Robust, real-time and autonomous monitoring of ecosystems with an open, low-cost, networked device

Sarab S. Sethi [(1)(2)(3)(a)], Robert M. Ewers [(1)], Nick S. Jones [(2)], David Orme [(1)], Lorenzo Picinali [(3)]

(1) Department of Life Sciences, Imperial College London
(2) Department of Mathematics, Imperial College London
(3) Dyson School of Design Engineering, Imperial College London
(a) s.sethi16@imperial.ac.uk

18 December 2017

Abstract

Automated methods of monitoring ecosystems provide a cost-effective way to track changes in natural system's dynamics across temporal and spatial scales. Whilst much work has been done on automated analyses, methods of recording and storing data captured from the field still require significant manual effort. Here, we introduce an open source, inexpensive, fully autonomous ecosystem monitoring unit for capturing and remotely transmitting continuous data streams from field sites over long time-periods. We focus on the case of autonomous acoustic monitoring of tropical rainforests, but we give examples of how the modular design is easily modified to collect data from alternative sensor types in any environment with mobile coverage. Having surveyed the existing methods, we show how our system can outperform comparable technologies for fractions of the cost. The solar powered device is based on a Raspberry Pi, and transmits data through a mobile network link to a central server to provide a near real-time stream of data. The system is robust to unreliable network signals, and has been shown to function in extreme environmental conditions, such as in the tropical rainforests of Sabah, Borneo. We provide full details on how to assemble the hardware, and the open-source software running on the Raspberry Pi. Paired with appropriate automated analysis techniques, this system could provide spatially dense, near real-time, continuous insights into ecosystem and biodiversity dynamics for a low cost.

1 Introduction

Rainforests in tropical regions around the world hold an enormous wealth of biodiversity, especially where undisturbed (Gibson et al., 2011). As the global population continues to grow these habitats have come under pressure from increasing levels of deforestation, affecting life within the forest (Sala et al., 2000; Sodhi et al., 2004). One way to quantify the effect of these changes is to track changes in biodiversity across temporal and spatial gradients. For example, the biodiversity at one site may be measured over time as the use of the forest changes (Magurran et al., 2010), or the biodiversity at various sites already experiencing different uses could be compared (Wilson et al., 2004). In practice, however, quantifying biodiversity is difficult (Gotelli and Colwell, 2001), with data routinely suffering from observer bias and from undersampling both spatially and temporally (Foster and Harmsen, 2012; Leach et al., 2016; Zwart et al., 2014). Increasingly scientists have moved towards automated methods of biodiversity assessment in order to bypass these limitations, a trend especially evident in the field of acoustic monitoring (Acevedo and Villanueva-Rivera, 2006; Pijanowski et al., 2011).

Any automated monitoring effort requires two fundamental stages: data recording and data analysis. Despite the fast pace of progress being made in automated acoustic data analysis techniques using machine learning methods such as convolutional neural networks (Cakir et al., 2016; Piczak, 2015; Salamon and Bello, 2016), unsupervised feature learning (Salamon et al., 2016; Stowell and Plumbley, 2014), Gaussian mixture models (GMM) (Lee et al., 2013; Zhao et al., 2017), hidden Markov models (HMM) (Aide et al., 2013; Ventura et al., 2015), and random forests (Bravo et al., 2017), progress on automated data recording for acoustic analyses has been less rapid.

Current standard practice within the bio-acoustics community for data collection is to use a semi-automated approach. Typically, a recording unit (e.g. from the Wildlife Acoustics Song Meter range www.wildlifeacoustics.com/) is deployed for a set amount of time, and subsequently manually collected from the field when the data analysis is to be done (Briggs et al., 2012; Darras et al., 2016; Heinicke et al., 2015; Newson et al., 2017; Wrege et al., 2017; Zwart et al., 2014). The duration of deployment is limited by both the local storage capacity of the recording device and its battery life. For example, performing continuous audible range recordings with a default configuration of the Wildlife Acoustics Song Meter 4 will allow a maximum deployment of 450 hours (18.75 days) before a battery replacement is required. Due to the high cost of commercially available equipment, inexpensive alternatives have been developed to perform the same task (Maina et al., 2016; Whytock and Christie, 2016). Nevertheless, these systems still require regular visits post-deployment to collect data and replace batteries, increasing their effective cost and limiting their potential scalability.

