistent application across the discipline. We break the acoustic indices calculations down into easy-to-follow steps to better enable practical application and critical interpretation of acoustic indices. We demonstrate typical soundscape patterns using a suite of 91 example audio recordings: 66 real-world

For affiliations refer to page 9.

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soundscapes from terrestrial, aquatic and subterranean systems around the world, and 25 synthetic files demonstrating archetypal soundscape patterns. Our interpretation figures signpost specific soundscape patterns likely to be reflected in acoustic indices' values.

4. This RShiny app is a living resource; additional acoustic indices will be added in the future through collaboration with authors of pre-existing and new indices. The app also serves as a best-practice template for the information required when publishing new acoustic indices, so that authors can facilitate the widest possible understanding and uptake of their indices. In turn, improved understanding of acoustic indices will aid effective hypothesis generation, application and interpretation in ecological research, ecosystem monitoring and conservation management.

KEY WORDS

autonomous recording unit, bioacoustics, ecoacoustics, passive acoustic monitoring, soundscape

1 | INTRODUCTION

Ecoacoustics, the study of environmental sound, offers ecological insights at scales ranging from individual organisms to whole ecosystems (Sueur & Farina, 2015). A foundational concept in ecoacoustics is the soundscape, which refers to all sound at a location, comprised of biological (biophony, e.g. vocalising animals), geophysical (geophony, e.g. the wind in vegetation) and anthropogenic sounds (anthropophony, sounds of human origin such as engine noise) (Pijanowski et al., 2011). In general, soundscape recordings are enormously complex and temporally variable and require summarising prior to ecological analysis.

There are two broad approaches to summarising audio recordings: sound event detection and whole soundscape analyses. Extracting and identifying individual calls or other sound events provides valuable ecological data (e.g. McGinn et al., 2023; Rhinehart et al., 2020; Wood et al., 2021), but this approach can be time-consuming, often requires specialist technical expertise, and assumes species' vocalisations are already known (Bradfer-Lawrence et al., 2023). Alternatively, a whole soundscape approach focuses on broader acoustic dynamics and patterns, offering insights into ecosystem functioning, integrity and complexity. Soundscape studies can provide novel perspectives in a broad range of ecological questions (Ross et al., 2023), for example this approach has been used to assess habitat quality, and the impacts of, and recovery from, disturbance (e.g. Barbaro et al., 2022; Burivalova et al., 2022; Gottesman et al., 2021).

Soundscape analyses often utilise acoustic indices—quantitative metrics reflecting a range of spectral, temporal and amplitude patterns in the soundscape (Sueur, 2018). These values can then be analysed in a range of ways: offering qualitative descriptions of soundscape patterns (Towsey et al., 2014); acting as proxies for biodiversity metrics such as species richness (Eldridge et al., 2018;

Sethi et al., 2023); and providing input for machine learning models (Bradfer-Lawrence et al., 2019; Do Nascimento et al., 2020). Machine learning approaches have also been used directly in similar contexts, with analysis of the model's learned features rather than the acoustic indices we discuss here (Sethi et al., 2020). However, while machine learning analyses can capture broad soundscape patterns, ecological insight is currently limited as learned features are generally not interpretable (although this situation will likely change with ongoing developments, see Gibb et al., 2024).

Acoustic index values can be readily generated in a range of programming environments, including R ('seewave', Sueur, Aubin, & Simonis, 2008; 'soundecology', Villanueva-Rivera & Pijanowski, 2018) and Python ('scikit-maad', Ulloa et al., 2021), in standalone software such as AnalysisPrograms.exe (Towsey et al., 2018) and Kaleidoscope Pro (Wildlife Acoustics), and in online platforms such as Arbimon (Rainforest Connection). While index values are straightforward to compute with such software, their interpretation can be challenging. Similar soundscape patterns can arise from very different sound sources, potentially confounding inference (Bradfer-Lawrence et al., 2023). This is particularly the case when using acoustic indices as proxies for biodiversity metrics, and contradictory patterns have been reported in the literature regarding the hypothesised link between acoustic diversity and biological diversity (Alcocer et al., 2022). This may stem from genuine differences among soundscapes from different ecosystems (e.g. Barbaro et al., 2022; Sethi et al., 2023), or from methodological decisions made during data collection and analysis (Bradfer-Lawrence et al., 2020; Gasc et al., 2015). Most soundscape analyses focus on human-audible frequencies (i.e., 20–20,000 Hz), and additional forethought will be required when calculating and interpreting acoustic indices from ultrasonic recordings (Silva et al., 2022) or those dominated by low-frequency sounds such as soil soundscapes (Metcalf et al., 2024).

