

## RESEARCH ARTICLE

# AudioMoth: Evaluation of a smart open acoustic device for monitoring biodiversity and the environment

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**Abstract**

1. The cost, usability and power efficiency of available wildlife monitoring equipment currently inhibits full ground-level coverage of many natural systems. Developments over the last decade in technology, open science, and the sharing economy promise to bring global access to more versatile and more affordable monitoring tools, to improve coverage for conservation researchers and managers.
2. Here we describe the development and proof-of-concept of a low-cost, small-sized and low-energy acoustic detector: "AudioMoth." The device is open-source and programmable, with diverse applications for recording animal calls or human activity at sample rates of up to 384 kHz. We briefly outline two ongoing real-world case studies of large-scale, long-term monitoring for biodiversity and exploitation of natural resources. These studies demonstrate the potential for AudioMoth to enable a substantial shift away from passive continuous recording by individual devices, towards smart detection by networks of devices flooding large and inaccessible ecosystems.
3. The case studies demonstrate one of the smart capabilities of AudioMoth, to trigger event logging on the basis of classification algorithms that identify specific acoustic events. An algorithm to trigger recordings of the New Forest cicada (*Cicadetta montana*) demonstrates the potential for AudioMoth to vastly improve the spatial and temporal coverage of surveys for the presence of cryptic animals. An algorithm for logging gunshot events has potential to identify a shotgun blast in tropical rainforest at distances of up to 500 m, extending to 1 km with continuous recording.
4. AudioMoth is more energy efficient than currently available passive acoustic monitoring devices, giving it considerably greater portability and longevity in the field with smaller batteries. At a build cost of ~US\$43 per unit, AudioMoth has potential for varied applications in large-scale, long-term acoustic surveys. With continuing developments in smart, energy-efficient algorithms and diminishing component costs, we are approaching the milestone of local communities being able to afford to remotely monitor their own natural resources.

**KEYWORDS**

acoustic monitoring, biodiversity monitoring, ecosystem management, gunshot detection, open science, open-source hardware, open-source software

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## 1 | INTRODUCTION

Emerging technologies for remote monitoring and species identification bring the promise of more affordable and versatile methods of sampling which are predicted to drive future conservation efforts (Pimm et al., 2015). Current methods often require expensive and complex equipment for aerial imagery (Morgan, Gergel, & Coops, 2010), acoustic sensing (Merchant et al., 2015), bio-telemetry (Cooke et al., 2004), and GPS tracking (Kays, Crofoot, Jetz, & Wikelski, 2015). The technical know-how and infrastructure needed to implement these devices in large-scale environmental monitoring often requires a total investment beyond the budgets assigned to conservation projects (James, Green, & Paine, 1999). This cost issue is being addressed with an increasingly free availability of online data sources such as satellite images (Kalyvas, Kokkos, & Tzouramanis, 2017). However, such databases cannot capture cryptic biodiversity and exploitation. For example, events which are hidden by tree cover, or those that are too fine-scale for image resolution, remain unaccounted for without ground-level monitoring (Peres, Barlow, & Laurance, 2006).

Full ground-level monitoring demands many surveyors or devices to cover an ecosystem effectively. Some contemporary sampling methods achieve coverage with semi-automated monitoring technology, for example camera traps triggered by infra-red sensors. Much of the methodology used in acoustic monitoring lags behind this trend, tending to feed large quantities of captured data through detection software after deployment (Mac Aodha et al., 2017). Despite the heavy demand on memory storage, passive acoustic monitoring (PAM) has proved useful for estimating ground-level biodiversity abundance and occurrence, particularly of smaller and more cryptic species (Newson, Bas, Murray, & Gillings, 2017), and it is often employed for analyses of soundscapes (Towsey et al., 2014). It has also been shown to have potential for monitoring exploitation of natural resources (Astaras, Linder, Wrege, Orume, & Macdonald, 2017). However, PAM devices used for long-term monitoring are limited by their size and weight due to their high power consumption (Wrege, Rowland, Keen, & Shiu, 2017). Moreover, the budget needed to purchase multiple devices and then process the captured data makes them impractical for many research studies or large-scale conservation deployments.

In recent years, researchers have started to look beyond commercially available options to field devices designed and built in partnership with engineers (Kwok, 2017). Research studies have reduced the cost of acoustic monitoring by re-purposing existing technologies (Gross, 2014), or implementing devices based on open-source modular computers with external sensors of fit-for-purpose quality. Recent examples include PAM devices built around the Raspberry Pi computer (Caldas-Morgan, Alvarez-Rosario, & Padovese, 2015; Sankupellay et al., 2016; wa Maina, Muchiri, & Njoroge, 2016) and Arduino computer (Razali et al., 2015; Shafiril, Yusoff, & Yusoff, 2016). For example, the Solo acoustic monitoring platform is based on the Raspberry Pi and an external microphone (Whytock & Christie, 2017), and costs just under ~US\$100. Devices such as Solo are often chosen for their computing power, customisation ability and programming simplicity, using high-level programming languages, such as Python. Despite

these advantages, devices based on modular computers present drawbacks for large-scale deployments. They demand considerable investment in time for setting up and configuring each device, involving hobbyist electronics and software development skills. The devices based on the Raspberry Pi have inefficient power optimisation and consequently require large batteries to sustain power over long periods. Solo for example, uses a 12 V car battery to compensate for its low power efficiency in long-term deployments. As with commercial PAM devices, the need for larger battery capacity often makes monitoring tools based on modular computers too bulky for field deployments in remote areas where sensors must be transported manually. New developments in lightweight commercial detectors are increasing the portability and usability of acoustic devices, such as the Peersonic RPA3 bat recorder costing ~US\$280 (Peersonic pricing page, 2017) or the ARBIMON recorder, which is based on a smartphone, costing ~US\$300 (ARBIMON pricing page, 2017). Despite substantial savings in size and usability, these devices present a high initial cost for large-scale studies requiring many devices to cover an area. They also present a lack of customisation compared to the modular computer-based devices. Publications on environmental acoustics to date overwhelmingly report data capture using commercially available, battery-powered, PAM devices. Many acoustic monitoring applications use the commercial Song Meter series from Wildlife Acoustics, with best-in-class audio quality at a unit cost of more than US\$1000 (Song Meter series product page, 2017).