Only a small handful of projects have attempted truly autonomous acoustic monitoring, notably Cyberforest (Saito et al., 2015) and ARBIMON (Aide et al., 2013). These systems employ solar panels to provide indefinite power sources, and remotely upload the audio data as it is recorded. Both systems, however, require large initial investments in infrastructure (e.g. satellite internet (Saito et al., 2015) and long distance RF communications equipment (Aide et al., 2013)) running into thousands of pounds per unit, which hinder their viability as a global solution.

Challenges such as providing a long-term power source and enabling automated data transmission are not unique to the field of acoustic monitoring. In this study we outline the design for an inexpensive autonomous ecosystem monitoring device based around a low-power Raspberry Pi, costing under £250 ($331 USD) per unit, which will enable continuous data collection from remote field sites. We present the specific case of an autonomous acoustic monitor. However, the modular design of the equipment facilitates long-term continuous monitoring from a variety of sensors with only minor modifications. We demonstrate this flexibility by implementing a time-lapse camera unit in place of a microphone.

The equipment has been successfully field-tested in the tropical rainforests of Sabah, Malaysia at the SAFE project field site (Ewers et al., 2011) over two trial periods spanning a total operational time of over 6 months. In addition to the hardware configuration, we provide open source code that runs upon the Raspberry Pi which can be customised to meet the requirements of individual projects (www.github.com/sarabsethi/rpi-eco-monitoring). Paired with the appropriate automated data analysis techniques, the proposed system can facilitate near real-time and continuous monitoring of rainforest biodiversity over extended periods of time.

2 Methods

2.1 A robust, open, autonomous and networked system design for real-time data capture

In this study, we describe the design of an autonomous ecosystem monitoring unit that will provide a near real-time continuous data stream from remote field sites over a period months, with no visits to the equipment required post deployment. The core requirements for the system are as follows. Data should be captured from the chosen sensor and uploaded automatically from the field even in the presence of unreliable and intermittent data connections. The data quality should be as high as possible to facilitate accurate analyses, whilst maintaining a balance with file size and working within the limitations of the data connection. Software running on the monitoring unit should be remotely modifiable to enable operational flexibility without requiring physical retrieval. The system should be powered by a renewable source so that battery replacements are not required during the deployment, and so that excessively large batteries are not a hindrance to installation.

Our implementation of this autonomous recording unit consists of three main components (Figure 1): (i) the core data capturing electronics based around a Raspberry Pi computer; (ii) a mobile network link to enable continuous remote uploading of the data; and (iii) a solar powered battery system as a renewable power source.