9

Soundscape examples

Sound source

Predawn tropical forest ▾

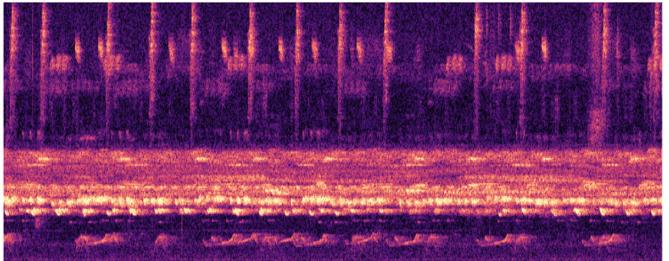
Play

Stop

ACI value

1856.35

Spectrogram

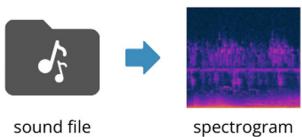


Metadata Predawn chorus in tropical forest, with high levels of acoustic activity from frogs, insects and nightjars. Amazon Research Centre, Amazonia Expeditions, Peru. Recorded at 05:23am on 23rd May 2022 with an AudioMoth recorder at 32 kHz by Nick Gardner.

10

Calculation

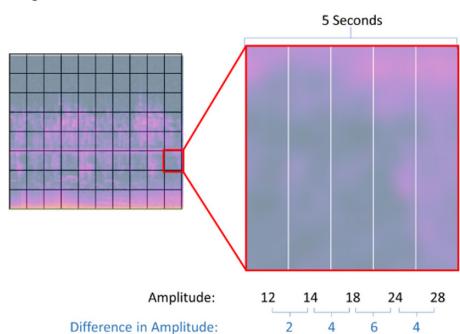
Step 1 - Generate spectrogram



Step 2 - Extract dB values for each spectrogram cell



Step 3: For each 5-second cluster in each frequency band:



3.1: Sum total amplitude value in all time steps

$$12 + 14 + 18 + 24 + 28 = 96$$

3.2: Sum total differences in amplitude among time steps

$$2 + 4 + 6 + 4 = 16$$

3.3: Calculate 'difference in amplitude' as proportion of 'total amplitude'

