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BioAcoustic Index Tool: Long-term biodiversity monitoring using on-sensor acoustic index calculations

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Abstract

Acoustic indices are valuable tools for measuring and tracking changes in biodiversity. However, the method used to collect acoustic index data can be made more effective by recent developments in electronics. The current process requires recording high-quality audio in the field and computing acoustic indices in the lab. This produces vast quantities of raw audio data, which limits the time that sensors can spend in the field and complicates data processing and analysis. Additionally, most field audio recorders are unable to log the full range of contextual environmental data that would help explain short-term variations. In this paper, we present the BioAcoustic Index Tool, a smart acoustic index and environmental sensor. The BioAcoustic Index Tool computes acoustic indices as audio is captured, storing only the index information, and logs temperature, humidity, and light levels. The sensor was able to operate completely autonomously for the entire five-month duration of the field study. In that time, it recorded over 4000 measurements of acoustic complexity and diversity all while producing the same amount of data that would be used to record 3 minutes of raw audio. These factors make the BioAcoustic Index Tool well-suited for large-scale, long-term acoustic biodiversity monitoring.

Abbreviations:

KEYWORDS

acoustic index, soundscape ecology, biodiversity, sensor, field recorder, open source

1. Introduction

The soundscape is a rich source of information about the state and health of an ecosystem. In particular, the calculation of acoustic indices from audio recordings of a soundscape provides stable quantitative metrics to monitor ecosystems for disturbances and changes in biodiversity. However, despite rapid advances in portable electronic technologies, the methods of calculating acoustic indices have not changed since the introduction of the concept by Boelman et al. (2007) and Sueur et al. (2008b).

Taking advantage of high-performance and low power consumption of modern microcontrollers, we have developed a tool to streamline the computation of acoustic indices, enable longer-term field studies, and add context to acoustic data by also recording environmental conditions. The BioAcoustic Index Tool (BAIT) skirts the

CONTACT David Kadish. Email: david.kadish@mau.se | This article has been accepted for publication in *Bioacoustics: The International Journal of Animal Sound and its Recording*, published by Taylor & Francis. Available online: <http://www.tandfonline.com/10.1080/09524622.2021.1939786>

data storage limitations of conventional audio field recorders by calculating acoustic indices in the field and storing only the index data, making it possible to leave a sensor in the field for months or even years at a time. At the same time, we have leveraged the flexibility of the onboard microcontroller to add additional sensors for light, temperature, and humidity. This means that acoustic index data can be correlated to the environmental conditions immediately surrounding the sensor. The ability to continuously monitor a soundscape over a period of months and years and to de-correlate a flexible range of environmental conditions from changes in the sonic environment has the potential to vastly improve the long-term monitoring of biodiversity using sound.

The use of sound as an indicator of biodiversity dates back at least to the publication of *Silent Spring* by Carson in 1962. As the concept of the soundscape was formalized by researchers such as Westerkamp (1974), Schafer (1977), and Truax (1978), soundscapes were recorded in analogue formats using portable stereo reel-to-reel recorders (Lyonblum 2017). By the mid-2000s digital recording and computing technologies had advanced to the point that larger-scale digital analysis of audio was possible.

These developments enabled the creation and use of the first acoustic indices for conducting quantitative analyses of biodiversity using sound (Boelman et al. 2007; Sueur et al. 2008b; Villanueva-Rivera et al. 2011) and the practice has expanded rapidly since then (Bradfer-Lawrence et al. 2019). These methods have the benefit of being able to estimate biodiversity without requiring the types of intensive surveys that have been traditionally used for assessing biodiversity (Sueur et al. 2008b; Buxton et al. 2018). The use of soundscape recordings and acoustic indices can help minimize disturbance of sensitive landscapes and reduce the cost of performing surveys while providing long-term data for assessing ecosystems.

The methods for collecting long-term soundscape data have changed little since the early days of soundscape recording. Typically, raw audio is recorded using purpose-built field audio recorders that remain in the field, untended, for anywhere from a few days to a few months (Pijanowski et al. 2011b; Pieretti et al. 2015; Gottesman et al. 2020). Commercial field recorders — such as the Song Meter from *Wildlife Acoustics* — are often used in these projects, but new, open-source tools such as AURITA (Beason et al. 2019) and the AudioMoth (Hill et al. 2019) that use electronics from the do-it-yourself (DIY) community are becoming more common as well.

Recordings are stored as high-quality audio files and collected at the end of the recording period for analysis in the lab. In the lab, recordings are preprocessed — this can include pre-filtering some audio frequencies (Towsey et al. 2014; Farina et al. 2021), removing noisy recordings (Righini and Pavan 2020), or subsampling the data in various ways (Towsey et al. 2014; Righini and Pavan 2020; Farina et al. 2021) — and then acoustic index calculations are performed.

This established method works well to capture acoustic index data, but has several drawbacks. An oft-mentioned difficulty for researchers is the sheer volume of data produced (Righini and Pavan 2020). Raw audio files require lots of storage (Bradfer-Lawrence et al. 2019) and significant data processing facilities (Towsey et al. 2014; Farina et al. 2021).

A single 15-minute uncompressed audio file, recorded at the 44.1 kHz in 16-bit stereo — a typical configuration for soundscape recordings — requires about 150MB of storage. Even with some of the largest (512GB) SD cards available, this means that a recorder is limited to about 850 hours (35 days) of continuous recording before the

Table 1.: Uses cases for different field recorders and sensors

To ...	Song Meter	AURITA	AudioMoth	SET	BAIT
record high-quality audio files for review and analysis in the lab	•	•	•	•	
log environmental data alongside acoustic indices				•	•
capture ultrasonic frequencies	•	•	•	•	
access pre-computed acoustic indices				•	•
be able to modify or hack your recorder		•	•		•
deploy sensors remotely for more than a few months					•
spend under \$100 (USD) per sensor			•		
spend under \$200 (USD) per sensor			•		•
spend under \$400 (USD) per sensor		•	•		•
spend under \$1000 (USD) per sensor	•	•	•	•	•

data must be collected¹. Researchers have also noted that archiving and processing all of that data presents its own set of challenges (Righini and Pavan 2020) and many authors describe trade-offs between the quality and depth of data they record and the storage and processing limitations they face.

The recorders that are currently used also lack a certain flexibility. They perform their assigned role of recording audio well but are limited to that particular task. Meanwhile, researchers have called for further integration of environmental data into soundscape studies to provide context for recordings and acoustic index measurements (Pijanowski et al. 2011b; Righini and Pavan 2020).

Tools like the aforementioned AURITA and the AudioMoth, as well as others like the Solo recorder (Whytock and Christie 2017), point to a way forward. These devices rely on recent developments in electronics and battery technology as well as the emergence of a vibrant DIY hardware community to create relatively cheap but powerful devices for recording the soundscape. These particular tools don't change how acoustic index data is collected, but related advances in DIY electronics have made powerful and efficient processors and sensors available to a wide community.

In particular, more microcontrollers — the small, embedded computers that power some of these sensors — are now capable of efficiently computing fast Fourier transforms (FFTs), the basis for producing spectrograms and many of the most popular acoustic indices. This enables them to perform the first stage of computation and analysis in the field, as the data is collected, instead of waiting to return to the lab with raw data. These microcontrollers have the additional benefit of being programmable — and therefore flexible in their operation — and can often connect to many peripherals including additional sensing equipment and devices for data storage and wireless communication.

There has been interest in deploying these types of technologies for ecological research. Guo et al. (2015) proposed that these types of smart sensors can improve ecological data collection by enabling continuous data acquisition and long-term operation in the field. Browning et al. (2017) and Greif and Yovel (2019) point out that onboard processing of raw data would dramatically reduce the amount of data that needs to be stored.

In the sonic domain, researchers have begun to test the use of on-sensor

¹This can be extended with recorders that feature multiple SD card slots, but one will still encounter limitations for long-term monitoring with this approach

analysis of sound. One such effort analyses acoustic data to track the grazing of cows (Deniz et al. 2017). Another uses deep learning neural networks to detect the vocalizations of different species urban bats (Balestrini et al. 2020). Other work has taken place in aquatic environments, where sound is the primary mode of communication (Baumgartner et al. 2013).

Finally, there is the Soundscape Explorer (terrestrial) (SET), developed by Luniletronik². It combines on-board computation of Acoustic Complexity Index (ACI) values with the logging of environmental data. It features two microphones — one for audible sound and one for ultrasonic detection — and can record for up to two weeks in a typical configuration³. While these features have proven useful in field studies (Farina et al. 2016; Farina and Salutari 2016; Farina 2019; Benocci et al. 2020), SET calculates only ACI and does not have solar charging capabilities, limiting its utility in long-term unsupervised studies⁴.

The BioAcoustic Index Tool is our attempt to fill that gap (see table 1). Using technologies associated with the DIY community, BAIT integrates a powerful microcontroller that calculates acoustic indices in real-time as sound is captured from the surroundings with environmental sensors that capture temperature, humidity, and light data. The resulting sensor captures acoustic index and environmental data while storing 40000 times less raw data than a conventional field audio recorder. Combined with the solar battery charging system, this allows the sensor to run autonomously and indefinitely in the field, without the need to change batteries or SD cards.

The ability to run these sensors without constant maintenance means that they are ideally suited to anchor large-scale, long-term acoustic biodiversity monitoring projects involving a grid of sensors spread out across a landscape. In the next section, we present the design of a prototype of this type of sensor system. We outline its capabilities and its drawbacks and, in later sections, discuss its applicability to existing and future studies.

2. Materials and Methods

The BioAcoustic Index Tool (BAIT) is a smart sensor that measures acoustic indices from the soundscape of an ecosystem and records those indices as well as other environmental data. Using a combination of onboard audio processing and solar power, BAIT was able to operate maintenance-free for nearly 6 months in a forest garden in southern Sweden.

The base of the sensor works in much the same way as any of the existing field recorders: it features a microphone, a processor, and an SD card. High-quality audio is captured and recorded to the SD card in much the same way as is done in the SongMeter recorders used by (Pieretti et al. 2015; Gottesman et al. 2020; Righini and Pavan 2020) and the Solo recorder used by (Bradfer-Lawrence et al. 2019)⁵.

The next step is where BAIT differs from a standard field recorder. Instead of leaving the audio files on the SD card to be collected and processed back in a lab, BAIT performs acoustic index calculations on-board, in the field. Once the acoustic indices are calculated for a particular audio file, the file is discarded and all that it

²<http://www.luniletronik.it/en/prodotto/set-soundscape-explorer-terrestrial/>

³Product specification at http://www.luniletronik.it/soundscape_explorer/.

⁴As SET is a closed-source commercial product, researchers are unable to expand its capabilities as needed.

⁵The microprocessor and microphone used in BAIT are similar to those found in the Solo recorder.

stores are the numbers representing the calculated acoustic indices⁶.

As predicted by Browning et al. (2017); Greif and Yovel (2019), performing calculations in-situ and discarding the raw audio results in a massive reduction in onboard data storage requirements. As such, storage capacity is no longer a limiting factor in the operating life of the sensor. A drawback of this approach, of course, is that it is no longer possible to reanalyze the raw audio or perform additional calculations or manual observations after the fact.

With storage capacity no longer a concern, the availability of power is now the main limiting factor for long-term operation of the sensor. A small, 2-watt solar panel powers the BioAcoustic Index Tool and charges its internal battery. While this configuration allowed the sensor to remain in the field recording data for over 6 months, it did not provide enough power or energy storage to allow the sensor to record continuously — especially in the darker, earlier months of the year. The sensor uptime is detailed in section 3.1.

2.1. Design

An important part of the BioAcoustic Index Tool is that the plans and code are open-source and therefore modifiable by researchers with specific needs. For example, knowing that there might not be enough power to carry out continuous recordings throughout the day and night, a researcher might modify the power management code to prioritize recording at dusk and dawn and only record during other times of the day if there is excess power available. They might also implement the calculation of other metrics that are useful for analyzing the soundscape.

In this section, we outline the design of BAIT to give the reader a general understanding of how the tool works. Further design and implementation details are described in section A.