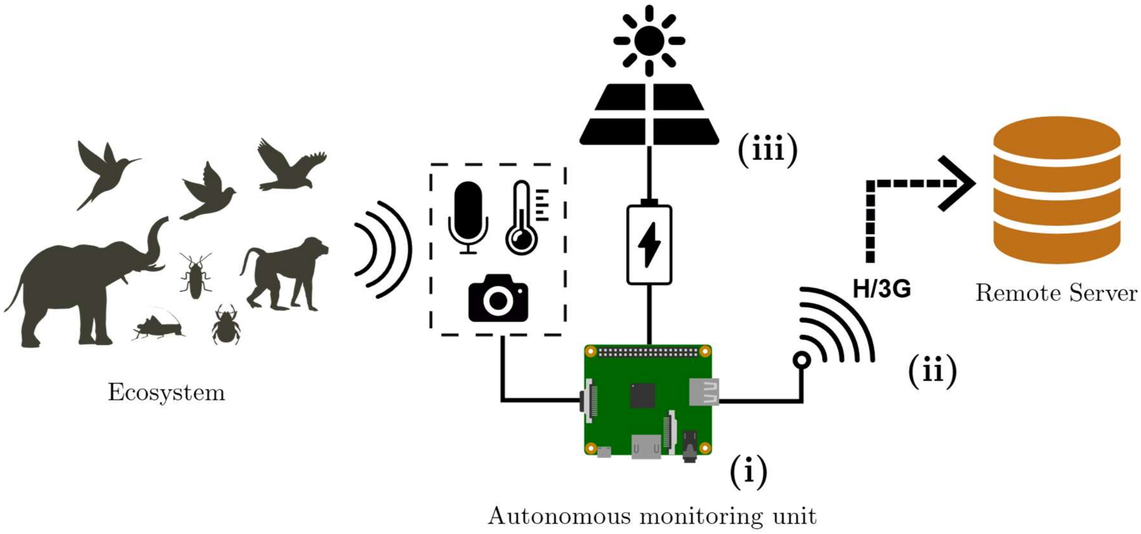

Figure 1: **A schematic of the autonomous ecosystem monitoring system.** Here we show how data is continuously captured from an ecosystem and uploaded automatically from the field to a remote server using our system. The monitoring unit itself consists of three core components: **(i)** the core data capturing electronics, **(ii)** a mobile network link for uploading data, and **(iii)** a solar power system.

The monitoring unit reboots each morning at a user-determined time (02:00 by default). On each boot, the latest version of the software running on the Raspberry Pi is pulled from a GitHub repository, and console logs generated from the previous day's operation are transmitted to the server. The logs provide an opportunity to conduct remote debugging, and the software updates allow modifications to be made to the data capturing and uploading logic without requiring physical retrieval of the monitoring units. These software updates add only a small amount to the total network load of the device; as of December 2017 the size of the repository is 242kB.

All software running on the Raspberry Pi has been made open-source on GitHub under the GNU GPLv3 license, and prepared Raspbian SD card images with the software pre-installed are also available online. Both can be found at www.github.com/sarabsethi/rpi-eco-monitoring.

2.2 Low cost core recording electronics

Capture, compression, storage and transfer of the data is managed by a Raspberry Pi A+ connected to a sensor input, and a Huawei E3531 USB 3G dongle for connection to the mobile network. The Raspberry Pi runs Python scripts on start-up which (after checking for software updates) employ a multi-threaded scheme to continuously record data from the sensor input, and simultaneously in the background compress and upload processed data files to a remote server.

In this study we focus on the application of acoustic monitoring, employing as a sensor a Rode SmartLav+ omnidirectional capacitor microphone connected through a Ugreen USB sound adaptor, as an alternative to the discontinued Cirrus Logic audio card header used in the Solo recorder (Whytock and Christie, 2016). Single channel 16-bit audio is recorded at a sampling rate of 44.1kHz (Nyquist frequency of 22.05kHz) in default segments of 20 minutes. Once one 20-minute segment has finished recording, the audio is stored in an uncompressed WAV file locally on the Pi, labelled according to its recording start date and time, and immediately the next recording begins.

Recording raw sensor data can result in very large file sizes. Thus, whilst not always necessary, for the case of remote acoustic monitoring it is desirable to compress the data prior to uploading. In a background thread the 20-minute raw WAV file is compressed to the lossy format MPEG Audio Layer III (MP3), employing the LAME codec with variable bit-rate encoding at the highest quality available ($\approx$ 245 kbit/s). This compression reduces each 20-minute file size from 105 MB to approximately 20 MB, achieving over 5x compression. Lossy compression was chosen over lossless compression to ensure manageable file sizes, and MP3 was chosen over other lossy compression formats (e.g. AAC) for its widespread use and flexibility. Similarly, for pictures the lossy JPEG scheme was used to compress images before transmission, reducing image file sizes by approximately a factor of four.