$$16 / 96 = 0.17$$

Step 4: Sum all 5-second proportion values (step 3.3) within each frequency band



Step 5: Sum across all frequency bands to get ACI

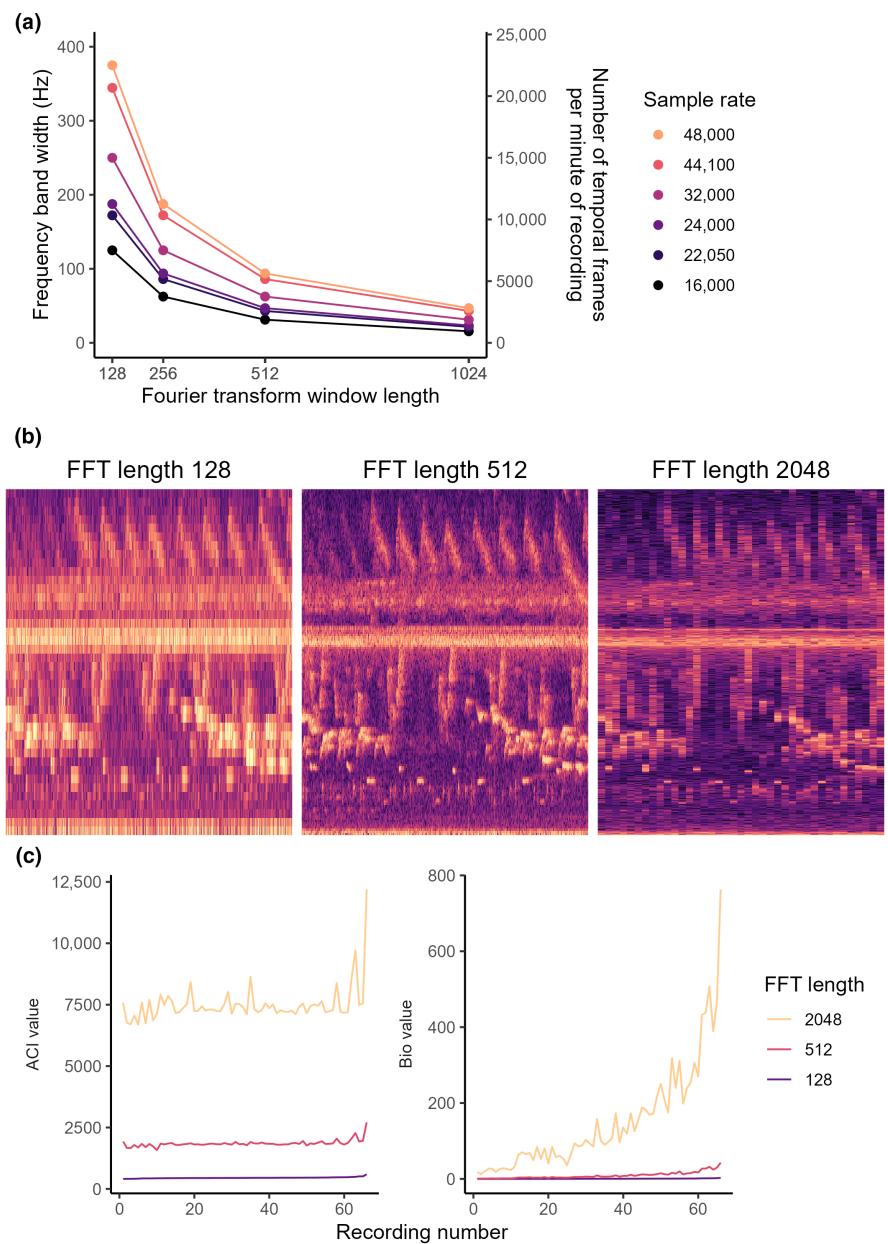
$$0.08 + 0.09 + 1.60 + 2.51 + 2.17 + 2.17 + 1.94 + 1.27 = 11.89$$

FIGURE 1 Example tab from the Acoustic Index User's Guide app, showing details for the Acoustic Complexity Index covering general information about the index, the example recordings and the index calculation steps. Numbers in circles refer to the points in the main text.

Acoustic Complexity Index	
General information	
1 Abbreviation	ACI
2 Original reference	Pieretti, N., Farina, A., & Morri, D. (2011). A new methodology to infer the singing activity of an avian community: The Acoustic Complexity Index (ACI). <i>Ecological indicators</i> , 11(3), 868-873.
3 Index description	Developed to be sensitive to irregular biophony, while filtering out persistent anthropophony.
4 Intended patterns	Greater levels of irregular biophony will give higher values. Constant sound, whether from anthropophony or other sources, has a minimal effect.
5 Reported patterns	Higher values can indicate storms, rain, insect stridulation or high levels of bird activity, while lower values could be associated with consistent cicada noise (Bradfer-Lawrence et al 2019).
6 Default settings	Seewave Function = "ACI". Min freq = 0 kHz, max freq = Nyquist, FFT = 512. Soundecology Function = "acoustic_complexity". Min freq = 0 kHz, max freq = Nyquist, FFT = 512, j (i.e., cluster length) = 5 seconds. Scikit-Maad Function = "acoustic_complexity_index". Min freq= 0 kHz, max freq = Nyquist, FFT = 512.
7 Sensitive to Fourier Transform window length?	Yes. ACI is cumulative, increasing window length will likely lead to higher values.
8 Output values	Real, positive values.

FIGURE 1 (Continued)

FIGURE 2 Effect of Fourier transform window length on the spectro-temporal resolution of spectrograms derived from recordings with different sampling rates, and the consequent effects on acoustic index values. (a) There is a direct trade-off between the number of frequency bands and the number of temporal frames. The number of frequency bands is half the window length, but the width of each band in Hz will vary depending on the sampling rate of the recording; larger window lengths improve frequency resolution (i.e., result in narrower frequency bands). The number of temporal frames is determined by the window length divided by the sampling rate; larger window lengths degrade temporal resolution (i.e., give fewer temporal frames). (b) Three example 10-s spectrograms from the same audio recording showing the effect of increasing window length on spectrogram resolution between 0 and 10 kHz, increasing frequency resolution at the expense of temporal resolution (window lengths from left to right: 128, 512, 2048). (c) For some indices this can have strong effects on acoustic index values. This might result in consistently higher values as in ACI (left), or incremental divergence as values increase such as Bio (right), further examples showing different patterns in the other indices are in Figure S1.