Here we describe the development and proof-of-concept of a smart, customisable, acoustic monitoring device called AudioMoth (AudioMoth home page, 2017). The device employs a low-power microcontroller and a microelectromechanical systems (MEMS) microphone to perform on-board real-time acoustic analysis, allowing relevant data to be filtered or classified before storage. This smart capability reduces both the storage requirement on the device and the post-processing budget after data collection. With less energy needed to power the device, it can run off smaller batteries. The device addresses the need for a versatile, small, low-cost, low-power monitoring tool for easy deployment in long-term biodiversity and environmental acoustic monitoring. AudioMoth aims to make a substantial step towards the future of acoustic technology, in covering large areas of inhospitable habitats with a network of devices (Browning, Gibb, Glover-Kapfer, & Jones, 2017).

## 2 | MATERIALS AND METHODS

Here we describe the design of the AudioMoth hardware and its customisable software, in the context of two ongoing monitoring studies aiming to achieve large-scale and long-term coverage with a large number of smart devices. The first study tests for presence of the New Forest cicada (*Cicadetta montana* Scopoli, 1772), an elusive species last sighted in the UK over 22 years ago (Pinchen & Ward, 2002, p. 134). The second study investigates the detection of gunshot events within tropical forests in Belize, Central America, in an area under pressure from poaching.

## 2.1 | Design

AudioMoth is built around an ARM Cortex-M4F microcontroller. The M-series processors are some of the most energy efficient microcontroller cores currently available. The M4F core used by AudioMoth has on-board floating-point signal processing functionality, allowing efficient processing of acoustic data at high speeds. AudioMoth can process data at sample rates up to 384 kHz in real-time, made possible by an additional 256-KB SRAM chip, which increases the amount of available processing time at ultrasonic frequencies. AudioMoth stores uncompressed WAV files to microSD card, with a capacity limit of 32 GB. AudioMoth can accommodate extensions to the board, such as external sensors or a wireless network unit, using a 6-pin peripheral module interface (PMOD) header that connects four general purpose input/output pins to the processor.

AudioMoth can easily be deployed as a scheduled recorder, without any requirement to code or to learn a computer programming language; however, to unlock the main advance that the device brings, users are encouraged to customise and design their own on-board software for filtering or classifying sounds as they happen. The user can modify and distribute AudioMoth's software for specific applications (AudioMoth's documented library, 2017), on the open MIT licence (Open MIT licence page, 2017). Modifications to the existing code upload easily onto the device without additional development boards, requiring just a microUSB cable and a paper clip to switch the device into USB programming mode. Having the ability to choose what to record introduces several benefits over acoustic methodologies that make use of continuously recording devices, especially in large scale and long-term deployments. For example, AudioMoth can be programmed to filter relevant sounds such that only those of interest are saved, thus reducing post-processing time, power usage and data storage requirements. In conjunction with its low power consumption while listening, and its full-spectrum frequency response, AudioMoth creates a unique opportunity for users to design specific classification algorithms for individual projects. In order to realise its performance capabilities, however, AudioMoth employs the low-level programming language, C, which requires a greater level of technical expertise than the less efficient high-level programming language, Python. Despite this constraint, AudioMoth achieves ultra-efficient power optimisation, high-speed data processing and a wide spectrum acoustic performance through the greater control over low-level processes.

AudioMoth uses the Goertzel filter for real-time classification algorithms. This filter evaluates specific terms of a fast Fourier transform on temporarily buffered audio samples without the computational expense of a complete transform. The outcome of each algorithm is used to trigger recordings to a microSD card.

To apply a Goertzel filter to an audio recording, the samples are split into  $N$  windows of length  $L$  given by:  $(s_{1,1}, \dots, s_{1,j}, \dots, s_{1,L}, \dots, s_{N,1}, \dots, s_{N,j}, \dots, s_{N,L})$  where  $1 \leq i \leq N$  and  $1 \leq j \leq L$ . The Goertzel filter then operates on each window, generating a magnitude  $m_i$ :

$$m_i = y_{i,L}^2 + y_{i,L-1}^2 - c \times y_{i,L} \times y_{i,L-1}. \quad (1)$$

In this expression,  $c$  is determined by the central frequency of the filter,  $f$ , and is given by:

$$c = 2 \cos\left(\frac{2\pi f}{f_s}\right), \quad (2)$$

where  $f_s$  is the sample rate of the recording. As the values of  $f$  and  $f_s$  do not change, the constant  $c$  is precomputed. The temporary sequence of values  $y$  is obtained from constant  $c$  and Hamming windowed data  $h_j$ :

$$y_{ij} = (h_j \times s_{ij}) + (c \times y_{ij-1}) - y_{ij-2}. \quad (3)$$

In order to prevent spectral leakage, a Hamming window is applied to the samples before the Goertzel filter in each case. The window itself uses constants  $\alpha$  and  $\beta$ , and can also be precomputed for a window of length  $L$  with  $\alpha = 0.54$  and  $\beta = 1 - \alpha = 0.46$ :

$$h_j = \alpha - \beta \cos\left(\frac{2\pi j}{L-1}\right). \quad (4)$$

Goertzel filters possess a bandwidth dictated by the sample rate and the number of samples used to form the final amplitude. The equation representing this relationship is arranged such that the length of a filter window  $L$  can be calculated, given a fixed bandwidth  $B$  and known sample rate  $f_s$ :

$$L = 4 \frac{f_s}{B}. \quad (5)$$

This allows the bandwidth of all Goertzel filters to be set to cover the range of frequencies used by the target vocalisation or acoustic event. We use the calculated magnitudes over  $N$  number of windows to produce a median. The subsequent comparison of this median to a calibrated threshold value identifies whether or not the sound present in the buffered audio samples is appropriate for recording.

## 2.2 | Purchase and configuration

Open-source, custom-designed and simply constructed hardware provides cost-effective access to technology for all. Simply constructed hardware can be bought at close to component prices, because the number of fabrication steps can be minimised. To enable simple construction of the device, its parts must be readily available and simple to fit together. Accordingly, the circuitry for AudioMoth uses online accessible components, which all fit on one side of a two-layer printed circuit board (PCB). This permits the acquisition of devices from a single PCB assembler. Such simply-constructed hardware can be manufactured and delivered as an immediately working product, in contrast to hardware with a complex construction requiring several stages of fabrication. Researchers can acquire working devices cheaply, achieving an economy of scale (Wheat, Wang, Byrnes, & Ranganathan, 2013) by joining an online collective purchasing group (GroupGets purchase page, 2017) which bulk orders from a single online web-based PCB assembler specialising in open-source fabrication (CircuitHub product page, 2017).