2.1.1. Electronics

The electronic core of BAIT is a microcontroller, a set of sensors, and a power-management system. The microcontroller captures sound and environmental readings from the sensors and stores the environmental readings on an onboard microSD card. The audio is processed in real-time using modified versions of the algorithms to calculate ACI and Acoustic Diversity Index (ADI) on streaming data. The power management system charges the battery and informs the microcontroller to enter a lower-power mode when the battery doesn't have enough charge to run the full-scale calculations.

The microcontroller is similar to the one used in the AudioMoth (Hill et al. 2019) — an ARM Cortex M4F. In place of using a customized circuit board to run the microcontroller as is done on the AudioMoth, BAIT uses the Teensy 3.6 USB Development board which includes electronics for basic functionality like power regulation, a real-time clock (RTC), and an onboard microSD card reader (see fig. 1). The Teensy is also Arduino-compatible and BAIT's firmware is written using Arduino libraries. These factors make it relatively easy to modify the design and the associated firmware.

⁶It is entirely possible to store more than just the acoustic indices. During our evaluation of BAIT, we also recorded intermediate computations to help verify the calculations of acoustic indices after the fact. BAIT is capable of retaining data at any level — including raw audio — for verification, data, audits, or additional analysis, but doing so would negate some of the benefits discussed later on.

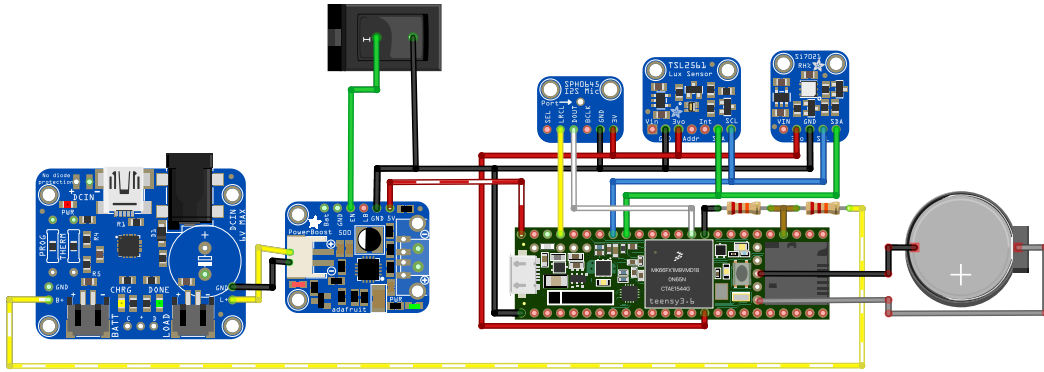


Figure 1.: Diagram of the electronic components and connections in BAIT prototype. This image was created with Fritzing (fritzing.org).

The sensor set includes a MEMS (microelectromechanical systems) microphone, a temperature and humidity sensor, and an ambient light sensor, all shown in fig. 1. The microphone captures soundscape data, while the other sensors enable the correlation of soundscape information with environmental data. The environmental sensors could also be used to schedule audio recordings or regulate power usage, though this is not currently implemented.

2.1.2. Firmware

The firmware⁷ for BAIT is written using the Arduino platform as well as libraries from Adafruit⁸ and PJRC⁹. It is modularly structured so that it is easy to add in the calculation of new bioacoustic and environmental measurements. It also incorporates two different power modes to enable proper charging of the batteries, while maintaining the collection of bioacoustic and environmental data as consistently as possible. The entire firmware is open-source and available on GitHub¹⁰.

The BAIT firmware controls sensor readings and data preprocessing; performs audio analysis and the calculation of acoustic indices; and manages the battery and power state of the system. The two main features of the BAIT firmware are the modified ADI and ACI algorithms and the power management system.

2.1.3. Acoustic index calculations

Two test acoustic indices were chosen for implementation in the prototype of BAIT: ADI and ACI. They were selected because both are well-documented and commonly-used in field studies. Their structure — operating on spectral representations of the audio — makes them suitable for implementation on a microcontroller that can perform FFTs. An overview of the implementation of these indices is given here, but a detailed description of the algorithm can be found in section A.2.

The ADI is an attempt to quantify the acoustic diversity of a sound. Defined by

⁷Firmware is software that is written for embedded computing, such as the microcontroller in BAIT.

⁸adafruit.com

⁹pjrc.com, the manufacturer of the Teensy

¹⁰github.com/dkadish/BioAcousticIndexTool

Villanueva-Rivera et al. (2011), the ADI operates between 0-10 kHz and calculates the Shannon entropy of the sound. This is done by dividing the frequency spectrum into 10 equal 1-kHz bands and assessing the proportion of FFT bins that contain energy above a defined threshold in each band. The Shannon index of these values is the ADI. A full calculation is shown in section A.2.1.

In the R implementation, this calculation is performed on a whole recording at once, calculating the proportion of positive bins at each frame. To efficiently calculate ADI on streaming data, BAIT collects a running sum of the number of times each FFT frequency bin exceeds the threshold along with a count of how many samples it has seen. These totals are divided at the end of the entire sample instead of at each frame, avoiding the accumulation of floating point errors over the course of the sample.

To calculate ACI in real-time on a microcontroller, it was necessary to translate the ACI algorithm into C++ but also to modify it to work with streaming data instead of a full audio file. Described in detail in Pieretti et al. (2011), the ACI represents the amount of variation of intensity of sound within frequency bands over the course of a recording fragment. It relies on the assumption that anthropogenic noises — for example, the droning of an aeroplane engine or the buzz of a factory — are often spectrally constrained and relatively constant, so it attempts to detect sounds that vary from moment-to-moment.

Normally, ACI is calculated for a complete audio file, but we modified the algorithm so that it could be computed in real-time as new audio was captured. Full details of the modified implementation can be found in section A.2.2.

2.1.4. Power modes

As storage space is no longer a limiting factor for BAIT, power is now the primary concern for the smart sensor. To conserve battery, two different power modes were designed, to maximize BAIT's operational time.

In the main, full-power mode, BAIT has all sensors enabled and records all of the available data. Audio is captured and indices are calculated in real-time as described above. Environmental data is captured and recorded to the microSD card. However, capturing and processing audio requires the processor to be constantly active. When only environmental data is collected, BAIT is active only a small fraction of the time, meaning that it consumes less power. As such, a second, low-power mode was developed to capture only environmental and battery data. When this mode is active BAIT is unable to capture or process audio, so the data from those times is not recorded.

For the prototype, these modes are used in two different ways. In mixed-power mode, BAIT alternates between full- and low-power modes every 15-minutes to extend the basic battery life of the system. It is assumed that this still provides a reasonable temporal resolution for soundscape index measurements. Secondly, the low-power mode is engaged when the battery level falls below a set level. This allows BAIT to continue to monitor environmental parameters and be ready to return to full-power mode once the battery charge increases.

Full details of how the power modes are designed and activated are available in section A.2.3.

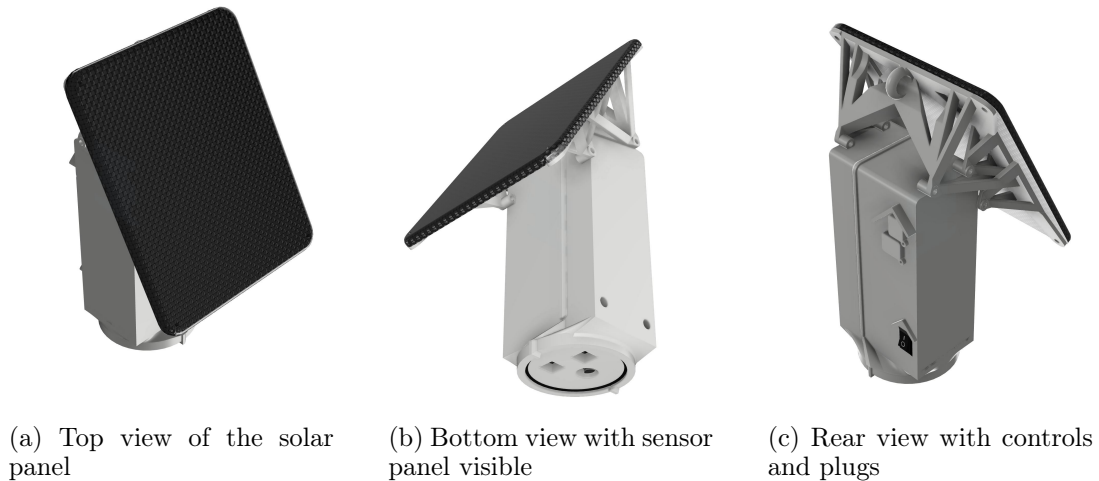


Figure 2.: Three renderings of the BioAcoustic Index Tool

2.1.5. Enclosure

The enclosure for the BioAcoustic Index Tool is 3D printed and the plans are freely available online¹¹. The enclosure was designed in Autodesk Fusion 360 and features a solar panel mount, an external power switch, a Micro-USB charging port, and a downward-facing sensor panel. The final design is shown in fig. 2.

The enclosure should not be considered water-proof, but with a good 3D print, it can last outside in a range of weather¹². To that end, the placement of the solar panel helps to protect the seam from heavy rain as does the placement of the sensors on the bottom of the device.

2.2. Field Experiments

The BioAcoustic Index Tool was tested in the field at a forest garden site called Holma Skogsträdgården in Höör, Sweden for approximately 5 months between February 18 and July 17, 2019. The site is an active educational forest garden set adjacent to a preschool and a forest garden teaching facility (Holma Folkhögskola), between a series of conventional farms on the outskirts of the town. A train line runs about 200m from the garden carrying local, regional, and long-distance passenger traffic as well as freight trains, and the sound of the passing trains echos loudly through the garden.

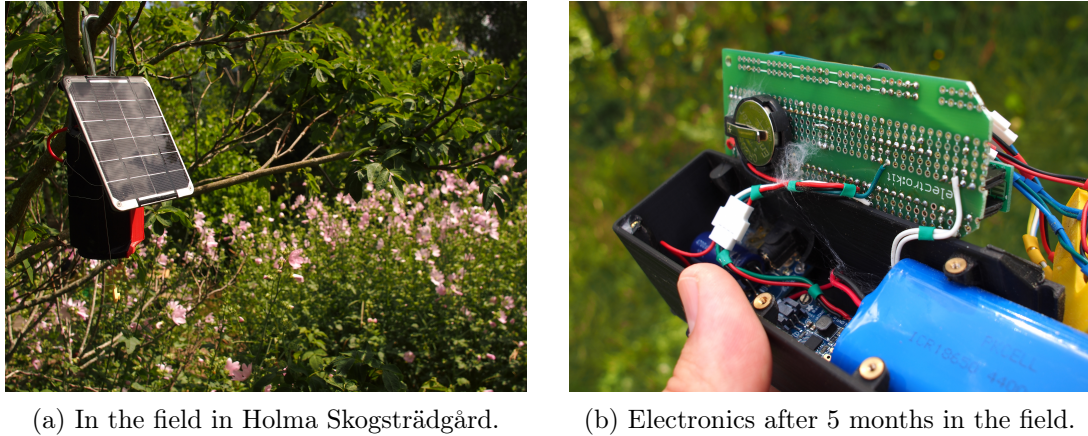
The garden itself features mixed groves of food-bearing trees, bushes, and perennial vegetables. Birds flit back and forth between the fruit trees and visit the sizeable on-site pond. Through the day, children from the preschool visit the garden to explore and classes from Holma Folkhögskola work and learn in the groves.

All of this activity provided a rich acoustic environment for testing BAIT. In addition to measuring the acoustic indices of the soundscape, the purpose of the trial was to establish the operating parameters for BAIT. This includes the following:

- Uptime: How many acoustic measurements is BAIT able to take using the

¹¹github.com/dkedish/BioAcousticIndexTool

¹²It worked for more than 6 months at a field site in southern Sweden and was not damaged by water in that time. That said, something did appear to have built a web inside the case and a solitary bee apparently took up residence in one of the screw recesses in the exterior of the case.



(a) In the field in Holma Skogsträdgård.

(b) Electronics after 5 months in the field.

Figure 3.: Views of the BioAcoustic Index Tool during the field experiments.