Critically, whether using acoustic indices for whole soundscape analyses or as biodiversity proxies, accurate interpretation requires a thorough background understanding of how soundscape patterns will be reflected in index values (Bradfer-Lawrence et al., 2023). However, until now it has been challenging to acquire the knowledge required for interpretation. Information about acoustic indices is spread across multiple, disparate publications (e.g. see Sueur, 2018; Sueur, Pavoine, et al., 2008; Villanueva-Rivera & Pijanowski, 2018) and, in some cases, details regarding their underlying calculations are limited. Extracting precise calculation details including undocumented nuances has hitherto required deconstructing the computational source code, representing a substantial barrier to wider use, comprehension and correct interpretation. Many indices have default parameters that could be altered to better suit specific use cases, but there are few resources exploring the effects of such changes (Metcalf et al., 2021, 2023). Uncertainty around the

interpretation of acoustic indices limits their effective use in surveys and monitoring, discourages new users and prevents the wider acceptance of ecoacoustics as an evidence tool that could guide policy formulation, conservation and land management.

2 | THE ACOUSTIC INDEX USER'S GUIDE

To facilitate greater understanding and uptake of acoustic indices, here we present The Acoustic Index User's Guide. This interactive RShiny web app helps users explore and understand eight of the most frequently used acoustic indices (Alcocer et al., 2022; Minello et al., 2021), which offer complementary categorisations of acoustic patterns (Bradfer-Lawrence et al., 2019). The web app can be accessed at https://ecohack.shinyapps.io/Acoustic_Index_Users_Guide/. For those who prefer to run the app locally, the current