Multiple devices are time-consuming to configure on commercial and modular computer-based PAM devices, requiring either an

LCD screen or manual assembly. Experience from users of devices such as Mataki (Mataki product page, 2017) suggests that conservation technology puts a premium on ease of configuration in the field. Accordingly, our open-source code includes a cross-platform configuration application, which can configure device settings in the field using a laptop and a USB cable. The configuration application is built on a free, open-source framework called Electron (Electron, 2017). Together with the configuration application, AudioMoth's default firmware enables the device to be used as a scheduled recorder. The configuration application features adjustable recording schedules, gain levels and sample rates. Using this configuration application makes it easier to configure large quantities of AudioMoths as PAM devices for multiple large-scale applications.

## 2.3 | Deployment

Portability in the field requires minimising the size and weight of devices, so as to maximise the number that can be carried on foot over rough terrain or to remote locations. AudioMoth has small  $0.4 \times 0.2 \text{ mm}^2$  (commonly referred to as 0402) surface-mount components, and a single  $4.72 \times 3.76 \text{ mm}^2$  inbuilt microphone. Its ultra low-powered embedded microcontroller has internal operational amplifiers to strengthen the analog microphone signal without additional external components and has sufficiently low energy consumption to allow powering by three lithium AA-cell batteries. AudioMoth has a unit size of  $58 \times 48 \times 18 \text{ mm}^3$  and a weight of 80 g, including batteries (Figure 1).

The single side of the PCB that takes all of the electronic components, including the microphone, faces onto the battery holder to protect the mounted components from knocks. AudioMoth captures sound through a 1-mm drill hole on the non-component layer of the PCB, on the opposite side of which sits the bottom-ported MEMS microphone as part of the analog audio circuitry. The fully assembled AudioMoth comprises a single, fixed unit. Users can choose how to house the unit. A plastic grip-sealed bag may suffice to prevent weather damage for short deployments. The device also fits easily within off-the-shelf housing or simple acrylic DIY casings.

AudioMoth is designed to make efficient use of its available storage by on-board real-time audio processing. The energy consumption while processing or during a calculation is negligible, consuming from 10 to 25 mW between the lowest and highest sample rates. Deployments in locations likely to trigger large quantities of recordings will more likely be limited by the microSD card capacity than the battery life.

## 2.4 | Case studies

### 2.4.1 | New Forest cicada

The first study aimed to test for an extant population of the only cicada species native to the UK, in the New Forest National Park ( $50^\circ 52' 34.7''\text{N}$ ,  $1^\circ 37' 53.5''\text{W}$ ) which is its last known area of



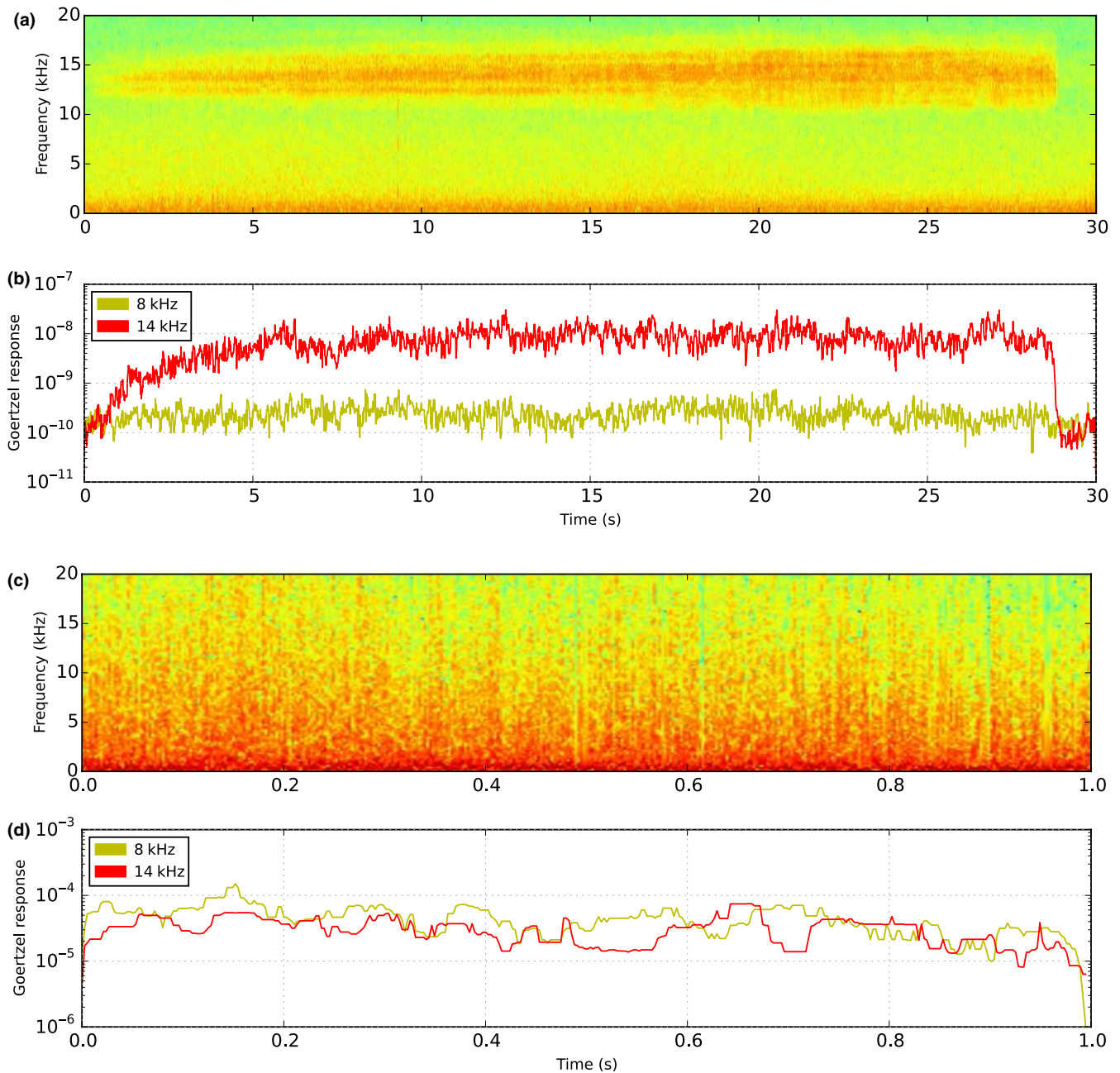
**FIGURE 1** An AudioMoth ( $48 \times 58 \times 18 \text{ mm}^3$ , 80 g) listening for the New Forest cicada, deployed within a grip-sealed bag using a cable tie to attach it to a tree branch