2.3 A robust mobile network upload

Once the compression is complete, the data file is uploaded to a central FTP server using the 3G dongle to connect to a mobile network. This system is designed to be deployed in remote regions, where the mobile network signal can drop out for days at a time due to poorly maintained infrastructure. Therefore, we have built robustness into our data uploading scheme to account for unreliable and intermittent connections, ensuring that data is still recorded from the sensor input continuously when the system is off-line, and subsequently uploaded to the server when a network connection is made available once again. The 20-minute duration of the recording and uploading cycle was chosen to ensure individual files were of a manageable size, without placing unnecessary load on the mobile network data link. If desired, this value (along with other recording and compression parameters used) can be modified in the open-source code to fit different use-cases.

Initially, an attempt is made to upload the compressed data file to the server. If the full file is received by the server, the local copy of the file is deleted on the client side. However, if a mobile connection is temporarily unavailable the monitoring system stores the data file locally and adds it to a queue. On the next upload cycle the system re-attempts the transfer of all data files still stored locally on the Raspberry Pi.

By deleting files that have successfully been uploaded, the storage space on the device only acts as a buffer between the monitoring system and the remote server. This is essential for a system to be able to monitor continuously over extended time periods. The default set-up for our autonomous recording unit includes a 64GB micro-SD card allowing for over one month of audio data to be stored locally at any one time. If this capacity is filled, new recordings are not captured until an internet connection is reinstated and the transfer of data to the server is resumed. In practice allowing for one month of offline data is an overly cautious approach, and unit cost can be reduced by using a smaller micro-SD card, especially when deploying recording units in areas with reliable data connections. Furthermore, unlike systems which implement live data streaming using packages such as DarkIce (a software which allows live streaming of audio directly from a sound card to a streaming server: www.darkice.org/), this uploading scheme deals with files in a general manner allowing the same code-base to be used when monitoring other forms of data, such as images or environmental measurements.

2.4 Continuous monitoring: solar power and batteries

To ensure fully continuous monitoring over a long time period we use a solar power system (Figure. 2). A Gamma 3.0 solar charge controller is connected to a 30W solar panel, a 12V 10Ah AGM (Absorbent Glass Mat) deep-cycle battery, and a 12V to 5V DC step down converter which ultimately powers the Raspberry Pi. The charge controller regulates the voltage coming from the solar panel and battery terminals to ensure a steady 12V DC is supplied to the load. In the case of an unusually long period of darkness the controller will stop providing current to the load to ensure the battery is not damaged from over-discharging. When there is sufficient power to recharge the battery up above a certain safety threshold, power is reinstated to the load terminals and the recording unit resumes usual operation.

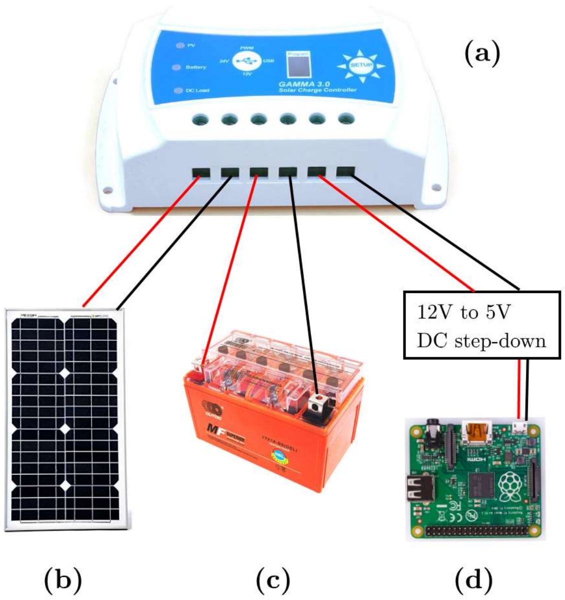

Figure 2: **A schematic of the solar power system used.** Here we show the solar power system used to power our recording unit continuously over long time periods. The components shown are: **(a)** a solar charge controller, **(b)** a 30W solar panel, **(c)** a 12V 10Ah AGM deep-cycle battery, and **(d)** the DC step down unit

connecting the 12V load terminal to the 5V Raspberry Pi power input. Red and black lines indicate wires carrying positive and negative voltages respectively.