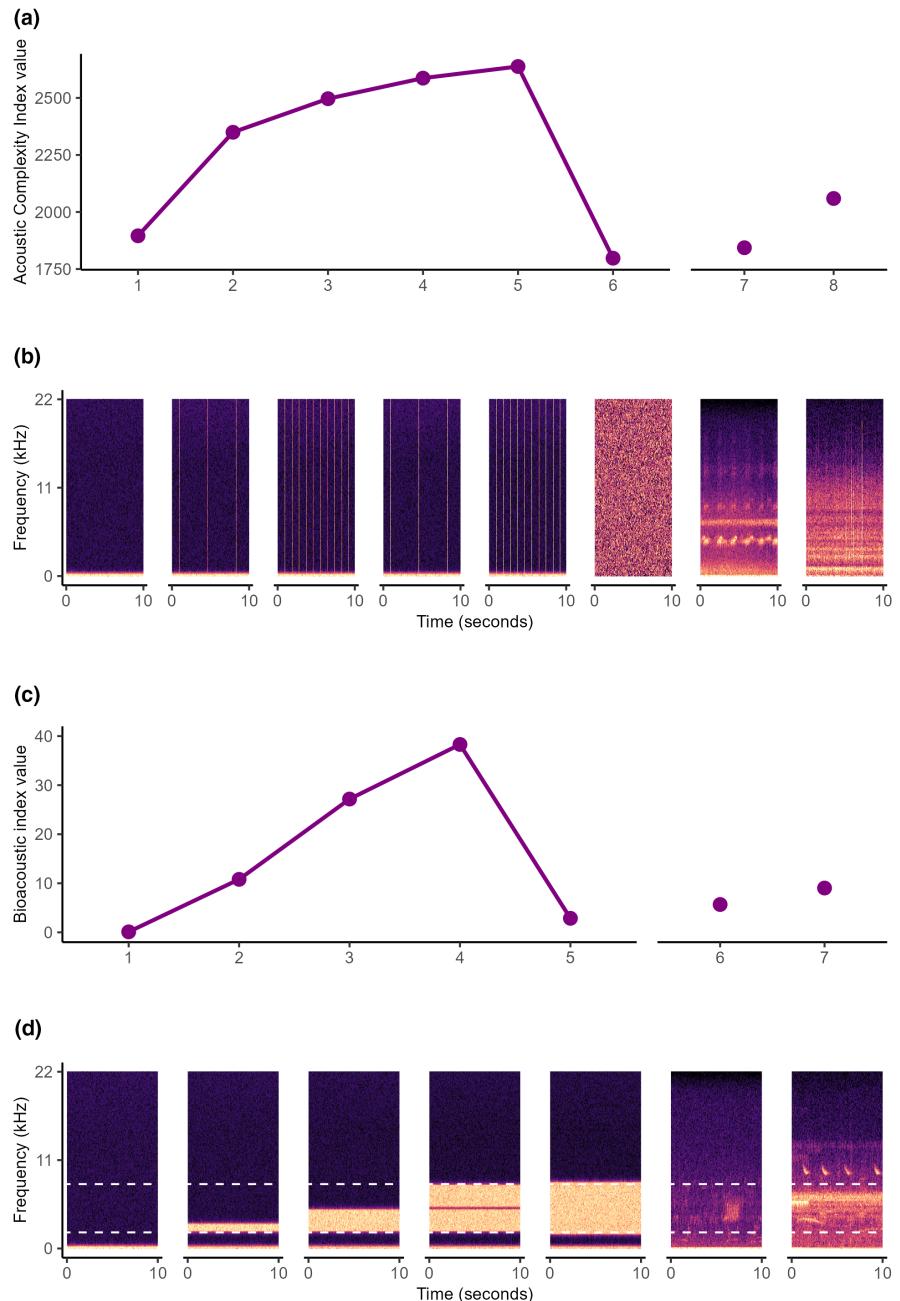


FIGURE 3 Understanding how acoustic indices reflect soundscape patterns is key to index selection and interpretation, shown here for two example indices. (a) shows Acoustic Complexity Index values from 1-min recordings, (b) shows 10-s sections of corresponding spectrograms for six synthesised (1–6) and two real-world (7 and 8) soundscapes. Index values increase with greater amplitude and temporal variability, but uniformly noisy soundscapes (6) have values as low as quiet soundscapes (1). (c) shows Bioacoustic Index values from 1-min recordings, (d) shows 10-s sections of corresponding spectrograms for five synthesised (1–5) and two real-world (6 and 7) soundscapes; white dashed lines indicate the frequency bounds for this index (default of 2–8 kHz). The Bioacoustic Index quantifies amplitude relative to the quietest frequency band, so that the index value increases up to soundscape 4, but then drops again in 5 because the soundscape is uniformly loud within the frequency bounds.

version can be downloaded from <https://doi.org/10.5281/zenodo.11041274>. Static pages of the current content are in the Supporting Information.

Collecting and pre-processing audio recordings are important steps in any ecoacoustics study, but we do not consider these here as there are many existing resources offering advice on study design (Metcalf et al., 2023; Sugai et al., 2020). In the Resources tab of the app, we provide links to some of these resources relating to monitoring protocols, equipment selection, methodology and analyses, including details of the programmes available for calculating acoustic indices. For those new to ecoacoustics, we also include a Glossary of commonly used terms.

Here, we highlight the key features of the Acoustic Index User's Guide that will assist users' selection and interpretation of acoustic indices. As noted above, there are a range of options for generating acoustic indices values, using either script-based or standalone programmes. These are largely straightforward to use, but understanding and interpreting the resulting values requires specialist knowledge, which is where the Acoustic Index User's Guide can help. Improved understanding will aid effective hypothesis generation, application and interpretation—helping users fulfil the critical goal of explaining the links between acoustic indices and soundscape patterns (Bradfer-Lawrence et al., 2023; Ross et al., 2021). We envisage the app as a useful tool for a wide range of existing and