- available power?
- Mode power usage: What is the power consumption of each mode in the field?
- Storage requirements: How much data is actually recorded?
- Environmental data correlation: How does the environmental data collected correlate to the measured acoustic indices?

3. Results

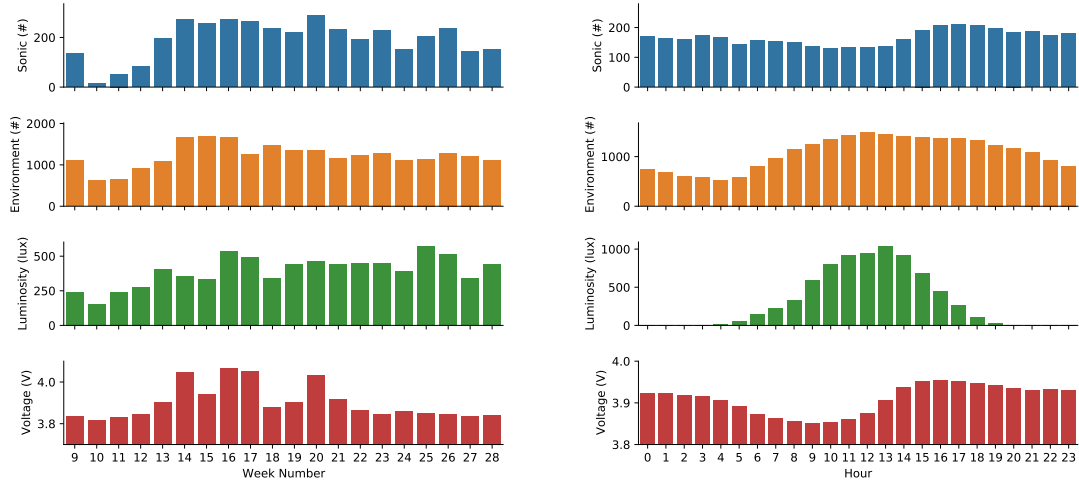
The field experiments were designed to validate the basic functionality of BAIT and to establish its operating parameters, as well as to produce a dataset that would demonstrate the types of relationships that could be explored using the sensor. In the following sections, we detail findings for operating parameters such as uptime, battery usage, and data production. We conduct a preliminary exploration of the collected acoustic index and environmental data and visualize the types of correlations that can be found in the dataset.

3.1. Uptime

Uptime refers to how many of the scheduled measurements were taken. For the prototype, acoustic index readings were generated from 15 minutes of audio every 30 minutes, so 100% uptime would correspond to 48 measurements per day for audio. Environmental readings were recorded every 5 minutes, so 100% uptime implies 288 measurements per day. The uptime depends on battery charge levels and power modes; for example, audio readings are suspended while the battery charge level is low, which causes the uptime to drop.

Uptime was calculated from the measurement counts visualised in fig. 4. Figure 4a shows the data organised by week to visualise seasonal changes in data collection. It depicts the number of acoustic index (blue) and environmental (orange) readings taken as well as the average light levels (green, in lumens) and battery voltage (red, in volts) for each week. The same data is shown in fig. 4b, organised instead by hour.

Overall, BAIT had an uptime of 57% for acoustic index measurements and 88% for environmental measurements. However, this varies widely by season and time of day. Seasonally, there's a large jump in uptime for acoustic index collection between



(a) Weekly grouping showing seasonal changes. Low light levels in February and March impeded solar charging, which interrupted audio readings.

(b) Hourly grouping showing diurnal changes. Midday sun drove charge levels higher which lead to increased readings in the afternoon and evening.

Figure 4.: Number of acoustic index (blue) and environmental (orange) readings taken and the average light levels (green, in lumens) and battery voltage (red, in volts). This visualises the uptime of the sensor and the main factors determining the sensor availability.

weeks 12 and 14 as average light levels increased and the battery was charged more regularly. Small variations in the average luminosity seem to correspond to large shifts in available power — and therefore the uptime — but this likely has to do with the positioning of the solar panel, meaning that the position and timing of the sunlight are perhaps more important than the average level. A more regular shift can be seen in the daily cycles (fig. 4b) as midday sun charges the battery, creating a spike in readings in the late afternoon as BAIT exits low-power mode.

3.2. Battery usage

In the lab, the power consumption of the microcontroller and sensor peripherals was measured to be 284 mW in full-power mode and 16 mW in low-power mode. At the 3.7 V nominal voltage of BAIT’s battery, this translates to a current draw of 76.8 mA in full-power mode and 4.3 mA in low-power mode. Given these rates and the 4400 mAh capacity of the battery, BAIT should be able to run continuously for just over 57 hours in full-power mode and a little over 1023 hours (around 42.5 days) in low-power mode without recharging.

These values are measured under ideal, laboratory settings and should be considered an upper bound on BAIT’s battery life. For a more detailed analysis of the battery operation see Appendix B.

3.3. Storage

The onboard processing of sound data means that a 15-minute analysis of the soundscape produces mere bytes of data. Over the approximately 5 months of data

collection, the sensor produced just under 15 MB of data. Though the sensor did have periods where it didn't record, the uptime was greater than 50%, so even at full power for the entire recording period, the sensor wouldn't have collected more than 30 MB of data. That's roughly equivalent to the size of 3 minutes of raw audio, recorded with standard settings. By comparison, generating the 4023 acoustic index measurements that BAIT captured using conventional recordings would have required the collection and processing of about 600 GB of raw audio.

3.4. Acoustic index

Of course, the primary task of the sensor is to capture acoustic index data. Over the course of the 5-month study period, BAIT captured 4023 measurements of each ACI and ADI. We present the collected data as it shows hourly and day-of-the-week patterns in fig. 5 with ACI shown in blue and ADI in orange.

One observes clear diurnal patterns in the measurements of both acoustic indices in fig. 5a. ACI exhibits a peak around midday with distinctive valleys around 3:00 and 19:00, while ADI has more of a plateau between 7:00 and 17:00. A study by Fairbrass et al. (2017) found that while ACI is correlated to biophony, ACI and ADI are also correlated to different types of anthrophony¹³. Given that, we expected to observe a difference between weekday and weekend patterns of the measured acoustic indices, however this is not the case in fig. 5b. The site is used during the week for teaching by Holma Folkhögskola — though there is not a constant presence there every day — and weekend events are sometimes hosted by a non-profit group that is associated with the site. It is possible that the use patterns at the site are irregular enough that there was no significant difference between human activity on weekdays and over the weekend to shift the distribution of measurements, though this issue requires further study.

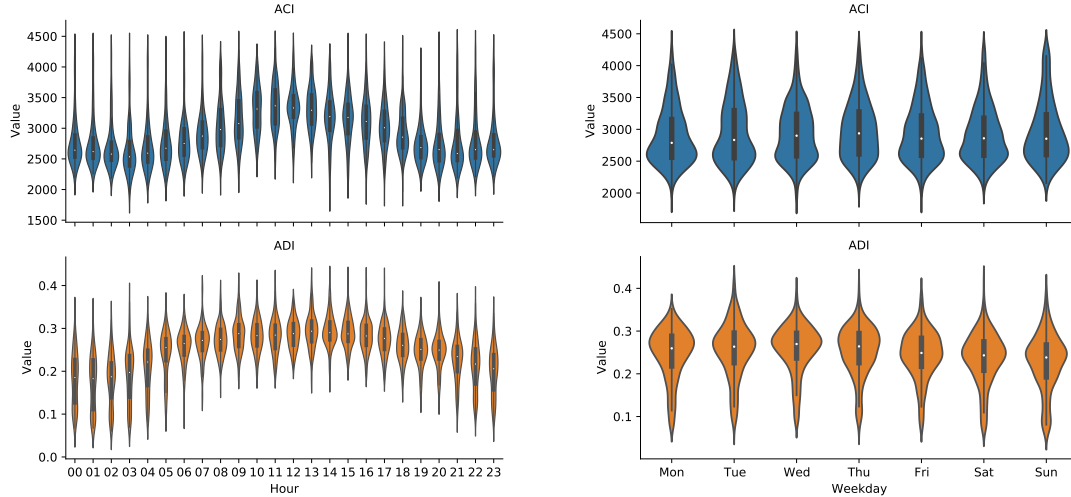
Interestingly, the shape of the plot of ADI in fig. 5a resembles the average ADI values that Villanueva-Rivera et al. (2011) found on agricultural sites in the paper where they first describe the metric. There, too, they recorded small peaks in the morning and evening with relatively flat values throughout the day and night.

3.5. Environmental Data Correlation

In addition to calculating acoustic indices, BAIT also records environmental data that can be used to understand the acoustic information that is captured. In their introduction to the field, Pijanowski et al. (2011a) pointed out that animal behaviour as well as soundwaves themselves are often modulated by environmental variables such as weather and light conditions. While it may be possible to use forecasts and weather station data to study the effects of environmental conditions on acoustic indices, onboard sensors can give a hyperlocal view of these phenomena.

The plots in fig. 6 visualize the relationships between ACI and ADI and the measured temperature, humidity, and luminosity. The data is displayed in a scatterplot matrix, which is used to show pairwise relationships between the different dimensions of a dataset. The scatterplot matrix has 3 distinct areas: the top-left area shows scatterplots of 2 of the measured variables along with a linear regression and its r^2 value; the

¹³ACI is positively correlated to the level of anthrophonic activity — defined as the area of a spectrogram that is covered by anthrophonic sound — while ADI is negatively correlated to anthrophonic diversity which reflects the number different types of anthrophonic sound. Notably, ACI and ADI are negatively correlated to the presence of electronic sounds and vehicular noise, while human speech is positively correlated to ACI but negatively correlated to ADI.



(a) Diurnal patterns of ACI and ADI. ACI shows a midday peak while ADI has more of a plateau pattern.

(b) Weekly patterns of ACI and ADI. There does not appear to be a strong pattern of difference between days of the week.

Figure 5.: Violin plots of ACI and ADI values, organized by hour and day to highlight diurnal and weekly patterns in the acoustic index measurements. Each violin shows the distribution of measurements over the category using a kernel density estimation. The violins also contain an internal box plot depicting the mean as a white dot and the quartiles as a black box.

diagonal shows the distribution of values for a single variable using a kernel density estimate (KDE)¹⁴; and the lower-right area shows scatterplots with contour lines highlighting areas of higher density. The data points and density estimates are coloured by month to help visualise seasonal changes in measurements.

In the top-left of fig. 6, the r^2 value is the square of the correlation coefficient of the linear regression and it indicates the level of interdependence of the 2 measured variables. The ACI-ADI plot (1st row, 2nd column) shows that the measured acoustic indices are relatively uncorrelated. This means that they appear to measure different aspects of the recorded soundscape and confirms the utility of having recording both metrics. Most highly correlated are the 3 environmental variables, as seen in the Temperature-Humidity, Temperature-Luminosity, and Humidity-Luminosity. Relative humidity — which is what is actually being measured — is defined in relation to temperature and days tend to be both warmer and brighter than nights, so these highly-correlated relationships are expected. Interestingly, ACI seems to be more strongly correlated to the environmental factors — especially humidity and luminosity — than temperature.

The density estimates along the diagonal show how the measurements of a single variable are distributed. As in a histogram, the x-axis shows the measured values and the y-axis depicts the relative density of measurements around that value. The ADI-ADI plot shows the distinct double-peak of the measured acoustic diversity with most of the measurement centred near ADI values of 0.2 or 0.55. ACI measurements also reveal a slight second peak, but it is much less pronounced than that of ADI.

¹⁴This is similar to a histogram, but generates a continuous plot showing the density of measurements around a particular value.