occupancy outside continental Europe. New Forest cicadas spend most of their lives underground as nymphs, emerging as adults in ~7-year cycles. The high-pitched call of the adult, at 14 kHz, is out of the hearing range of most humans other than children. This life history and behaviour has made it difficult to search for the species in manual surveys. Until now, listening devices have been too expensive, energy-hungry and intrusive to deploy in long-term systematic surveys over the large scale of the cicada's potential range. In a first such systematic survey, 87 AudioMoths were deployed in four locations for 2- to 3-month periods from spring to early-summer of 2016 and 2017 in the New Forest. Devices were positioned in habitats considered most likely to support the species, based on previous entomological surveys and historical records of occurrence.

Recordings of the species made in Slovenia were used to characterise the song of the male cicada, as an extended buzz lasting 30 s, with a dominant 14 kHz frequency band. Because this frequency is rarely present in the calls of other insect species found in the New Forest, the 14 kHz component of the New Forest cicada song was used to inform the detection algorithm. The ratio of the 14 kHz component to the 8 kHz component of each sample produced an identifier robust to broad spectrum noise. This ratio overcame an issue with algorithms simply using 14 kHz, which were prone to false positives from white noise interference caused by strong wind or by movement in close proximity to the microphone. A recording was triggered by a high ratio, resulting from a high 14 kHz value and a low 8 kHz value. A low ratio that might result from high values at both 14 and 8 kHz was more likely to be wind than a cicada call (Figure 2).

AudioMoth operated on a duty cycle routine, waking every 5 s to listen for ~200 ms. When awake and listening, the detection algorithm





**FIGURE 2** Spectrogram and Goertzel responses used to classify the cicada song: (a) the New Forest cicada recording taken in Slovenia; (b) the Goertzel filter response to this same recording, with the species detected and distinguished from wind interference by the presence of a 14 kHz component and an absence of the 8 kHz component; (c) wind noise spectrogram of a recording taken in the New Forest; (d) the Goertzel filter value in response to the wind noise recording taken in the New Forest, with the species not detected because the 14 kHz component and the 8 kHz are both high

cycled through buffered samples. Goertzel filtering was applied sequentially to sections of the buffer using a moving window. This produced a magnitude for each of the 14 kHz and 8 kHz bands in the window. The 14:8 kHz ratio of magnitudes for each window then produced 128 values, from which was derived a median ratio. If this median exceeded a calibrated threshold, it triggered a 30-s recording; otherwise the device returned to sleep until the next wakeup period in 5 s.

#### 2.4.2 | Gunshots in tropical forests

The second study aimed to test the detection range of AudioMoth for capturing gunshot events in mature, deciduous, broadleaf tropical rainforests in Pook's Hill Reserve, a private nature reserve in Belize ( $17^{\circ}09'27.2''\text{N}$ ,  $88^{\circ}51'15.6''\text{W}$ ). Acoustic monitoring devices used for gunshot detection are currently deployed in urban environments to alert relevant authorities of events in real time (Choi, Librett, &

Collins, 2014). Such applications require numerous large and mains-powered devices, positioned on the tops of buildings in strategic locations. These systems are impractical in the natural environment, away from a power source and in situations where large devices are prone to unwanted discovery and destruction, as commonly occurs with camera trapping (Jumeau, Petrod, & Handrich, 2017). Applications relating to resource exploitation require small-sized, low-energy and low-cost devices, suitable for cryptic deployment of sufficient numbers for a grid that achieves full coverage of large tracts of exploitable habitat, often in remote terrain, over a continuous period of several months. Many of the natural environments most prone to poaching have no Wi-Fi or mobile coverage, ruling out the use of cloud-based acoustic systems (Rainforest Connection home page, 2017). This applies to the Pook's Hill Reserve in Belize.

Here 36 AudioMoths were deployed in pairs, one set to detect gunshots and the other set to record continuously. The devices were positioned at 13 sites on hilly terrain, 60–160 m a.s.l. Five sites were set along a 1.2 km transect, with a pair of devices pinned to both the east and west side of a tree trunk. The remaining eight sites were distributed over a grid north and south of the transect with a pair of devices at each site, all with the same (easterly) orientation, representative of a real-world scenario. All sites were separated from each other by 200 m. Sixty-five controlled gunshots were fired in sets at various locations within the grid, aiming either east or west to test detection capabilities of the devices with respect to the orientation and distance of the sound source. Two common gun types for hunting in the area were used: a 12 gauge (Baikal MP-18EM-M) shotgun and a 16 gauge (Rossi single shot) shotgun.

The wide array of false-positive sources and variation in gunshot amplitude due to factors such as distance and topography means that an algorithm for detecting gunshots must accommodate various components of the acoustic pulse, such as the initial muzzle blast, and the various stages during its sound propagation. When recorded at close range, the initial muzzle blast consists of a loud impulse covering a wide range of frequencies. As the sound propagates from the gunshot to the detector, the high frequency components start to decay as they are absorbed into the air and the surrounding environment. The gunshot detection algorithm for AudioMoth used the characteristic rate at which select frequencies peak and then decay from the initial muzzle blast, determined by ground-truthing trials in the forest.

To characterise the gunshot features, we developed a four state hidden Markov model and used the Viterbi algorithm (Forney, 1973) to establish the most likely path through the four states taken by the recording. These states are as follows: silence, initial impulse, decay and tail, each representing a distinct stage of a shotgun blast. Each state is represented by three frequency components, extracted using Goertzel filtering around 2,000, 1,200 and 400 Hz (Figure 3). These states were modelled from recordings of gunshots taken at the field site, by manually classifying blocks of samples within each recording as one of the four states and then fitting log-normal distributions to each (Figure 4). These probability distributions then formed the hidden Markov model, on which an implementation of the Viterbi algorithm was run. The vast majority of windows returned a series of silence states, with the

distributions representing this state being robust enough to contain likely false positives such as branches snapping. The algorithm deemed the window to contain a shot only when the selection of states returned by the Viterbi algorithm included all three states that represent a gunshot, in their expected sequence. This triggered AudioMoth to save the current buffer containing the shot.