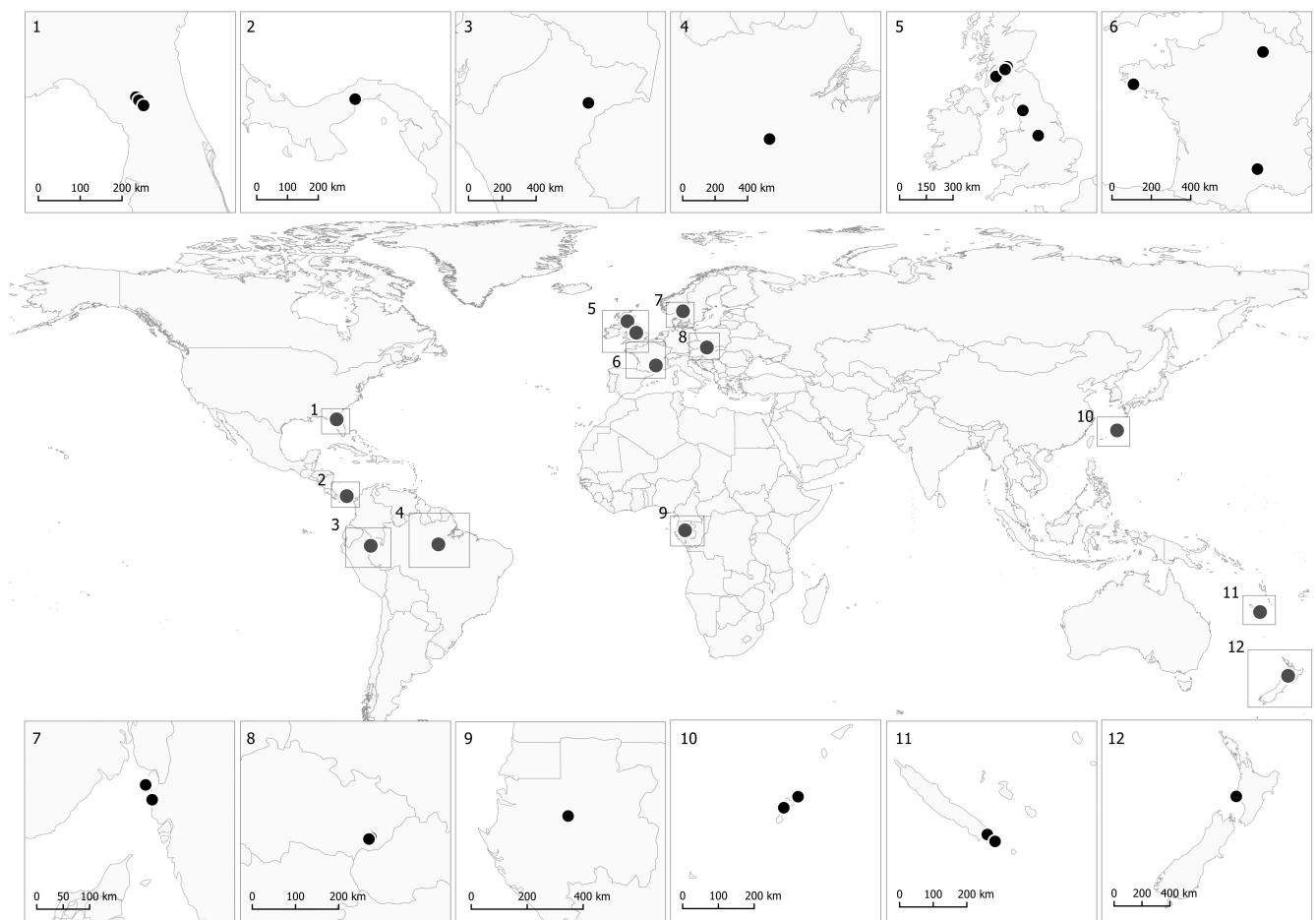


FIGURE 4 Map of the 23 locations where example real-world recordings were collected between 2017 and 2023. In some cases, more than one recording was collected at an individual site, giving a total of 66 1-min recordings.

aspirational acousticians, including researchers, students, land managers and ecological practitioners.

2.1 | Understanding acoustic indices

The indices included in the app so far are: Acoustic Complexity Index (ACI; Pieretti et al., 2011); Acoustic Diversity Index (ADI) and Acoustic Evenness Index (Aeve; Villanueva-Rivera et al., 2011); Bioacoustic Index (Bio; Boelman et al., 2007); Acoustic Entropy (H) and its spectral (H_f) and temporal (H_t) components (Sueur, Pavoine, et al., 2008); and Normalised Difference Soundscape Index (NDSI; Kasten et al., 2012).