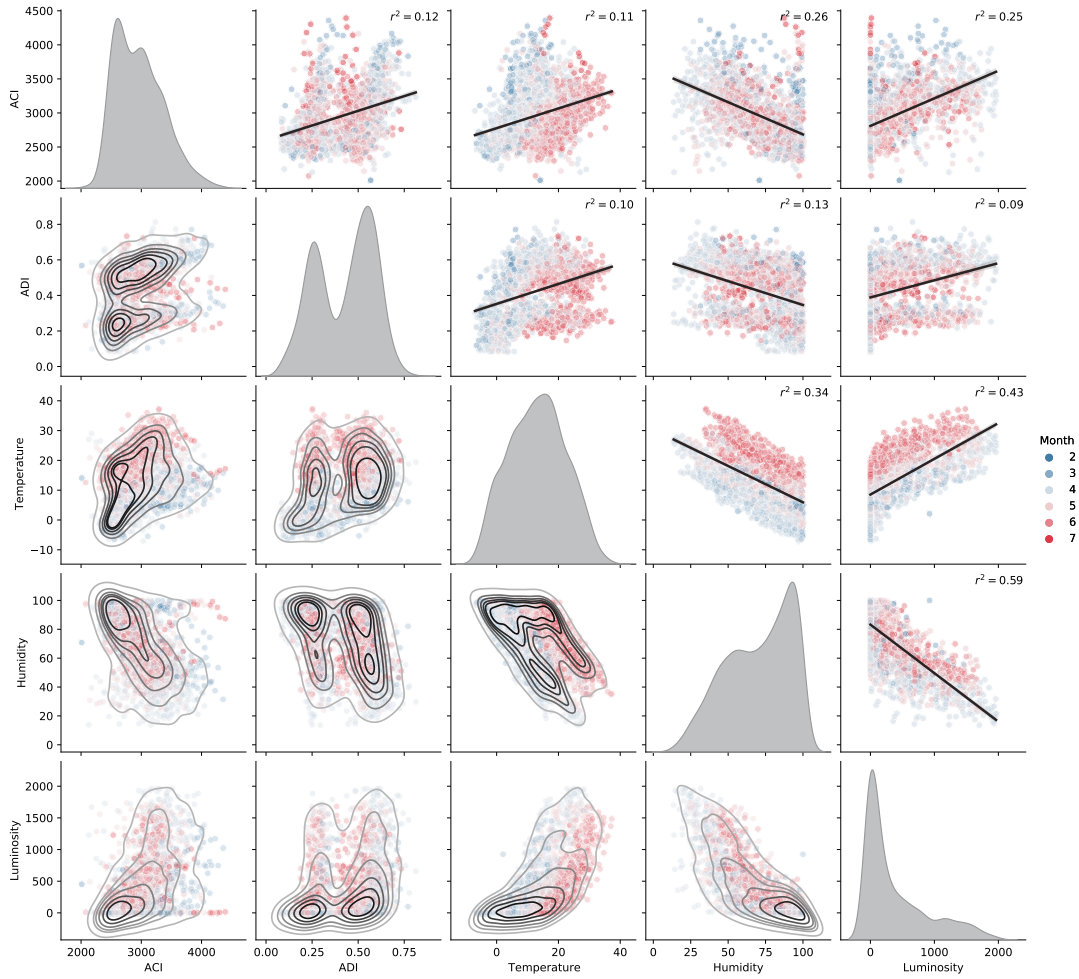


Figure 6.: A scatterplot matrix of the measured acoustic indices and environmental factors. The data is coloured by month to illustrate how the relationships change seasonally. The plots along the diagonal are density plots which — like histograms — show how each measured variable is distributed. The scatter plots above and below the diagonal show the relationships between the x- and y-axis variables; those above the diagonal are annotated with a linear regression while those below the diagonal show the density of the data using contour lines to illustrate areas of increasing density. These plots are useful as an overview of the data that has been collected. For example, the ADI-ADI plot found along the diagonal in the second column of the second row shows that ADI values cluster around two values — 0.2 and 0.55. The ACI-Luminosity plot in the first row shows that there’s a relatively strong correlation between the two measurements (compared to the other factors), which makes sense given the strong diurnal patterns seen in the ACI plot in fig. 5a. Directly below that plot, the correlation between ADI — which has a much flatter daytime curve in fig. 5a — and Luminosity is shown to be quite a bit weaker.

The plots in the bottom-right side of fig. 6 show the density of points in bivariate distributions using a 2-dimensional KDE to create an overlay much like a topographical map. Darker contours outline areas of higher density, while lighter contours show more diffuse measurements. They help to reveal the manner in which variables are correlated. For example, the Temperature-ADI plot reveals an unexpected pattern. The plot shows a deep impression in between the two peaks that are centred around temperatures of about 15°C and ADI values of 0.2 and 0.55. This means that ADI values are actually most divergent at temperatures around 15°C, while outside of that range, the ADI measurements are more uniform.

These plots demonstrate the utility of collecting environmental data alongside acoustic indices measurements. Patterns in the data are evident with only the basic visualisations presented here. Further analyses could help to decorrelate the environmental measurements from the acoustic data to better understand both the impact of environmental conditions on acoustic index measurements and long-term trends in biodiversity measurements conducted under varying environmental conditions.

4. Discussion

The results in the previous section indicate how the BAIT prototype performs in the field. But what do they mean for its potential use in future field studies? What kind of performance can be expected in the field, what kinds of data can researchers expect to collect, and how might BAIT be improved to address some of its drawbacks and deficiencies and to add functionality?

4.1. Data Storage

Data storage and management are often cited as key limitations for soundscape studies (Towsey et al. 2014; Bradfer-Lawrence et al. 2019; Righini and Pavan 2020; Farina et al. 2021). In the field test, BAIT generated 4023 data points for each of the acoustic indices that it measured. Each data point was based on 15 minutes of audio which, had it been captured as raw audio using a conventional field recorder, would have required about 600 GB of storage capacity.

In contrast, BAIT produced just 15 MB worth of data over the course of 5 months in the field, capturing 2 acoustic indices twice-per-hour and 3 points of environmental data at 5-minute intervals. This represents a reduction in the data output of a sensor by a factor of 40000. At these data production rates, the size of available storage is no longer a limiting factor in the ability of the sensor to run autonomously in the field for an indefinite period.

4.2. Power

The next key limitation is the availability of power. Soundscape recordings are often conducted well away from the electrical grid and so battery power becomes essential for running recording devices. Processing data in the field does require far more power than simply recording audio files and, as such, BAIT requires a solar panel to maintain sufficient power to operate. This has both advantages and disadvantages. BAIT was able to operate over a long time (the device was still running at the end of the 5-month

test period) but the uptime was intermittent, with BAIT recording environmental data in 88% of the time-periods but acoustic indices in only 57% of the scheduled times. The recording periods for the acoustic indices were biased towards the afternoon and evening as the device often lost power in the morning after a night of recording drawing on power stored during the previous day.

4.3. Available Data

In the end, what matters most is what data is available to a researcher. The most important benefit of BAIT — the ability to capture acoustic index data without needing to store raw audio files — will be the most difficult for some researchers to accept. Without access to the raw audio, they cannot re-process the audio after having listened to the recordings, they cannot run additional analyses after the fact, and — perhaps most importantly for some — they will be unable to listen to the soundscape and interpret the recordings themselves (Righini and Pavan 2020; Farina et al. 2021). It is important to not discount what is learned qualitatively about a field site through the active listening of someone with a well-tuned ear for the details of a soundscape¹⁵.

That said, something is gained as well here. The automation of the process of generating acoustic indices saves computing time and effort, but also minimizes the opportunity for human data processing errors. In their 2018 paper on sources of errors in scientific studies, Brown et al. identify *errors of data management* as one of four major types of study error. In automating a large part of the initial data analysis, BAIT minimizes the risk of introducing errors between the capture of audio data and the calculation of acoustic indices. It means that different recordings will not, for example, accidentally be processed by different implementations of an acoustic index algorithm¹⁶ or using different parameters and settings.

In addition, the recording of synchronized environmental data has the potential to add new explanatory power to acoustic index measurements. Pijanowski et al. (2011a) describe the impact of what they call *atmospheric dynamics* on the composition of the soundscape. These conditions can have direct impacts on the measured soundscape, such as when wind and rain produce sound, but they also have indirect impacts. Animals often modulate their sound production in response to environmental factors (Pijanowski et al. 2011a) — think of cricket chirp rates responding to changes in temperature — and the actual propagation of sound also depends in part on atmospheric conditions (Ingård 1953) Pijanowski et al. (2011b) set the improvement of understanding of the relationship between environmental conditions and sound as one of six major themes in the field of soundscape ecology and the availability of a tool that records these conditions alongside soundscape data could prove to be an important step toward that goal.

4.4. Use Case

A number of recent studies have used acoustic indices — and ADI or ACI in particular — to investigate ecological questions and might have benefited from the use of a tool like BAIT (Farina et al. 2013; Farina and Pieretti 2014; Towsey et al. 2014; Bradfer-Lawrence et al. 2019; Righini and Pavan 2020; Farina et al. 2021). Some additional

¹⁵One possible way to mitigate this by conducting a type of mixed-mode recording is discussed in section 4.5.5

¹⁶The R packages `seewave` and `soundecology` produce different ACI values, see <https://cran.r-project.org/web/packages/soundecology/vignettes/ACIandSeewave.html>

Table 2.: Common acoustic indices and their status in BAIT

Index	Source	BAIT Status
Acoustic Complexity Index (ACI)	Pieretti et al. (2011)	working ^a
Acoustic Diversity Index (ADI)	Villanueva-Rivera et al. (2011)	working ^a
Bioacoustic Index (BI)	Boelman et al. (2007)	easily implemented ^b
Acoustic Evenness Index (AEI)	Villanueva-Rivera et al. (2011)	easily implemented ^b
BIOPHONY	Righini and Pavan (2020)	easily implemented ^b
Acoustic Entropy Index (H)	Sueur et al. (2008b)	not implemented ^c
Spectral Entropy (H_f) ^d	Sueur et al. (2008b)	easily implemented ^b
Normalised Difference Soundscape Index (NDSI)	Kasten et al. (2012)	not implemented ^c

^afully implemented and tested in the prototype

^bnot in the prototype but can be calculated using the same process as working acoustic indices

^cnot implemented, requires new processes not used in the prototype

^dSpectral Entropy (H_f) is actually one half of the calculation of the Acoustic Entropy Index, which is the sum of the spectral and temporal entropies of a signal.

studies have employed the SET, which provides some of the same benefits as does BAIT (Farina et al. 2016; Farina and Salutari 2016; Farina 2019; Benocci et al. 2020).

To better understand the use cases for BAIT, it is useful to examine in detail a single study that used conventional recording methods to understand how it would be changed by the introduction of BAIT. Righini and Pavan (2020) set out to characterize the soundscape of a nature reserve and compare the soundscape inside and outside the reserve using the recordings from three field sites. They used a Song Meter 3 field recorder to capture 45600 minutes (488.30 GB) of recorded audio, recording the first 10 minutes of every 30-minute period over the course of a month.

The study included qualitative and quantitative analysis, listening to recordings and viewing their spectrograms as well as calculating a set of seven acoustic indices. The study found significant differences between daytime and nighttime activity for all three sites as well as differences between the two sites within the reserve and the site outside the reserve. In addition to an analysis of the full dataset, Righini and Pavan also performed some manual filtering of the data. They listened to all of the recorded data and excluded files that featured heavy wind or rain and then compared the resulting indices to those calculated with the full dataset.

How would the study have been different if the authors had been able to use the BioAcoustic Index Tool in place of the SM3 Field Recorders? The data collection would have been similar, though they would have had the ability to leave the sensors in the field for far longer, no longer having to worry about data storage and processing capabilities¹⁷. Much of the quantitative analysis would also remain the same; of the seven acoustic indices that are calculated, two are already implemented on BAIT and three others can be easily added to the system (see table 2 for details). Two others — Acoustic Entropy Index (H) and Normalised Difference Soundscape Index (NDSI) — would require additional programming to implement on BAIT as they do not use the same underlying processes already employed by the ACI and ADI calculations. The qualitative analysis, on the other hand, would not be possible in the same manner. BAIT does not currently record audio or spectrograms — though it is possible to do so (see section 4.5.5) — so the researchers would be unable to listen to recordings and

¹⁷In prototype testing, BAIT did not always have enough power to sample at every scheduled point, but this could be mitigated using a larger solar panel and battery and the lighter recording schedule of this study — 10 minutes every half hour as opposed to 15 in the BAIT test.

observe spectrograms in the way that they did in the study.