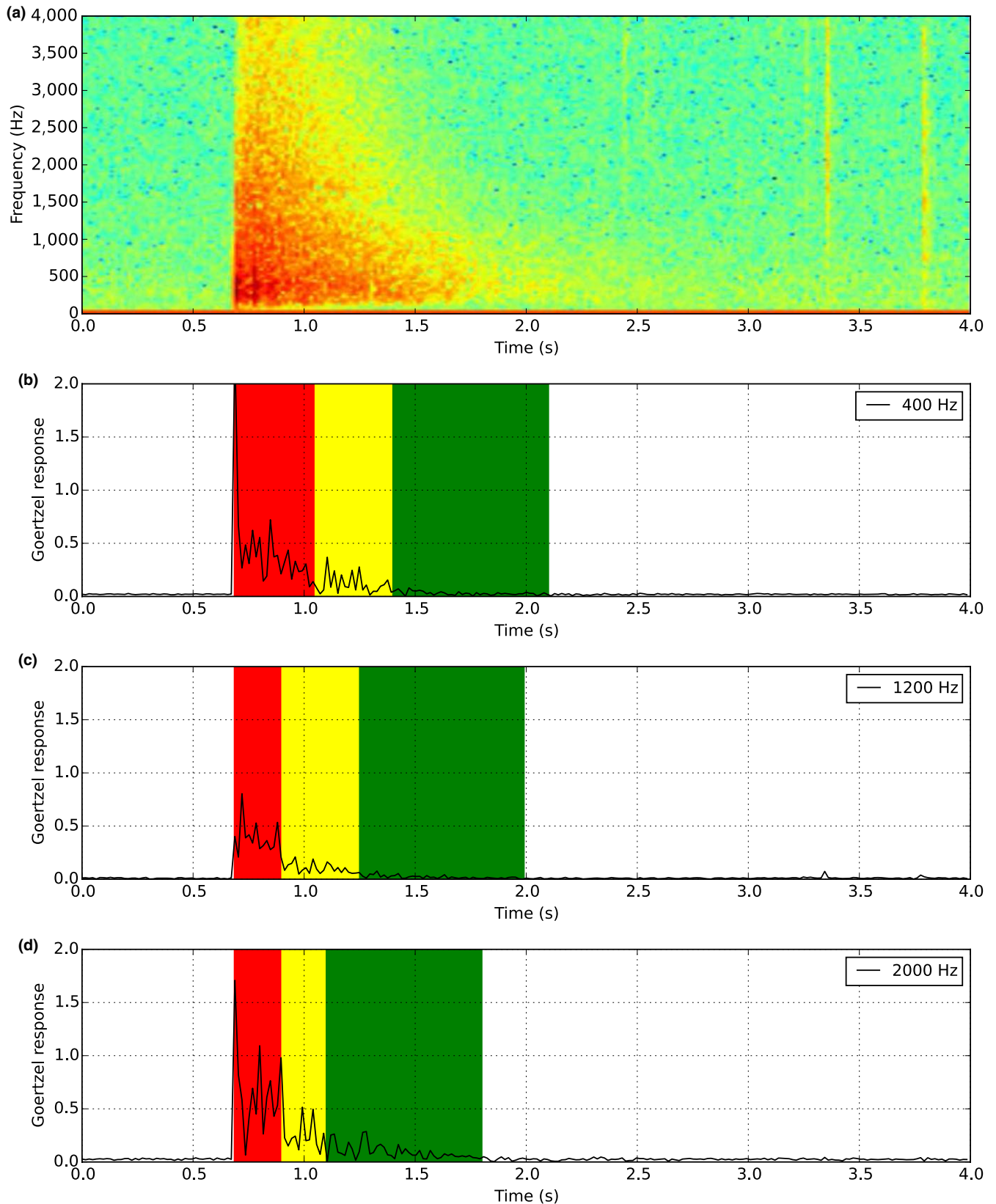
The ground-truth dataset revealed that gunshots in the tropical forest environment last ~1 s before decaying beyond detection. Unlike for the 30-s cicada call, a duty cycle hoping to catch the event in one of the listening periods would result in a high number of false negative responses. Accordingly, the AudioMoths were programmed to listen constantly throughout the assigned period, using a three element circular buffer to collect audio samples in one buffer while performing analysis on the two previous consecutively filled buffers. This resulted in an implementation with no breaks in listening, whilst limiting all analysis to calculations that could be performed in the time it took to fill one of the buffers.