2.5 Full component list

Table 1 shows the full parts list required to build our autonomous ecosystem monitoring unit, along with typical costs for each component in the case of acoustic monitoring. The total unit cost comes to a one-off cost of £227.40 plus £30 per month for the mobile network data link (Celcom Malaysia). This is the default configuration, however the costs can be reduced by a number of means, for example by forgoing the solar component or using a smaller local micro-SD card.

For comparison, a basic setup of the Wildlife Acoustic Song Meter 4 (SM4) comes to over $1000 USD (~£749), and no configurations are available which offer solar power or remote data uploading. The ARBIMON permanent station, despite not providing a continuous audio stream (only one of every ten minutes is recorded), otherwise provides comparable functionality to our autonomous recording units and costs $4000 USD (~£2994) not including the cost of a data link (Aide et al., 2013). We further note that all design specifications and code for our system monitor is open source, which is not the case for these comparison systems.

Table 1: **Autonomous acoustic monitoring unit cost breakdown.** Parts list and typical costs for one autonomous ecosystem monitoring unit assembled in the UK, as of August 2017. In this case the system is configured for acoustic monitoring

Item	Cost (GBP £)
One-off costs	
Raspberry Pi A+	21.59
SanDisk 64GB SD card	17.39
Huawei E3531 3G dongle	21.00
Dri-box weatherproof box	10.09
Anker powered USB hub	20.00
12V to 5V DC step down converter	6.29
12V 10Ah AGM deep-cycle battery	23.98
Solar charge controller	10.99

30W solar panel	45.08
Audio sensor costs	
Ugreen USB audio card	6.99
Rode SmartLav + electret microphone	44.00
Operational costs	
60GB data sim card	30.00 per month
Total	**227.40 + 30 per month**

2.6 Alternative sensor types and configurations

The modular design of the autonomous recording unit, with the robust data uploading scheme creates a device that is flexible enough to collect data of many other types, as well as the example of audible range audio used here. For example, in two units the audio card and microphone was replaced with a standard 5MP USB camera. In these units, a single image was captured every 20 minutes and was uploaded to the server, allowing us to create a long term time-lapse series. Similar modifications could be made to facilitate long term autonomous data collection of other data types such as air temperature, wind-speed, light levels, rainfall and motion-activated camera traps. Additionally, audio data from an array of microphones could be recorded from one device to enable spatial localisation of specific calls within the soundscape, or ultrasonic microphones could be substituted to target different taxa such as bats. It should be noted that recording continuous audio data over long time-periods is a far more challenging task than sensing most other environmental variables, in terms of the reliability required, power consumption, and the volume of data being handled. Therefore, when considering other sensor types it is likely that other components in the system can be replaced with cheaper alternatives to save costs.

To an extent, all components are customisable but specific examples include: (i) reducing the size of the SD card in applications with lesser data requirements (e.g. temperature and humidity measurements), or in locations with more reliable internet connections; (ii) increasing the size of the solar panel and battery for sensors that consume more power (e.g. pH measuring devices); or (iii) swapping in a more powerful Raspberry Pi model when increased computing power is required (e.g. when processing high definition video).

3 Field Trials

Our field tests have been primarily based at the SAFE project, a large-scale fragmentation experiment located in the tropical rainforests of Sabah, Malaysia (Ewers et al., 2011). Additionally, long-term tests have been carried out in a residential area of London, UK to show the systems viability in temperate climates with less consistent sunlight.