However, BAIT would come with one important additional benefit. Righini and Pavan write that there are unaccounted for differences between the three sites during the daytime that probably depend on environmental factors. ‘These results indicate the need to have more information of environmental parameters at very local levels and thus the need to add at least light, temperature, humidity and wind sensors to acoustic recorders.’ (Righini and Pavan 2020) BAIT performs precisely this function, measuring light, temperature, and humidity on the sensor alongside the acoustic index data.

4.5. Future Developments

Even in its current form as a first prototype and proof-of-concept, BAIT can produce interesting datasets over a long period of time in the field. However, there are a range of improvements that should be undertaken to enhance current performance and add functionality.

4.5.1. Power

The power system is the most obvious candidate for some improvements. The easiest way to improve the uptime for the sensor would be to simply increase the size of the battery and the solar panel. A larger battery would allow the system to store more energy during sunny times to help eliminate the dip in recordings during the early morning hours and a larger panel could take better advantage of the available solar energy to capture more energy when it is available.

The power modes could also be adjusted for more effective operation. The system could be adjusted to prioritize certain times of the day — for example, dawn and dusk when there is often increased acoustic activity. Or it could be programmed to ensure that there is roughly even sampling of all of the times of the day so that less sampling is done during the evening when the battery is often more fully charged to save power for morning samples.

A third power mode could also be introduced that would capture but not process audio. The processing is particularly power-intensive, so when battery levels are lower or there is little sun, BAIT could capture audio, but wait to process it until reserve solar power is available and then delete the raw audio files to regain the storage space.

Additionally, there is some indication that BAIT was sampling more than necessary in the field trial. Pieretti et al. (2015) suggest that capturing audio for one of every five minutes is sufficient to accurately characterize a soundscape using ACI. Therefore it is possible to change the sensor scheduling to lower the amount and duration of audio capture and index computation, which would further extend the battery life of the sensor.

A combination of these approaches could increase the uptime for soundscape recording and improve the quality and distribution of data that is collected without intensive hardware revisions. However, on the electronic hardware side, an improved battery management system that could track current draw and power usage would be a boon to the system’s ability to self-regulate and switch between power modes. This kind of improvement should be high on the list of priorities for the next major hardware revision.

4.5.2. *Wireless*

There’s a benefit to the reduction of data that BAIT produces that has been alluded to, but not discussed in full. With the daily data production in kilobytes (KB), it becomes more feasible — both in terms of power requirements and cost of transmission — to send data from remote locations back to a lab as it is being collected. Wireless transmission can be expensive both in terms of power requirements and the price of bandwidth in remote areas, so minimizing the data to be transferred is essential.

Existing acoustic monitoring systems such as Echo Box and the SAFE Acoustics monitoring network have used popular consumer wireless communications infrastructure such as WiFi and cellular networks (Balestrini et al. 2020; Sethi et al. 2020). However, remote areas where these types of devices are often deployed sometimes lack the required cellular and WiFi infrastructure. In these circumstances, it becomes necessary to transmit data by longer-range modes of communication. In practice, this would likely mean linking individual sensors by a mesh network to a common base station with a satellite or landline Internet connection. IoT wireless technologies like LoRaWAN (Vangelista et al. 2015; Margelis et al. 2015) or ZigBee (Safaric and Malaric 2006) could play this role; both are low-power mesh networking technologies designed for embedded systems.

Wireless signalling would draw some battery power, but the BioAcoustic Index Tool could collect data until it is charged to its highest power level before sending a burst of collected data back to the lab through its wireless networking system. This feature would help to make the device fully autonomous and able to operate basically without service at all, barring equipment failures. The same connection could be used to send device status updates and even potentially to adjust sampling schedules and parameters based on data observed back in the lab.

This would allow BAIT to operate as part of a large-scale, long-term, fully autonomous network of hundreds or thousands of acoustic biodiversity monitoring sensors. The ability to leave a sensor in the field indefinitely and to collect data remotely could enable entirely new types of long-term tracking studies.

4.5.3. *Additional indices*

For the prototype, we calculated two indices: ADI and ACI. They were chosen for their importance in the field and their relative ease of calculation. However, several other acoustic indices use similarly structured computations that would not be difficult to implement on BAIT using the structure that we have developed. These include Bioacoustic Index (BI) (Boelman et al. 2007), Acoustic Evenness Index (AEI) (Villanueva-Rivera et al. 2011), and BIOPHONY (Righini and Pavan 2020), as well as spectral entropy (Toh et al. 2005). These indices are some of the key components of the `soundecology` (Villanueva-Rivera and Pijanowski 2018) and `seewave` (Sueur et al. 2008a) R packages that are commonly used in soundscape ecology studies.

Because the code for BAIT is open-source, anyone can modify the firmware that performs these calculations and it is possible to add new indices as they are defined in the literature.

4.5.4. *Environmental sensors*

For the prototype, temperature, humidity, and light level sensors were chosen for inclusion in BAIT because the sensors are readily available and provide a good overview of the environmental conditions at a particular location. But there are many

other sensors that are available for more detailed detection of particular parameters, depending on the needs of a particular research project.

An anemometer could be a particularly useful addition to the toolkit as wind can be a significant factor in some of the acoustic index calculations (Righini and Pavan 2020). A soil moisture or rainwater sensor could provide additional details about the hydraulic conditions at a site, and as rain is another significant source of geophonic sound that can affect calculations.

Those represent the most obvious additions to BAIT’s sensor toolkit, but one could imagine how the addition of more specialized sensors like geophones for detecting seismic events and air quality sensors for detecting vehicular emissions and forest fires might prove useful for particular studies. It would be impossible — and probably unhelpful — to exhaustively list all of the sensors that one could attach to BAIT, but the point here is to note that the system is extendible and can be modified to the specific sensory needs of a study.

4.5.5. *Mixed-mode data collection*

One of the most significant drawbacks of BAIT is that it saves no raw audio. This is a purposeful feature of the system, but it also means that there is nothing for researchers to listen to for a more experiential or qualitative impression of their field site. While this type of knowledge is seldom referred to specifically in written research, listening to the soundscape can give the researcher context and a connection to the site that the raw acoustic index data cannot provide on its own. For some, this is a crucial part of their work (Righini and Pavan 2020).

Though the prototype is set up this way, there is no reason that saving raw audio has to be an all-or-nothing proposal. It is possible to save particular samples of audio to the storage medium or even to record all possible audio and delete samples selectively to free up space as necessary. Intermediate calculations such as the raw FFT data — or FFTs averaged over time — could be stored to generate spectrograms upon collection. The system could be programmed to retain data for anomalous events that produce extreme acoustic index or environmental data to later diagnose the causes and impacts of these events.

These strategies could help to alleviate researcher concerns about the quality of data collected and can be used to perform confidence checks to confirm the accuracy of calculations. They can be used as data samples that can be examined in detail and used to illustrate the processes used for acoustic index calculations.

4.5.6. *Embedded smart sensors*

This section has so far focused on future improvements to BAIT specifically, but it is prudent to note the potential of smart sensors in general to enable new types of acoustic and ecological research. The practice of moving processing power to peripheral sensors is part of a broader trend in computing called *edge computing* (Shi et al. 2016). As microcontrollers have gotten smaller, more efficient, more powerful, and more accessible, it has become increasingly possible to perform complex computation in embedded contexts.

These shifts are occurring rapidly. A 2018 study detailed a multilevel frog detection system that performed initial data analysis on an embedded device, followed by further analysis on a cloud server (Roe et al. 2018). Only two years later, a paper proposed running a full deep learning neural network classifier designed to detect bird calls right

on the sensor (Sturley and Matalonga 2020) and Balestrini et al. (2020) have produced a network of sensors with an embedded deep learning-based bat detector and classifier. These solutions use embedded computers (the Raspberry Pi and Intel Edison), but it is actually possible to run some neural networks on microcontrollers that use a fraction of the power of even these lightweight systems (Falbo et al. 2020).

As these trends continue, it should be possible to perform more accurate species and event detection as well as advanced index calculation on-site. These changes will open new opportunities for acoustic population and biodiversity surveys as well as long-term monitoring of ecosystems.

4.6. Conclusion

The BioAcoustic Index Tool is a shift from the conventional field audio recorder and is unlikely to replace them where researchers are interested in performing in-depth analysis of a particular soundscape. However, it would be a boon to a project interested in the calculation of acoustic indices over a broad spatial and temporal field. The ability to generate acoustic index data at a large number of sample points over a long study time could enable new kinds of soundscape surveys that track patterns over months, years, and decades. The inclusion of synchronized environmental data gives researchers the tools for better understanding of how environmental conditions modulate the soundscape and impact measured acoustic indices. And the use of an open platform for BAIT enables researchers to extend the platform with new sensors and calculations as needed.

A tool like BAIT makes it possible to envision the creation of permanent acoustic biodiversity monitoring networks featuring tens, hundreds, and even thousands of sensors spread across a landscape. With wireless connections, these networks could generate a high-resolution overview of shifting biodiversity levels. It would be possible to measure seasonal and annual changes in biodiversity and better understand how environmental factors contribute to acoustic measurements of biodiversity as well as changes in biodiversity itself. The fully-automated pipeline that produces acoustic index data at the sensor would allow ecologists to focus on the interpretation of the acoustic index data instead of the process of its collection and computation.

The approach is indicative of a coming shift in the collection, processing, and analysis of acoustic data and soundscape recordings. BAIT and future sensors like it have the potential to move the first level of ecological data processing from the lab to the field and, in doing so, easing the process of collecting and analyzing data about soundscapes.

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Disclosure statement

The authors declare no potential conflict of interest.

Data Availability statement

The data that support the findings of this study are openly available on figshare.com. The raw data collected from the sensor is stored at <http://doi.org/10.6084/m9.figshare.13607198> and processed data used for analysis and to generate plots in the paper is stored at <http://doi.org/10.6084/m9.figshare.13607132>.

References

- Balestrini M, Gallacher S, Rogers Y. 2020. Moving HCI Outdoors: Lessons Learned from Conducting Research in the Wild. In: McCrickard DS, Jones M, Stelter TL, editors. *Hci outdoors: Theory, design, methods and applications*. Springer International Publishing; chap. 4; p. 83–98.
- Baumgartner MF, Fratantoni DM, Hurst TP, Brown MW, Cole TVN, Van Parijs SM, Johnson M. 2013. Real-time reporting of baleen whale passive acoustic detections from ocean gliders. *The Journal of the Acoustical Society of America*. 134(3).
- Beason RD, Riesch R, Koricheva J. 2019. AURITA: an affordable, autonomous recording device for acoustic monitoring of audible and ultrasonic frequencies. *Bioacoustics*. 28(4).
- Benocci R, Brambilla G, Bisceglie A, Zambon G. 2020. Eco-acoustic indices to evaluate soundscape degradation due to human intrusion. *Sustainability (Switzerland)*. 12(24).
- Boelman NT, Asner GP, Hart PJ, Martin RE. 2007. Multi-Trophic Invasion Resistance in Hawaii: Bioacoustics, Field Surveys, and Airborne Remote Sensing. *Ecological Applications*. 17(8).
- Bradfer-Lawrence T, Gardner N, Bunnefeld L, Bunnefeld N, Willis SG, Dent DH. 2019. Guidelines for the use of acoustic indices in environmental research. *Methods in Ecology and Evolution*. 10(10).
- Brown AW, Kaiser KA, Allison DB. 2018. Issues with data and analyses: Errors, underlying themes, and potential solutions. *Proceedings of the National Academy of Sciences*. 115(11).
- Browning E, Gib R, Glover-Kapfer P, Jones K. 2017. Passive acoustic monitoring in ecology and conservation. Report No: 2.
- Buxton RT, McKenna MF, Clapp M, Meyer E, Stabenau E, Angeloni LM, Crooks K, Wittemyer G. 2018. Efficacy of extracting indices from large-scale acoustic recordings to monitor biodiversity. *Conservation Biology*. 32(5).
- Carson R. 1962. *Silent Spring*. New York: Houghton Mifflin Company.
- Deniz NN, Chelotti JO, Galli JR, Planisich AM, Larripa MJ, Leonardo Rufiner H, Giovanini LL. 2017. Embedded system for real-time monitoring of foraging behavior of grazing cattle using acoustic signals. *Computers and Electronics in Agriculture*. 138.
- Fairbrass AJ, Rennert P, Williams C, Titheridge H, Jones KE. 2017. Biases of acoustic indices measuring biodiversity in urban areas. *Ecological Indicators*. 83.
- Falbo V, Apicella T, Aurioso D, Danese L, Bellotti F, Berta R, De Gloria A. 2020. Analyzing Machine Learning on Mainstream Microcontrollers. In: Saponara S, Gloria AD, editors. *Applications in electronics pervading industry, environment and society*. Springer, Cham; chap. 12; p. 103–108.
- Farina A. 2019. Acoustic codes from a rural sanctuary: How ecoacoustic events operate across a landscape scale. *Biosystems*. 183.
- Farina A, Pieretti N. 2014. Sonic environment and vegetation structure: A methodological approach for a soundscape analysis of a Mediterranean maqui. *Ecological Informatics*. 21.