### 3 | RESULTS AND DISCUSSION

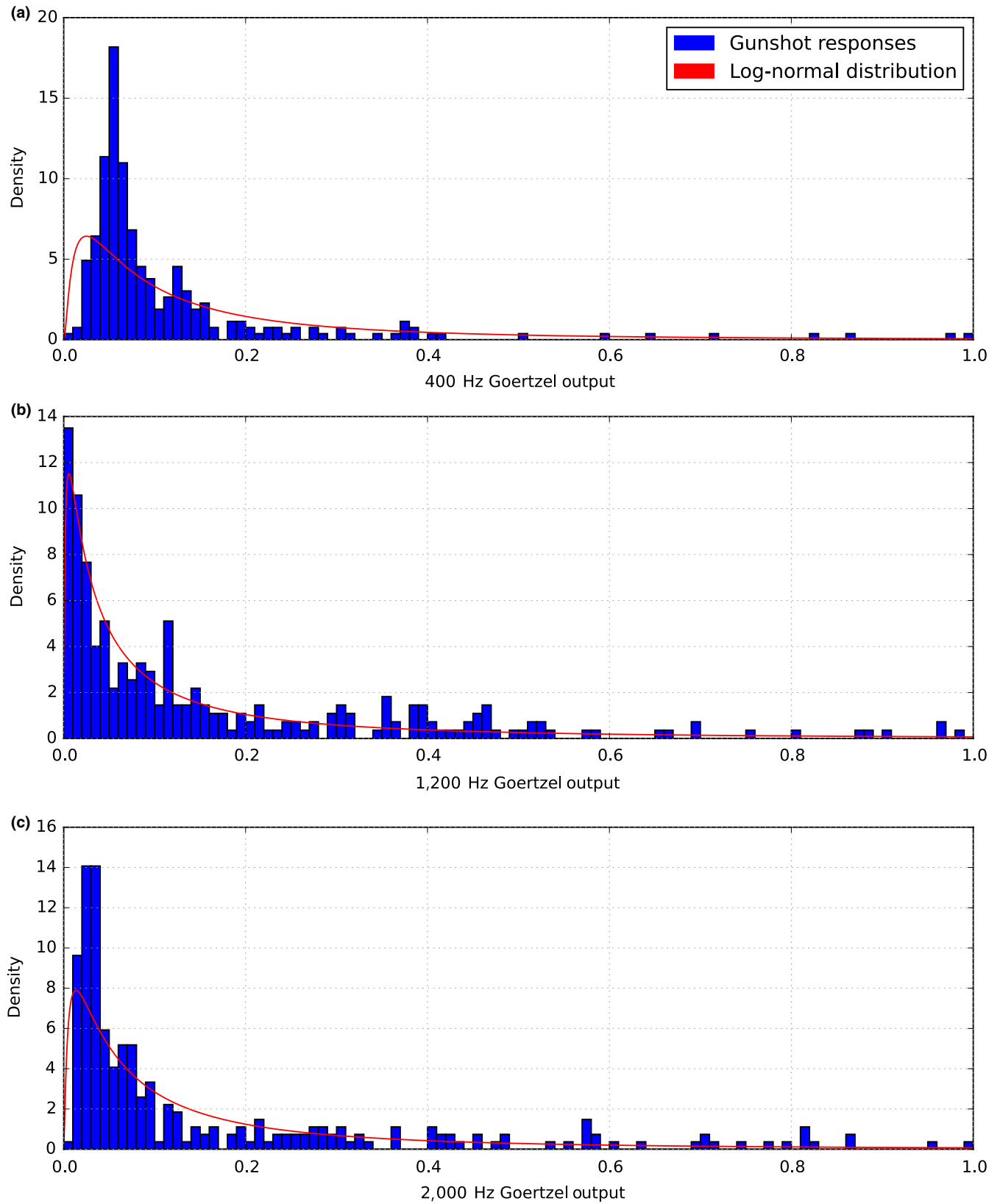
#### 3.1 | Detection capabilities

For the first case study, the detection capabilities of the device were tested by playing the cicada recordings captured from Slovenia inside an anechoic chamber. When the cicada recording was played in conjunction with a collection of 5-s recordings of background noise captured in the New Forest, the algorithm achieved a true positive rate of 0.98 and a false positive rate of 0.01. These tests verified its ability to react to low amplitude cicada recordings. The devices responded to a 14 kHz ~60 dB SPL test tone within a range of 10 m in a forest environment. The test tone was played from a smartphone with the volume measured from a sound level meter 200 mm away from the smart phone speaker. After deployment in the field, devices were collected and all of the triggered recordings were consolidated into a grid of spectrograms. Potential true positive recordings were identified by visual inspection of this grid over periods when local weather data indicated suitable conditions for emergence. Playback of these candidate recordings, however, revealed no calls of the New Forest cicada over the two-year study.

For the second case study, gunshot amplitude diminished with distance from the sound source as expected, and was affected further by the orientations of the device and the gun. The rate of decline with distance in gunshot amplitude increased substantially when the device faced away from the source, and it increased slightly when the gun was facing away from the device (Figure 5). In earlier pilot trials in the same area during 2016, the probability of an audible signal in continuous recordings was 98% at ≤300 m, declining to 93% at ≤1 km, from a total of 120 gunshots. The captured data were run through the detection algorithm after deployment, which identified gunshots at up to 500 m with a success rate of 66%, decreasing to 50% at 1 km. At this furthest distance, devices facing towards the gunshot were 80% more likely to detect it than devices facing away. In the available 1-s time interval for processing each buffer of samples, the algorithm took just



**FIGURE 3** Spectrogram and Goertzel responses used to classify gunshots: (a) spectrogram of a gunshot recording taken in Belize at 400-m distance from the source, (b)–(d) the 400, 1,200 and 2,000 Hz Goertzel filter values in response to the gunshot recording, at 2,000 Hz showing high frequency sound decay. Response periods are colour-coded according to the selected states used to build the classification model: initial impulse (red), decay (yellow), tail (green)



**FIGURE 4** Response densities of the three Goertzel filter outputs for gunshots collected at various distances in Belize. Each histogram shows a fitted log-normal distribution for gunshot detection at the impulse state. The Goertzel filters were centred at (a) 400 Hz, (b) 1,200 Hz and (c) 2,000 Hz



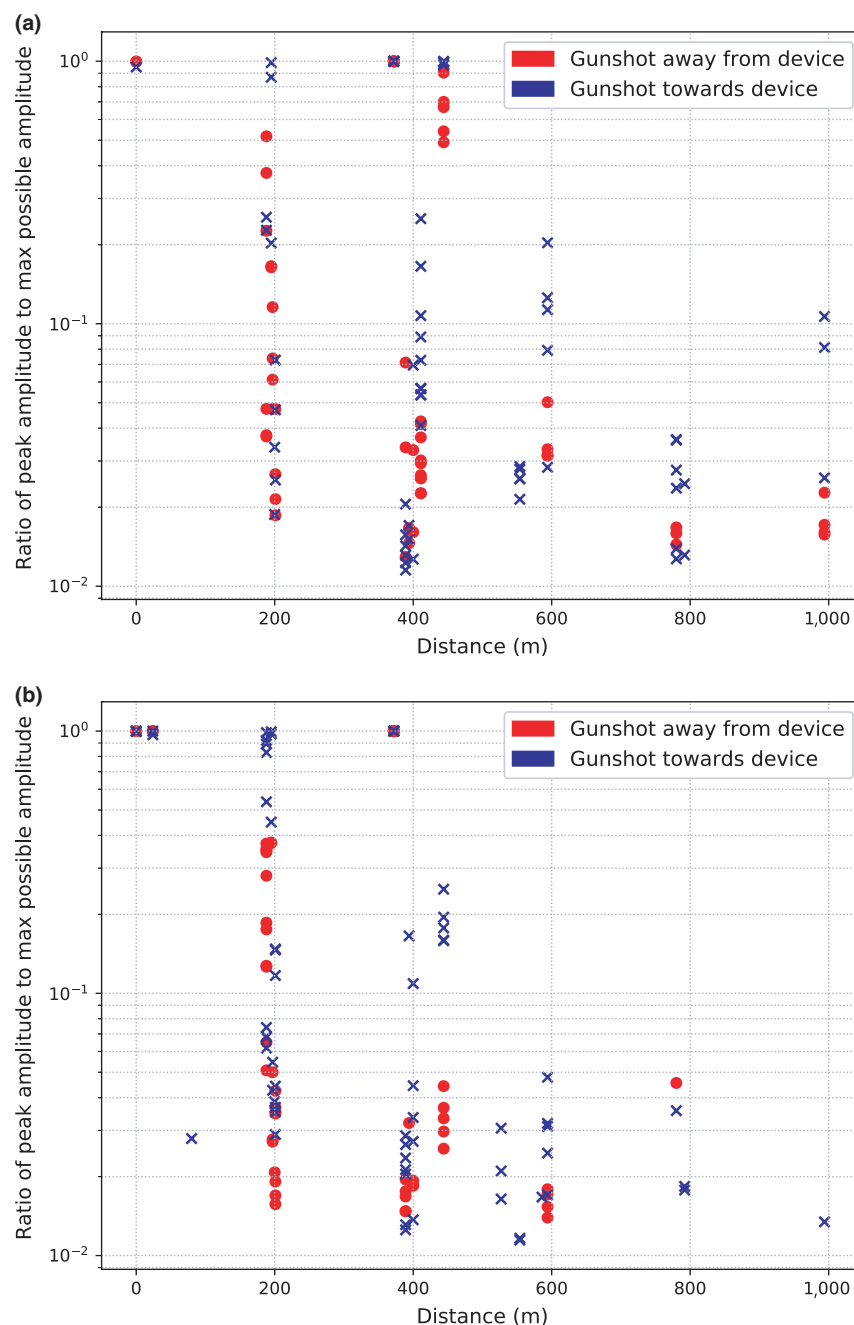
40 ms to run, using just 4% of the available processing time. Future iterations of the algorithm will make use of the remaining 960 ms of computational time to take into account variations in acoustic structure due to orientations of the device and sound source.