In March 2017 two acoustic monitoring units and two time-lapse camera units were deployed (Figure. 3) at SAFE over a period of four months. One audio recording unit was placed in primary rainforest and the other was placed in an area of heavily logged forest. The two time-lapse cameras were placed on top of a 53 m tall carbon flux tower, and to a 50 m tree overlooking the SAFE camp respectively. These trials highlighted that low quality SLA batteries showed sensitivity to high temperatures and deep-cycling, and therefore all four monitoring units had occasional periods of inactivity as the batteries deteriorated over the deployment. These batteries were replaced with deep cycle AGM batteries in subsequent iterations of the system, rectifying the issue. Despite the battery deterioration, the monitoring units continued to boot and resume recording of data automatically when enough power was available and the remote uploading scheme performed as designed, as all files that were recorded on the monitoring units were uploaded successfully to the remote server despite regular periods of network outages.

In October 2017 a further four acoustic monitoring units were deployed at SAFE (three in logged forest and one in primary forest). All four units from the second deployment were still operating as designed as of December 2017. One further acoustic recorder has been intermittently tested at a residential location in central London since March 2016.

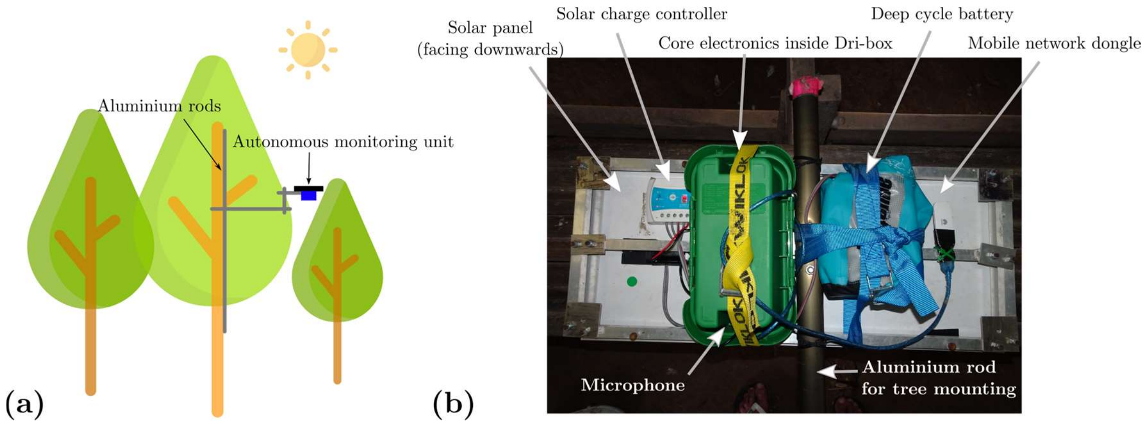

Figure 3: **Canopy mounting of the autonomous monitoring unit.** Here we display how the autonomous acoustic monitoring units were mounted in the canopy at SAFE Project. **(a)** A series of aluminium rods were affixed to the tree to allow the solar panel to reach direct sunlight out of the shade of the canopy. **(b)** A close-up view of the inverted monitoring unit with all components attached

3.1 Acoustic monitoring

Over 4,400 total hours of audio (approx. 275 GB) has been recorded and transmitted from the SAFE project sites from the six acoustic monitors. From the acoustic monitoring unit in London, over 4,000 hours (approx. 250GB) of data has been recorded and uploaded. The longest fully continuous period of acoustic monitoring from the tropical forest recorders is still ongoing, and currently stands at 744 hours (31 days).

A one-week period of continuous audio data spanning 16-23 November 2017 from a logged forest site in SAFE is visualised in Figure 4 (a) using a false colour index spectrogram (Towsey et al., 2014) (www.github.com/sarabsethi/false_colour_index_spectrogram). A daily periodicity is clearly visible in the spectrogram, most notably due to the difference in vocalisation patterns between the diurnal and nocturnal taxa recorded. In Figure 4 (b) we calculate the acoustic diversity index (ADI) (Villanueva-Rivera et al., 2011) (www.github.com/sandoval31/Acoustic_Indices) for one minute at 12.20pm each day over a period of three months at a logged forest site starting from 12 April 2017.