- Farina A, Pieretti N, Morganti N. 2013. Acoustic patterns of an invasive species: the Red-billed Leiothrix (*Leiothrix lutea* Scopoli 1786) in a Mediterranean shrubland. *Bioacoustics*. 22(3).
- Farina A, Pieretti N, Salutari P, Tognari E, Lombardi A. 2016. The Application of the Acoustic Complexity Indices (ACI) to Ecoacoustic Event Detection and Identification (EEDI) Modeling. *Biosemiotics*. 9(2).
- Farina A, Righini R, Fuller S, Li P, Pavan G. 2021. Acoustic complexity indices reveal the acoustic communities of the old-growth Mediterranean forest of Sasso Fratino Integral Natural Reserve (Central Italy). *Ecological Indicators*. 120.
- Farina A, Salutari P. 2016. Applying the Ecoacoustic Event Detection and Identification (EEDI) Model to the Analysis of Acoustic Complexity. Report No.:
- Gottesman BL, Francomano D, Zhao Z, Bellisario K, Ghadiri M, Broadhead T, Gasc A, Pijanowski BC. 2020. Acoustic monitoring reveals diversity and surprising dynamics in tropical freshwater soundscapes. *Freshwater Biology*. 65(1).
- Greif S, Yovel Y. 2019. Using on-board sound recordings to infer behaviour of free-moving wild animals. *Journal of Experimental Biology*. 222(February).
- Guo S, Qiang M, Luan X, Xu P, He G, Yin X, Xi L, Jin X, Shao J, Chen X, et al. 2015. The application of the Internet of Things to animal ecology. *Integrative Zoology*. 10(6).
- Hill AP, Prince P, Snaddon JL, Doncaster CP, Rogers A. 2019. AudioMoth: A low-cost acoustic device for monitoring biodiversity and the environment. *HardwareX*. 6.
- Ingård U. 1953. A Review of the Influence of Meteorological Conditions on Sound Propagation. *The Journal of the Acoustical Society of America*. 25(3).
- Kasten EP, Gage SH, Fox J, Joo W. 2012. The remote environmental assessment laboratory's acoustic library: An archive for studying soundscape ecology. *Ecological Informatics*. 12.
- Lyonblum EZS. 2017. An Omnivorous Ear: The Creative Practice of Field Recording [Doctor of Philosophy (PhD)]. University of Cambridge.
- Margelis G, Piechocki R, Kalessi D, Thomas P. 2015. Low Throughput Networks for the IoT: Lessons learned from industrial implementations. *IEEE World Forum on Internet of Things, WF-IoT 2015 - Proceedings*.
- Pieretti N, Duarte M, Sousa-Lima R, Rodrigues M, Young R, Farina A. 2015. Determining Temporal Sampling Schemes for Passive Acoustic Studies in Different Tropical Ecosystems. *Tropical Conservation Science*. 8(1).
- Pieretti N, Farina A, Morri D. 2011. A new methodology to infer the singing activity of an avian community: The Acoustic Complexity Index (ACI). *Ecological Indicators*. 11(3).
- Pijanowski BC, Farina A, Gage SH, Dumyahn SL, Krause BL. 2011a. What is soundscape ecology? An introduction and overview of an emerging new science. *Landscape Ecology*. 26(9).
- Pijanowski BC, Villanueva-Rivera LJ, Dumyahn SL, Farina A, Krause BL, Napoletano BM, Gage SH, Pieretti N. 2011b. Soundscape Ecology: The Science of Sound in the Landscape. *BioScience*. 61(3).
- Righini R, Pavan G. 2020. A soundscape assessment of the Sasso Fratino Integral Nature Reserve in the Central Apennines, Italy. *Biodiversity*. 21(1).
- Roe P, Ferroudj M, Towsey M, Schwarzkopf L. 2018. Catching toad calls in the cloud: Commodity edge computing for flexible analysis of big sound data. *Proceedings - IEEE 14th International Conference on eScience, e-Science 2018*.
- Safaric S, Malaric K. 2006. ZigBee wireless standard. In: *Proceedings ELMAR 2006*; jun. IEEE. p. 259–262. June.
- Schafer RM. 1977. *The Tuning of the World*. vol. 1st. New York, N.Y.: Random House.
- Sethi SS, Ewers RM, Jones NS, Signorelli A, Picinali L, Orme CDL. 2020. SAFE Acoustics: An open-source, real-time eco-acoustic monitoring network in the tropical rainforests of Borneo. *Methods in Ecology and Evolution*. 11(10).
- Shi W, Cao J, Zhang Q, Li Y, Xu L. 2016. Edge Computing: Vision and Challenges. *IEEE Internet of Things Journal*. 3(5).
- Sturley S, Matalonga S. 2020. PANDI: A Hybrid Open Source Edge-based System for Environmental and Real-Time Passive Acoustic Monitoring - Prototype Design and

- Development. 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology, IRASET 2020.
- Sueur J, Aubin T, Simons C. 2008a. Seewave, A Free Modular Tool for Sound Analysis and Synthesis. *Bioacoustics*. 18(2).
- Sueur J, Pavoine S, Hamerlynck O, Duvail S. 2008b. Rapid acoustic survey for biodiversity appraisal. *PLoS ONE*. 3(12).
- Toh AM, Togneri R, Nordholm S. 2005. Spectral Entropy As Speech Features. In: *Proceedings of PEECS*. p. 60–65. 1.
- Towsey M, Wimmer J, Williamson I, Roe P. 2014. The use of acoustic indices to determine avian species richness in audio-recordings of the environment. *Ecological Informatics*. 21.
- Truax B. 1978. *The World Soundscape Project's Handbook for acoustic ecology*. 1st ed. A.R.C. Publications. Music of the environment series.
- Vangelista L, Zanella A, Zorzi M. 2015. Long-Range IoT Technologies: The Dawn of LoRa™. In: Atanasovski V, Leon-Garcia A, editors. *Future access enablers for ubiquitous and intelligent infrastructures*. (Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering; vol. 159). Cham: Springer International Publishing; p. 51–58.
- Villanueva-Rivera LJ. 2015. *Indices and ecoinformatics tools for the study of soundscape dynamics* [Doctor of Philosophy]. Purdue University.
- Villanueva-Rivera LJ, Pijanowski BC. 2018. *soundecology: Soundscape Ecology - R package*; mar.
- Villanueva-Rivera LJ, Pijanowski BC, Doucette J, Pekin B. 2011. A primer of acoustic analysis for landscape ecologists. *Landscape Ecology*. 26(9).
- Westerkamp H. 1974. Soundwalking. *Sound Heritage*. 3(4).
- Whytock RC, Christie J. 2017. Solo: an open source, customizable and inexpensive audio recorder for bioacoustic research. *Methods in Ecology and Evolution*. 8(3).

Appendix A Design

The design of the BioAcoustic Index Tool is described in section 2.1, however specific implementation details are important for the reproduction of BAIT. Here, the specific electronic components, algorithms, and programming strategies are detailed to make it possible to build and extend BAIT for future studies.

A.1. Electronics

The BAIT design is based around the Teensy 3.6, which features an ARM Cortex M4 processor. The processor includes a floating point unit (FPU), which allows it to perform calculations with floating point numbers in a relatively efficient and accurate manner. The remainder of BAIT is divided into a power management system and a sensor system.

The primary sensor is the microphone, an Integrated Inter-IC Sound Bus (I²S) microelectromechanical systems (MEMS) chip-based microphone that mounts directly onto a PCB. The microphone chip captures sound with a flat response curve in the 100 Hz to 10 kHz range and digitizes it before sending it forward to the microcontroller over an I²S bus. The SPH0645 was selected for its cost-effectiveness and the ease of connecting it to the system given the pre-digitized signal that it produces, however, its linear response range of 100-10k Hz might be a limiting factor to others interested in using the tool. Fortunately, it is possible to replace this device with an external microphone for sample collection, if a different frequency response is desired.

In addition to the microphone, the BAIT features a set of environmental sensors that can gather data that can help to provide context to the bioacoustic indices and result in a deeper understanding of the patterns of biodiversity (Pijanowski et al. 2011a). Two sensors are engaged in this environmental data collection and they capture light levels, ambient temperature and relative humidity. The Si7021 from Silicon Labs measures both ambient temperature and relative humidity and gives digital readings in degrees Celsius and percentage. The TSL2561 measures the intensity of the ambient light in lux.

A full list of the electronic components used in the prototype and their cost is available in table 3.

A.2. Firmware

The firmware for BAIT is written using the Arduino platform as well as libraries from Adafruit¹⁸ and PJRC¹⁹. It is modularly structured so that it is easy to add in the calculation of new bioacoustic and environmental measurements. It also incorporates two different power modes to enable proper charging of the batteries, while maintaining the collection of bioacoustic and environmental data as consistently as possible.

The major contribution of the BAIT firmware is the translation of the algorithms for the calculation of two bioacoustic indices into C++ and their transformation from offline post-processing algorithms into code that runs efficiently online and in real-time. The ACI and ADI were implemented in this way and each required different modifications.

The full firmware is available on GitHub at github.com/dkedish/BioAcousticIndexTool.

A.2.1. ADI calculation

Defined in (Villanueva-Rivera et al. 2011), the ADI operates between 0-10 kHz and calculates the Shannon entropy of the sound by dividing the frequency spectrum into 10 equal 1-kHz bands and applying Equation 1, where p_i is the proportion of sound in frequency band i .

$$H' = - \sum_{i=1}^S p_i \ln p_i \quad (1)$$

Note that this proportion p_i is understood as the proportion of FFT bins within the frequency band i that are above a defined threshold. What results is a measure of the diversity of the soundscape in terms of how the sounds are spread across the frequency spectrum over the period of measurement.

In the R implementation, this calculation is performed on a whole recording at once. It calculates a spectrogram for the entire file and then collects the overall level in each band for use in calculating diversity. The BAIT does not have the luxury of a complete sound file, so it instead collects a running sum of the power in each frequency bin along with a count of how many samples it has seen. p_i is tracked frame-by-frame, calculating a running sum of the number of bins with values above the threshold (P_i) and tracking the number of frames seen (N). When the ADI value is calculated for a length of time,

¹⁸adafruit.com

¹⁹pjrc.com, the manufacturer of the Teensy

Equation 2 is applied to avoid accumulating floating point errors.

$$p_i = \left(\sum_{i=0}^N P_i \right) / N \quad (2)$$

Now, Equation 1 can be applied as in the original implementation and the ADI can be calculated for a longer span of time, emulating the way that a whole sound file is processed.

A.2.2. ACI Calculation

The transformation of the ACI calculation is somewhat more complex. Described in detail in Pieretti et al. (2011), the ACI represents the amount of variation of intensity of sound within frequency bands over the course of a recording fragment. It relies on the assumption that anthropogenic noises — for example, the droning of an aeroplane engine or the buzz of a factory — are often spectrally constrained and relatively constant, so it attempts to detect sounds that vary from moment-to-moment.