### 3.2 | Deployment logistics, field configuration and durability

A single AudioMoth has a build cost of ~US\$43 (Table S1). Group purchasing brings the price down to ~US\$30, on an order of 500 devices delivered assembled, pre-programmed and ready for deployment. This economy of scale is particularly relevant to large-scale monitoring, for example of forest exploitation where many devices are needed to cover

large tracts of protected forest. With a gunshot detection distance of up to 500 m, a single AudioMoth would monitor an area of ~0.8 km<sup>2</sup>. Thirty AudioMoths, bought with group purchasing, would have a total cost of ~US\$900, and the capability for monitoring an area of ~24 km<sup>2</sup>. The low cost of AudioMoth allows researchers to deploy more devices with their budgets, allowing them to ask bigger research questions.

With AudioMoth's small dimensions when using AA-cell batteries, more than 100 devices can fit into a standard field backpack with a 25-L capacity. For deployments in rough terrain, such as areas of tropical forest, this ability to carry multiple devices greatly facilitates field deployments and reduces the infrastructure needed to achieve a large-scale study.



**FIGURE 5** Ratio of gunshot peak amplitudes relative to the maximum possible amplitude, from continuously recording AudioMoths. (a) Devices facing towards the gunshot source, demonstrating a higher performance of audio capturing ability; (b) devices facing away from the gunshot source, demonstrating a lower performance of audio capturing ability

During the preparation stage in the first case study, the user required on average 10 s to configure each device to a pre-set configuration over USB. Eighty-seven devices were configured in total, taking under 20 min to prepare them all for a deployable state. Further possibilities exist to program multiple devices simultaneously by audio signals played through a computer speaker (Jewell, Costanza, & Kittley-Davies, 2015). This could bring substantial time savings for large-scale deployments.

During the New Forest deployment, 23% of devices suffered some level of water damage, due to heavy rain and failure of the grip sealed bag. The rainforest deployment trialled a commercial waterproof electronics enclosure, combined with an acoustic waterproof permeable membrane and silica gel sachets to absorb moisture. All these additional parts cost a total of ~US\$8 (Table S1). This combination provided an effective protection for the duration of the study, with the membrane allowing sound penetration to the microphone.

### 3.3 | Data storage and energy consumption

In the first case study, the 5-month total period of field deployment of 87 AudioMoths resulted in 129 hr of audio triggered by positive algorithm responses. These were identified as false positives from a number of sources, including dog whistles, leaf noise during strong winds, and bird songs. In comparison, recording continuously for 12 hr per day over the same period would have created 156,600 hr of audio data for analyses. The capacity to perform real-time detection with a programmable algorithm vastly reduces on-board memory requirements, and post-deployment data analyses. Although detection capability is also available on commercial devices, such as the Peersonic RPA3 and SM3BAT/SM4BAT bat detectors, users have limited ability to customise the in-built classification algorithm. AudioMoth's software allows users to have complete control over their on-board detection algorithms for their specific application, thereby greatly reducing the need for post-processing software to analyse data after deployment.

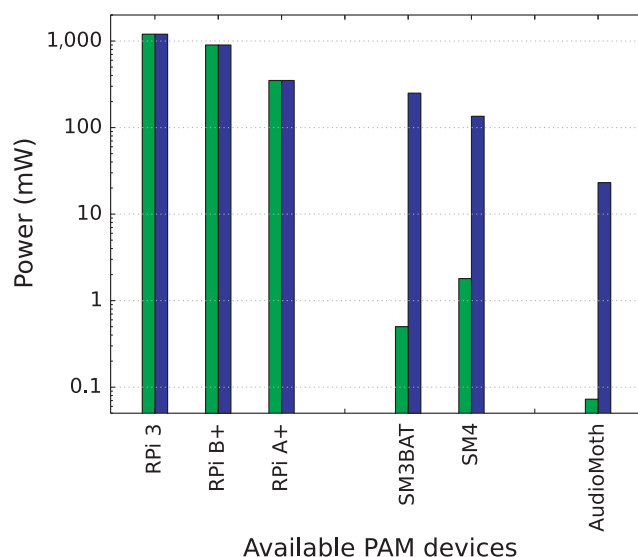
The most energy intensive task on AudioMoth was writing data to the microSD card, which consumed 17–70 mW, depending on the configured sample rate and model of microSD card. In the first case study, recording to a 16 GB Hama microSD card with UHS speed class 3 at 48 kHz consumed on average 23 mW of power. In the second case study, the same microSD card at 8 kHz consumed on average 17 mW. For applications requiring ultrasonic frequencies with sample rates up to 384 kHz the power consumption can reach 70 mW. Power consumption reduced to 25 mW or less when classifying audio in real time, and to 80  $\mu$ W when sleeping between samples, outside scheduled wake-up periods, or in standby mode. The low demand in standby would allow AudioMoth to keep track of time for approximately 6 years in that mode, using three AA-cell lithium batteries. In the first case study, the devices remained powered for the total 2- and 3-month periods they were deployed for.