Each of the acoustic indices has a single dedicated tab, with a consistent structure to facilitate end-user understanding of the soundscape patterns they reflect and their underlying calculations, as shown in the example tab for ACI that contains following sections (numbers correspond to circles in Figure 1):

1. Index name and abbreviation.
2. Original reference that introduced the index.
3. Index description outlining the rationale underlying the index.

4. Intended patterns offering a general description of the soundscape features the index is intended to reflect, based on details in the original reference.
5. Reported patterns in the wider literature, as these sometimes diverge from those in the original reference, either due to system-specific differences, or methodological choices (such as altering index parameters).
6. Default settings including the frequency ranges and Fourier Transform window lengths used in a range of script-based and standalone programmes.
7. Sensitivity to Fourier Transform window length, indicating the likely effects of increasing the window length on index values (Box 1).
8. Numeric properties of the Output values, such as the bounds, range and distribution.
9. Example sound recordings selected using a dropdown menu, from our collection of 91 1-min recordings (see below). A spectrogram for the first 20s of the chosen recording is displayed, and users can opt to play the audio recording. The index value is displayed (generated with a Fourier Transform window of 512), along with a description of the broad soundscape patterns present in the recording and recording metadata.

10. Index calculations broken down into a series of steps with illustrative figures. These are based on calculations in the R packages 'seewave' (Sueur, Aubin, & Simonis, 2008) and 'soundecology' (Villanueva-Rivera et al., 2011), as these were either the original implementations of the indices, or the functions were constructed with input from the index creators. It is important to note that some packages and platforms may have implemented these indices in different ways, meaning they have different calculation steps or do not return identical values to the methods presented here (Villanueva-Rivera, 2015).

2.2 | Validating and interpreting acoustic indices

Two crucial steps in any acoustic indices study are validation and interpretation. Users need to statistically test assumed links between indices patterns and response variables, explain what the index values imply about soundscape patterns and, ideally, their ecological relevance (Bradfer-Lawrence et al., 2023). Doing so will require sound-truthing recordings to determine the likely sources of soundscape features. To aid users in identifying soundscape features that may be driving acoustic indices values, we demonstrate patterns using synthesised soundscapes in the *Which indices?* tab of the app (Figure 3; Figures S2–S6).

Some key points to bear in mind when interpreting index values:

1. In general, any additional sound is likely to increase acoustic diversity, and in turn this will influence acoustic indices values. However, this 'diversity' could be from a new source (e.g. the beginning of a rainstorm), or an existing source making a different sound (e.g. an individual bird varying its call). There are also occasions when certain broadband sounds, such as heavy rain, can mask other sounds leading to a reduction in acoustic diversity (Figure 3). Hence, users need to consider the ecological relevance of any soundscape change.
2. Different sound types will affect indices differently, even if the total amount of acoustic energy is the same. For instance, contrast a bird chorus that has rapid variation among frequencies and over time, with a continuous insect chorus which covers a broad frequency range and varies little over time (Figure 3).
3. One individual index value on its own is rarely interpretable and ecological relevance can only be derived from a series of values from multiple acoustic samples. For example, the temporal variability in index values among sites can provide important insights into habitat quality and ecosystem response to perturbation (Bradfer-Lawrence et al., 2019; Burivalova et al., 2019).
4. Precise indices values will depend on the recording protocol (Metcalf et al., 2023), use of compression (Heath et al., 2021), calculation software (Villanueva-Rivera, 2015) and index parameters, such as frequency bounds (Metcalf et al., 2021). Of particular importance is the link between the sample rate of the recordings and the Fourier Transform window length, as this determines

the resolution of the spectrogram which forms the basis of most acoustic indices calculations (Box 1).

5. If different types of sound create similar spectrogram patterns, they will result in similar index values (Bradfer-Lawrence et al., 2023). Identifying and resolving such confounds relies on sound-truthing recordings and contrasting multiple indices.