Over the course of a user-defined temporal step (j)²⁰, the difference in intensities from between samples (d_k) at a particular frequency bin (Δf_l) is calculated as

$$d_k = |I_k - I_{k+1}| \quad (3)$$

These differences are summed over the entire temporal window and divided by the total observed acoustic intensity over that period as in Equation 4, resulting in a measure of the ACI for a particular frequency bin and temporal step ($ACI_{j,l}$).

$$ACI_{j,l} = \frac{\sum_{k=1}^{n-1} d_k}{\sum_{k=1}^n I_k} \quad (4)$$

These measurements are added up for all q frequency bins and all m temporal steps in a recording to determine the total ACI for the audio clip as

$$ACI_{\text{tot}} = \sum_{l=1}^q \sum_{j=1}^m ACI_{j,l} \quad (5)$$

To perform this calculation efficiently, BAIT retains a running tabulation of the total ACI (ACI_{tot}), the sum of the difference between samples in the same frequency bin (D), the total acoustic intensity in the same frequency bin (I). It also stores the previous intensity measurement for each band (I_{k-1}) so that the difference (d_{k-1}) can be calculated. At the end of each temporal window, these values can be reset except for ACI_{tot} , which is retained and saved to a file at the end of the recording period.

The conversion of these scripts from post-processing calculations to ones that can be performed on streaming data saves a great deal of data and enables the processing of sound on the microcontroller without taxing its memory resources.

²⁰These are also referred to as clumps in (Farina et al. 2016). BAIT defaults to 30s.

A.2.3. Power Modes

The BAIT has two power modes that are switched between automatically as the system’s battery charges and discharges. The main power mode measures acoustic and atmospheric data and is active when the battery is charged over 3.7V, as measured by an onboard voltage divider. In this mode, audio is captured and realtime calculations are done to log ACI and ADI.

These calculations, however, are quite power-intensive and inhibit the charging of the battery when they are engaged. To maintain data logs, but allow the battery to charge when it is low, a low power mode is engaged below the threshold of 3.7V, in which the BAIT records only environmental data and turns the acoustic systems off to save energy. Since the atmospheric measurements are intermittent, the microcontroller can sleep in between measurement cycles, drastically reducing the power requirements²¹.

The sleep cycle is also modulated by the measurement process. ACI and ADI are calculated in 15-minute segments on the BAIT²². If low-power mode were to engage during the middle of a 15-minute measurement cycle, all data gathered before the invocation of low-power mode would be wasted. To avoid this pattern, BAIT inhibits the application of low-power mode during acoustic index calculation. After the cycle has completed and useful data are collected, then the BAIT is allowed to sleep for a cycle.

A.3. Enclosure

The enclosure is 3D printed from polylactic acid (PLA) on an Ultimaker 2 printer. It features a detachable sensor panel with cut-outs for the 3 sensors, a port for power delivery, and an external power switch. The case has mount points for a 3D-printed solar panel mount and hanging system to suspend it from a tree in the study environment. Internally, the enclosure has mount points for the power management PCBs and a cradle for the battery pack that powers the system. All of the screw points are augmented with metal heat-set inserts to strengthen the screw points. Designs were done using Autodesk’s Fusion 360 software and sliced on Ultimaker’s CURA. Design files are available in the project’s GitHub repository at github.com/dkedish/BioAcousticIndexTool.

Appendix B Battery Life

Section 3.2 describes a laboratory-based analysis that establishes the upper bound on the battery life of BAIT without recharging using the solar panel. However, there are serious limitations to these calculations. The battery capacity is negatively impacted by both high and low temperatures, so the capacity in field situations is likely to be less than 4400 mAh. These measurements also exclude the voltage boost electronics used to convert the 3.7 V supply from the battery to the 5 V supply expected by the Teensy 3.6. The boost electronics operate at 90% efficiency²³, meaning some power is lost in the conversion. As such, these numbers should be treated as an upper limit on the possible performance of the battery.

To establish more realistic operating parameters, it was necessary to gather data in

²¹As opposed to the acoustic measurements which require continuous, intensive calculations.

²²Emulating 15-minute recordings of soundscapes.

²³Product specification and datasheet available at <https://www.adafruit.com/product/1903>

Table 3.: Parts list and prices for the prototype of BAIT

Part	Price (USD)
Solar Charger v2	17.50
PowerBoost 500	9.95
4400 mAh Li-Ion Battery	19.95
Si7021 Temperature and Humidity Sensor	8.95
TSL2561 Light Sensor	5.95
I2S MEMS Microphone	6.95
Teensy 3.6	29.95
Solar Panel (2W)	29.00
22k Ohm resistor	0.75
SD Card (16 GB)	9.95
Coin cell mount	0.95
Coin cell battery	0.95
On/Off Switch	0.95
Total*	141.75

*Total cost for the purchased breakout boards and components. Does not include the cost of the 3D printed enclosure, breadboards, and consumable parts such as screws, wire, etc.

the field. This presented another challenge as the prototype cannot directly measure power consumption. The battery voltage measurements used for switching between power modes can reveal something about the battery’s state. However, it is important to note that the discharge profile of the lithium-ion battery pack is highly nonlinear so these analyses can also only provide an estimate of the power consumption of BAIT.

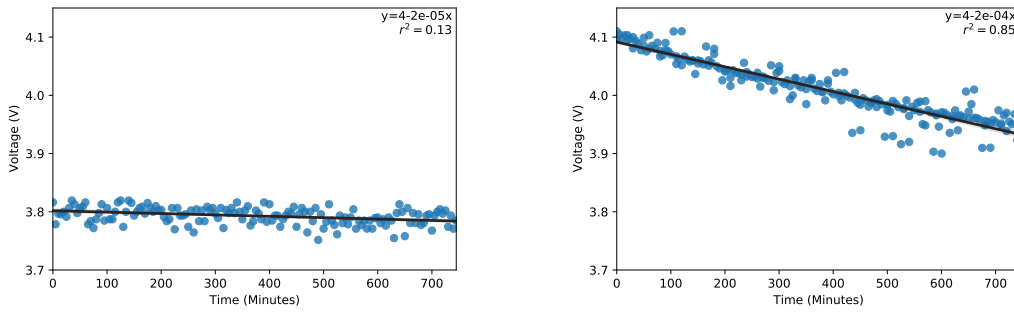
Voltage change in the two power modes was estimated by analysing the drop in voltage during times when the luminosity was near-zero and therefore the system was not being charged by the sun. In mixed-power mode, where audio is being captured and processed, the battery voltage was falling at a rate of about 12.3 mV/hour. In contrast, in low-power mode, the battery voltage was falling at a little over a tenth of that, 1.5 mV/hour. The data behind this calculation is shown in fig. 7.

The battery can be charged to 4.2V and mixed-power mode is engaged until it reaches 3.7V, so without any solar charging, the sensor can read and process audio for at least 40 hours²⁴. It is also possible to increase the operational time by switching to a larger solar panel or battery. A larger capacity battery would allow the sensor to store more power when the sun is shining to increase the time that it could run without charging. And a larger panel could collect more energy from the available light in order to charge the battery faster and more often.

Appendix C ACI Algorithm Verification

The ACI algorithm has a number of different implementations that produce slightly different results. The implementations in the R packages `seewave` (Sueur et al. 2008a) and `soundecology` (Villanueva-Rivera and Pijanowski 2018) have differences in their outputs, which are documented in the notes for the `soundecology` package at <https://cran.r-project.org/web/packages/soundecology/vignettes/ACIandSeewave.html>. There, Villanueva-Rivera attributes the differences to slight variations in the implementation of the clumping argument, j .

²⁴Again, this is approximate as the discharge curve for lithium-ion batteries is non-linear.



(a) Low-power mode voltage drop. The trend line shows a drop of 0.02 mV/min (1.5 mV/hour) in low-power mode.

(b) Mixed-power mode voltage drop. The trend line shows a drop of 0.20 mV/min (12.3 mV/hour) in mixed-power mode.

Figure 7.: Voltage drop under different power modes when there is no sunlight charging the batteries via the solar panel.

Here, the implementation in BAIT is compared to the `soundecology` implementation to verify the accuracy of the approach to calculating ACI as a running sum. The test is conducted using audio recordings that were used in a comparison of the ACI results from `soundecology` and another implementation of the ACI algorithm, a plugin for the WaveSurfer software called `SoundscapeMeter.1.0.14.05.2012` (Villanueva-Rivera 2015). The recordings were resampled to 44.1 kHz (originally 48 kHz) to meet the requirements for the code to play WAV files from an SD card in the Teensy Audio Library.

The material — including code, audio, and data files — used for these tests is available on figshare at <http://dx.doi.org/10.6084/m9.figshare.14445348>.

C.1. FFT

The spectrograms produced by the microcontroller in BAIT and the `spectro` function of the `seewave` package²⁵ are slightly different. This is shown in detail in fig. 8, which plots the two spectrograms along with the differences between the two, once the values are normalized²⁶. This means that for the same audio, BAIT will inevitably produce a different result from `soundecology` (and therefore other implementations as well). For this reason, caution should be used when comparing ACI results computed using different methods.

C.2. ACI Computation

To bypass the difference in FFT implementations and verify the remainder of the algorithm, we used a modified version of the `acoustic_complexity` function from `soundecology` which calculates ACI from FFT values saved in a CSV file instead of

²⁵This is used to produce an FFT representation of the sound for analysis in the `soundecology` package.

²⁶Note that the BAIT spectrogram shown here has a change from the implementation used in the BAIT prototype field experiment. The default setting for the microcontroller's FFT library averages together 8 readings to produce a single temporal value for each frequency. This went unnoticed prior to the field experiment, so the data in the testing of the prototype used this setting. This has been corrected in the latest version of the code (version 0.2 on Github at <https://github.com/dkadish/BioAcousticIndexTool/releases/tag/0.2>) so that no averaging of the FFT readings is done.

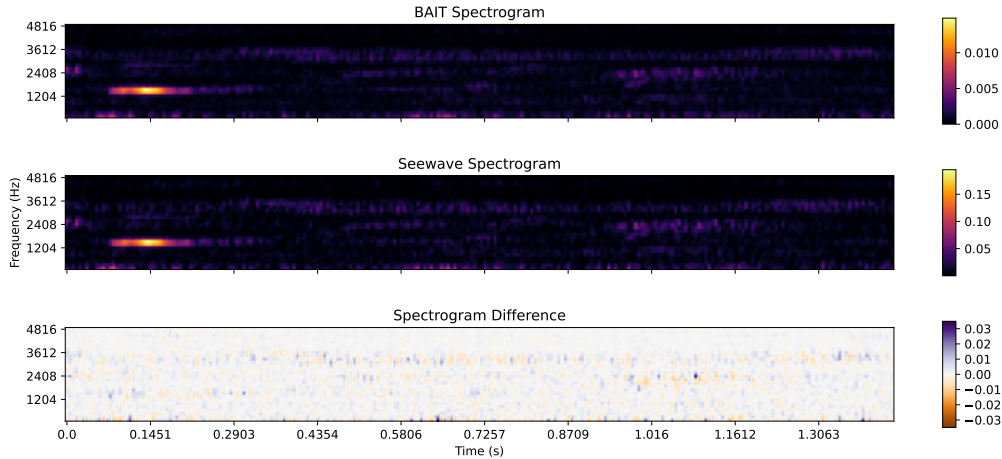


Figure 8.: Spectrograms of the lower frequencies from the first portion of 6.wav. The top image is the spectrogram generated by BAIT, the middle image is the spectrogram generated using `seewave`, and the final image is the difference between the two (normalized) spectrograms.

from a raw audio file²⁷. To generate the CSV file, BAIT runs test code²⁸ that computes the ACI of a sound file while recording the FFT values to its SD card as they are computed.

Here, a second discrepancy between the two implementations is clear in the clumping procedure — the same site as the difference between the `soundecology` and `seewave` versions of the algorithm. The `soundecology` implementation of ACI calculates a variable called `I_per_j` at the beginning of its computation, which is the number of temporal frames per cluster. This fixed variable is calculated as the integer (`floor`) of j , the number of clumps divided by Δ_{tk} , the time per frame. Each clump, then, is calculated from a fixed number of FFT readings.