The complexity of the processor for an intelligent device directly affects its power consumption, which in turn affects the size and weight requirements of its power supply. A modular computer-based

PAM device such as Solo continuously runs a Linux operating system during operation (Whytock & Christie, 2017). These devices consume anywhere from 400 mW to 1,000 mW when idle (Figure 6), with minimal to no power management available during operation. In contrast, AudioMoth's processing comes from an ultra-low energy microcontroller, which has complete control over its power management, meaning it can run embedded code fast enough to power down and sleep between individual microphone samples. Even during recording to microSD card at 48 kHz, AudioMoth is ~15 times more energy efficient than the most energy efficient modular computer-based PAM device, and ~4,000 times more energy efficient during its idle state.

## 4 | WIDER APPLICATIONS

The development of AudioMoth has been driven by demand from the environmental monitoring and conservation community, with numerous partnerships around the world testing the device for diverse applications. During 2016 and 2017, 160 prototype devices were deployed with the default recording software. For example, 20 AudioMoths were installed across the main island of Madeira in 2016 as part of a larger survey of bat populations to investigate anthropogenic impacts on native fauna. This project captured more than 1TB of data, which is contributing to analyses of long-term population trends to aid in future conservation efforts (Gibb, 2016). The ultrasonic capabilities of AudioMoth were also used in two studies in Southampton city, UK. The first study left the devices



**FIGURE 6** Power consumption comparisons of currently available passive acoustic monitoring (PAM) devices, when idle (green) and when recording to microSD card at 48 kHz (blue). RPi devices are all modular computers constructed on a Raspberry Pi; B+ was used by Razali et al. (2015) for monitoring rainforest health; A+ was used by Caldas-Morgan et al. (2015) for monitoring underwater industrial activities, and Whytock and Christie (2017) for their Solo device. SM devices are commercially available from Wildlife Acoustics

unattended during nocturnal recordings of bats, in urban locations where larger and more financially valuable commercial devices would be vulnerable to theft. The second study used AudioMoth in a handheld application mapping ultrasonic noise produced by the city. This study required the ultrasonic and light-weight capabilities of AudioMoth for recording on foot. Lastly, a field expedition in 2017 used the AudioMoth with a detection algorithm to record the IUCN Red-Listed Cuban greater funnel-eared bat (*Natalus primus*), currently known to inhabit only one 20-km<sup>2</sup> area of the Guanahacabibes National Park in Cuba (Wearn, 2017). AudioMoth devices captured calls of free-flying individuals in recordings at a sample rate of 250 kHz.

Further developments are exploring the potential for networking AudioMoth by LoRa radio, to link them to a base station for real-time signalling of acoustic events triggered by the detection algorithm. Although this capability adds ~US\$30 to price, the devices are sufficiently cheap to make it a potentially cost-effective option for capacity building. AudioMoth also has the ability to record alternative types of data to memory, instead of memory inefficient uncompressed WAV files. For example, AudioMoth can summarise the important characteristics of sounds with measurements known as acoustic indices (Towsey, Wimmer, Williamson, & Roe, 2014). Acoustic indices can summarise recordings into meaningful characteristics, such as the frequency distribution and acoustic power, which can be viewed as false colour images to aid the assessment of biodiversity (Sueur, Farina, Gasc, Pieretti, & Pavoine, 2014). As these indices require less space to store than raw audio, devices using them are less constrained by limited storage capacities. In addition, significant energy benefits accrue from writing small summary files to the SD card, rather than raw audio files. We are currently developing real-time acoustic indices that make use of the fast processing available on-board the AudioMoth hardware. Future work will continue to test the feasibility of deployments by drone (Project Erebus AudioMoth flight test page, 2017), again only possible for small and cheap devices.

While the configuration software enables a basic level of device customisation with minimal technical expertise, knowledge in programming low-level C is required to achieve full use of AudioMoth's flexibility and produce new detection algorithm implementations. Bringing technology such as AudioMoth to less technically skilled users remains an ongoing challenge in the area of conservation technology. We see possibilities for progress in the future with solutions such as compilers that generate C code from simplified implementations of digital signal processing techniques.

## 5 | CONCLUSION

The purchasing opportunities available for simply designed, open-source and configurable hardware can dramatically reduce the financial cost and time commitment required for environmental monitoring on large spatial and temporal scales. Monitoring projects can address bigger questions with access to smart, small and power-efficient devices such as AudioMoth. We are now close to being able to flood

large areas with these devices, for improved coverage of obscured, remote or inhospitable ecosystems. High initial investment costs remain the biggest barrier for conservation projects in poorer areas. AudioMoth provides opportunities for groups with limited budgets to perform systematic bioacoustics research, for example by benefiting from economies of scale in group purchases. With further developments in the new technologies described here, we are getting closer to achieving a basic requirement of sustainable development, that local communities can afford to monitor their own natural resources.

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## AUTHORS' CONTRIBUTIONS

All authors contributed to the final design of AudioMoth. A.P.H., P.P. and A.R. led hardware and software development. A.R., A.P.H. and P.P. conceived, designed and executed the New Forest cicada study. All authors contributed to the gunshot study, with E.P.C., A.P.H. and P.P. leading its conception, design and execution. A.H. and P.P. wrote the manuscript with revisions by all authors.

## DATA ACCESSIBILITY

All open-source software can be accessed on the project's associated Github page <https://doi.org/10.5258/soton/d0332> (Prince, Rogers, & Hill, 2017). All open-source hardware can be accessed on the project's associated CircuitHub page <https://doi.org/10.5258/soton/d0334> (Hill, Rogers, & Prince, 2017). Gunshot data used in Figure 5 are deposited in the Dryad Digital Repository <https://doi.org/10.5061/dryad.369n9> (Hill et al., 2017).

## COMPETING INTERESTS

All of AudioMoth's hardware and software is open-source. We have no competing financial interests with respect to the published work.

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## SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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