3 | ADDITIONAL CONTENT

There are two further tabs in the app:

- (i) *Example recordings.* We have assembled a set of 91 1-min recordings (Bradfer-Lawrence, Abrahams, et al., 2024). 66 were collected in air, water and soil, from sites around the world (Figure 4). They include a wide range of soundscape patterns, reflecting diverse sources of sound including biophony, geophony and anthropophony. The recordings were collected with a range of equipment and sample rates; full details are available in the associated metadata file. We also include 25 synthetic soundscapes created with Audacity software. Collectively, these offer users the opportunity to explore a variety of soundscapes and cultivate their understanding of the links between acoustic

BOX 1 Effect of spectrogram dimensions on acoustic indices values

Digital audio recordings in .wav format are a single long vector of values. For most acoustic indices, this vector needs to be converted to a spectrogram using a Fourier Transform prior to index calculation (Sueur, 2018). A spectrogram is a matrix of amplitude values providing a visual representation of the sound signal, with time on the x-axis and frequency on the y-axis (Figure 2). Given a recording of a set duration, the number of cells in a spectrogram is constant, but the size of the Fourier transform window determines the trade-off between temporal and frequency resolution (Figure 2).

Until now, the implications of spectrogram resolution on acoustic indices have been largely overlooked, despite their potentially critical influence on the values returned. For example, where an index is cumulative, increasing the number of frequency bands will—on average—lead to higher index values regardless of the soundscape patterns (Figure 2; Figure S1). Although this feature should not affect comparisons within recording sets (assuming common recording and calculation settings), it does hinder comparisons among studies. In the dedicated index tabs (Section 2.1), we highlight which indices are sensitive to spectrogram dimensions, indicating the effects of altering the Fourier Transform window.

patterns and indices values. The recordings are free to use under a CC-BY licence and can be downloaded along with the metadata from <https://doi.org/10.5281/zenodo.11004284>.

- (ii) **About this guide.** Introducing the project's origins, the app's creators and suggested citation.

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4 | FUTURE DEVELOPMENTS AND CONCLUSION

The key motivation for creating the Acoustic Index User's Guide as an Rshiny app was to ensure that it remains an up-to-date resource, growing with the ongoing expansion of ecoacoustics and incorporating specific development of new acoustic indices or best practices for existing indices as they become available. In line with the ethos of open science, we welcome input from other users who would be interested in helping to create additional pages, either for existing indices we have not yet covered or new ones when they are developed. We encourage interested individuals to contact the authors.

Validation and interpretation are key steps in acoustic indices research that are sometimes neglected (Alcocer et al., 2022; Bradfer-Lawrence et al., 2023). The Acoustic Index User's Guide should help remedy that by providing current, easy-to-follow guidance in using acoustic indices and so offer the knowledge base for researchers to deliver informed interpretation of soundscape patterns. We hope that all researchers can use this guide to accurately link ecoacoustics with a wide range of key ecological processes for research in conservation and environmental management.

AUTHOR CONTRIBUTIONS

Tom Bradfer-Lawrence devised the initial concept and led the writing of the manuscript. Brad Duthie led the coding of the app. Jérémie S. P. Froidevaux secured the funding. All authors developed and expanded the original idea, generated content for the app, commented on manuscript drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The current version of the app is available from https://ecohack.shinyapps.io/Acoustic_Index_Users_Guide/. A baseline version of the app which can be run locally is available from <https://zenodo.org/records/11041274> (Bradfer-Lawrence, Duthie, et al., 2024). The example recordings are available in .wav format along with metadata from <https://zenodo.org/records/11004284> (Bradfer-Lawrence, Abrahams, et al., 2024).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1: Effect of Fourier Transform (FFT) window length on acoustic index values.

Figure S2: Acoustic Diversity Index values from 60-s recordings, and 10-s sections of corresponding spectrograms for five synthesised (1–5) and two real-world (6 and 7) soundscapes.

Figure S3: Acoustic Evenness Index values from 60-s recordings, and 10-s sections of corresponding spectrograms for five synthesised (1–5) and two real-world (6 and 7) soundscapes.

Figure S4: Spectral Entropy Index values from 60-s recordings, and 10-s sections of corresponding spectrograms for five synthesised (1–5) and two real-world (6 and 7) soundscapes.

Figure S5: Temporal Entropy Index values from 60-s recordings, and 10-s sections of corresponding spectrograms for five synthesised (1–5) and two real-world (6 and 7) soundscapes.

Figure S6: Normalised Difference Soundscape Index values from 60-s recordings, and 10-s sections of corresponding spectrograms for five synthesised (1–7) and two real-world (8 and 9) soundscapes.

File S1: Current content of the Acoustic Index User's Guide app.

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