BAIT, however, operates in real-time and therefore does not have the ability to look back over a fixed sound file and determine a static number of bins per clump. The number of FFT readings per clump is controlled by the timing of the microcontroller. If the clump time is set for 5 seconds, the clump rolls over once 5 seconds have passed. This leads to slight variations in the clump size if the FFT frame rate does not divide evenly into the clump time.

To account for this, the test code on BAIT also records the ACI_j value for each cluster j as well as the number of FFT readings processed at the end of the frame. That number of FFT readings is then used in the modified version of the `acoustic_complexity` function from `soundecology` so that its clumps are calculated on the same number of frames. This allows for a direct comparison between the ACI calculations of BAIT and the `soundecology` package.

Figure 9 shows the total ACI value for each clump (ACI_j) calculated by BAIT and the modified `acoustic_complexity` function from the `soundecology` package.

²⁷The R notebook containing that test code is available on figshare at <http://dx.doi.org/10.6084/m9.figshare.14445348>.

²⁸The code that generates the CSV is available at https://github.com/dkadish/BioAcousticIndexTool/blob/0.2/firmware/bait/src/test_save_spectro.cpp.

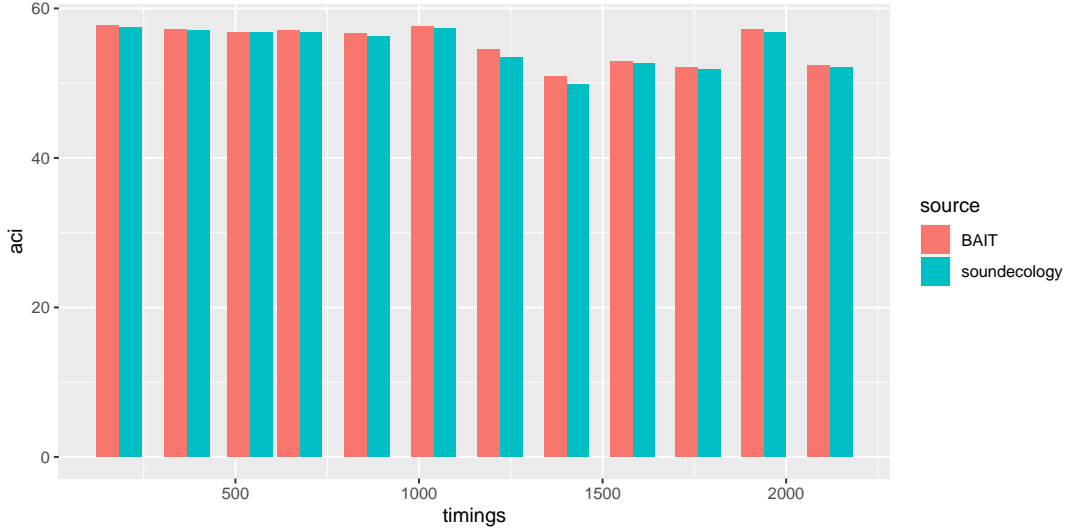


Figure 9.: ACI totals from each clump (ACI_j) in the calculation on the test file.

The slight discrepancy in each value is caused by floating-point calculation errors. The FFT values from the microcontroller are saved to CSV with a 6-digit decimal precision, which leads to rounding errors when those numbers are imported into R. Additionally, the microcontroller computes floating point numbers at single (32-bit) precision, while R uses double (64-bit) precision leading to further minor differences in the results.

However, it is clear from the plot in fig. 9 that the algorithm implemented on the microcontroller in BAIT is the same as the one implemented in `soundecology`. The total ACI values that are calculated using that process — 598.18 from `soundecology` and 597.61 from BAIT — differ only by rounding errors within the calculation.

C.3. Comparability

Though the cluster-by-cluster computation is the similar, implementation differences between the real-time ACI computation on BAIT and the file-based computation on a computer will produce different results for the same sound. Therefore, it is inadvisable to directly compare ACI results obtained with BAIT with those obtained by recording sound and computing the ACI using implementations in R.

An examination of the waveforms of selected audio files reveals a pattern. Figure 11 shows 3 files where the ACI values computed using BAIT and the `soundecology` R package were similar and 3 where there were large differences in the values. From this sample, it appears that similar results were produced for sounds with higher amplitudes.

This can be shown formally. The median of the amplitude envelope (M) is a measure of the amplitude of a sound over an entire recording. The Shapiro-Wilk test shows the distributions of the difference between calculated ACI values and the median of the amplitude envelopes to not be normally distributed ($p = 8.2e - 3$ and $p = 2.4e - 3$ respectively), so correlation is tested using Spearman’s rank-order correlation. The test shows a strong negative correlation ($\rho = -0.95$, $P = 2.2e - 16$), meaning that the larger difference in computed ACI values occurs in conjunction with quieter sounds.

This can likely be attributed to difference in precision discussed in section C.2.

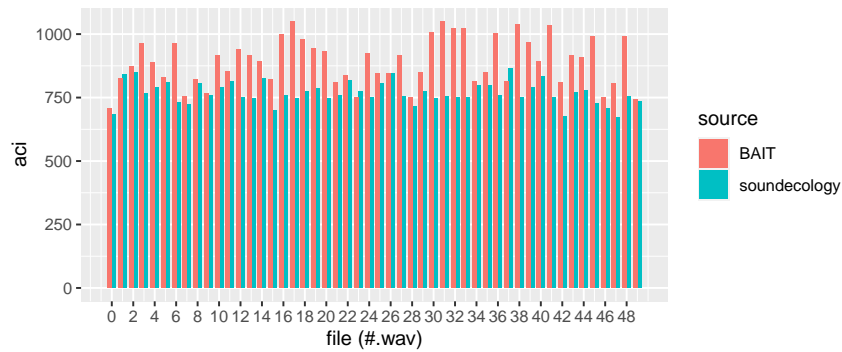


Figure 10.: ACI totals from each of the 50 test files in the first set of test data at <https://doi.org/10.6084/m9.figshare.1036395.v1>.

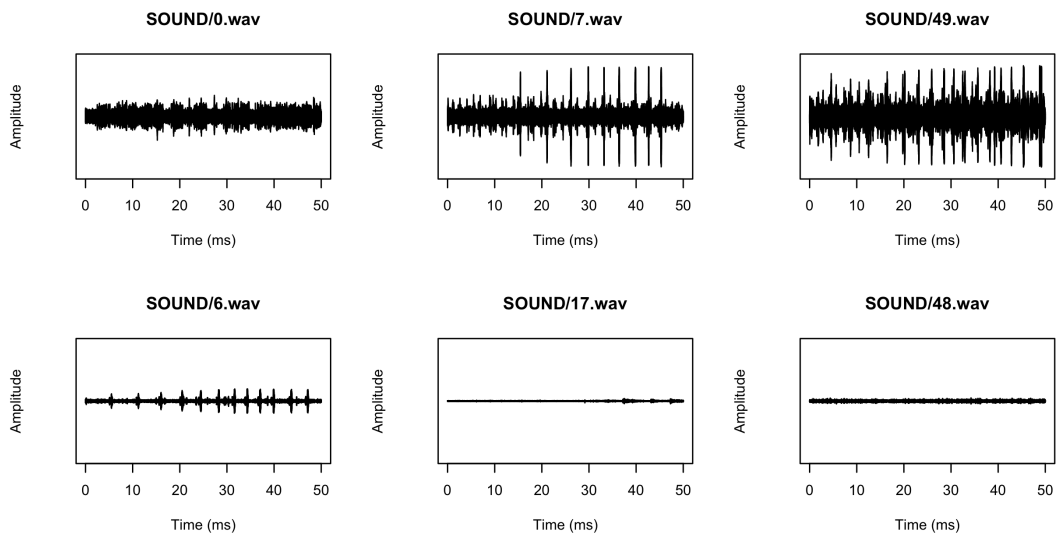


Figure 11.: Waveforms of a selection of the audio files from fig. 10. The ACI values for the audio files in the top row were similar when calculated with BAIT and the soundecology R package, while those in the lower row differed more significantly.

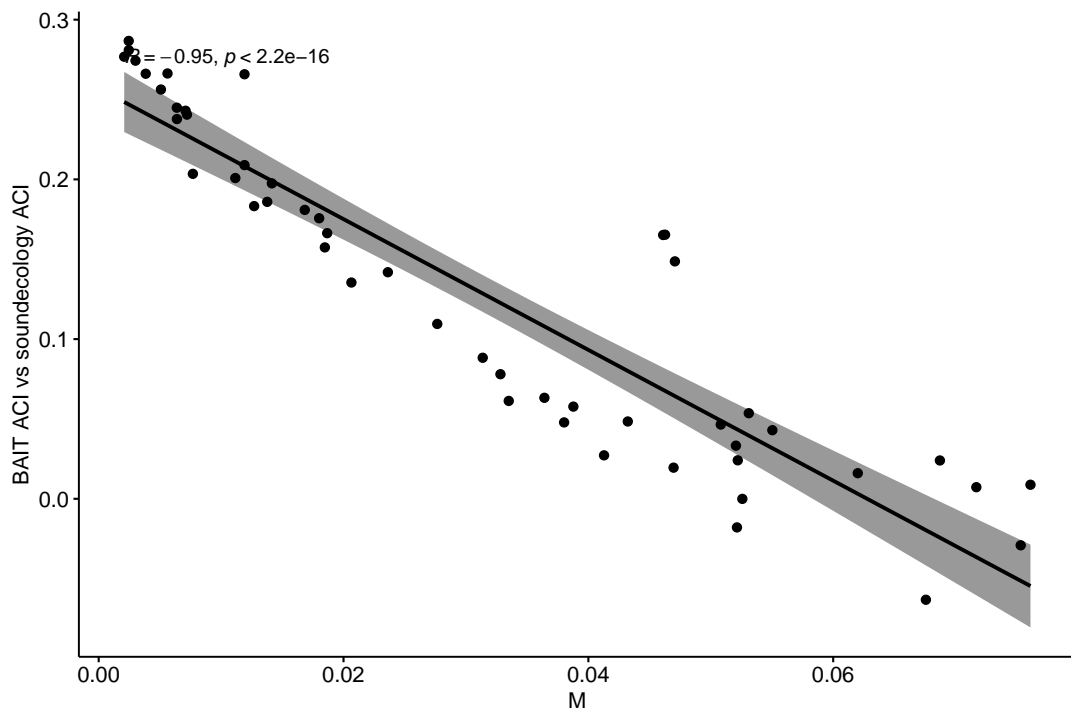


Figure 12.: Spearman's rank-order correlation for the difference in calculated ACI and the median of the amplitude envelope of a sound file. The two have a strong negative correlation ($\rho = -0.95, P = 2.2e - 16$) indicating that differences in computation are associated with quieter sounds.

Quieter sounds — those with lower median amplitudes — produce smaller values in an FFT. These smaller signals amplify the precision errors that arise due to the 16-bit operation of the microcontroller, leading to greater differences in the final ACI calculation.

Appendix D FFT Filtering

Farina et al. (2016) introduce two modifications to the original ACI algorithm. They discuss the presence of artifacts in the FFT caused by microphone noise, analog-to-digital converter (ADC) errors, and introduced electronic noise and how these artifacts can cause inaccurate measurements of acoustic complexity.

The first modification is the addition of fixed-value threshold to eliminate spurious pulses from the FFT matrix. Any FFT values below the threshold are discarded and replaced with 0 in the FFT.

A second modification then eliminates these erroneous values from the overall ACI calculation. In the calculation of d_k (eq. (3)), the absolute difference between adjacent values in the FFT matrix, the calculation is treated as 0 if either of the values is 0. The modified version of eq. (3) is shown in eq. (6).

$$d_k = \begin{cases} 0 & \text{if } I_k = 0 \text{ or } I_{k+1} = 0 \\ |I_k - I_{k+1}| & \text{else} \end{cases} \quad (6)$$

This modified version of the ACI is used in the latest version of SoundscapeMeter (2.0). The option to perform this type of filtering has also been added to the latest version of the BAIT firmware, found at github.com/dkadish/BioAcousticIndexTool, for compatibility. It is enabled by setting the `doFilter` and `doDiscardAdjacentZeros` flags to `true` when instantiating the `ACI_TemporalWindow` class in the main function.