Such a visualisation facilitates easy outlier identification. For example, in this case the low ADI value seen at day 0 is caused by anthropogenic noise recorded during installation of the unit, and at day 57 is caused by a Wreathed Hornbill calling in the foreground which is not heard at this time of day in the other recordings.

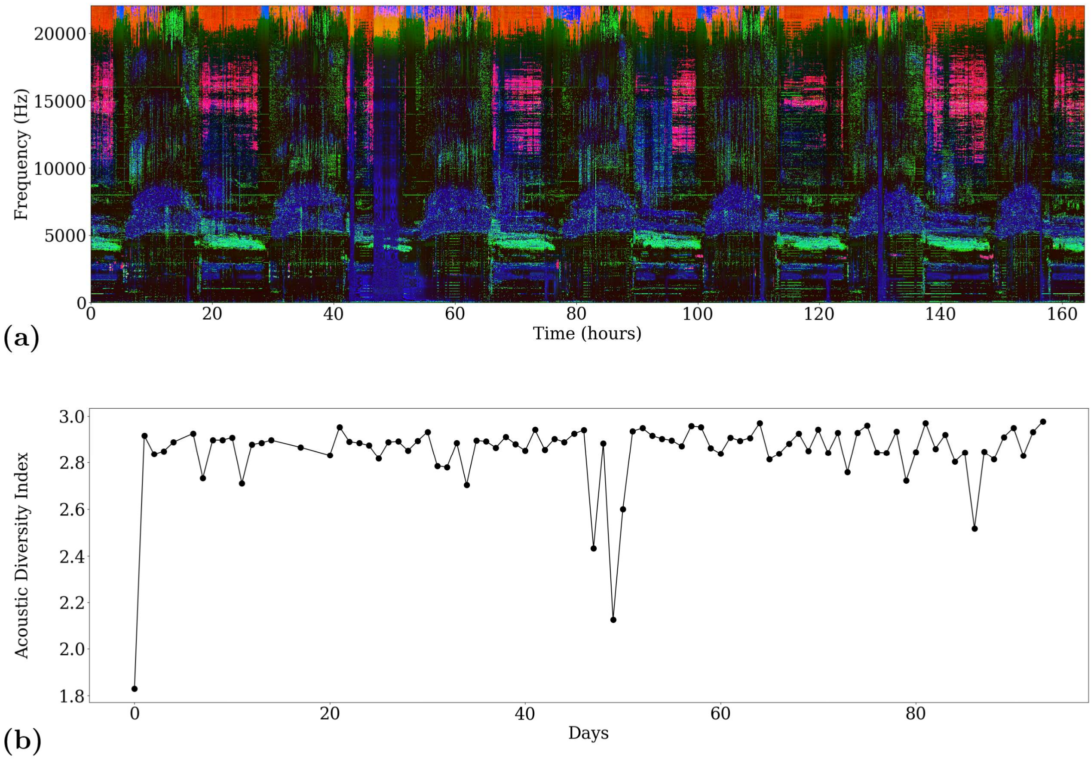

Figure 4: **Long duration audio data visualisations.** A continuous one-week period of audio recorded from SAFE project is displayed in **(a)** using a false colour index spectrogram. In **(b)** the acoustic diversity index is calculated and plotted for one minute at 12.20pm each day over a monitoring period of three months.

Prolonged exposure to high temperature and humidity could have an adverse effect upon the electronics within our system. Through our first round of field tests we demonstrated that even after a six-month deployment in a tropical rainforest the autonomous monitoring system was able to record and remotely transmit data, having been exposed to temperatures up to approximately 31.5 degrees Celsius and an average 614mm of precipitation per month. Furthermore, we measured the frequency response of the microphone to a logarithmic sinus sweep test between 20Hz and 20kHz and found no significant difference in response between a new microphone and one that had been deployed for 26 weeks at the SAFE project (Figure 5) (www.github.com/sarabsethi/mic_sweep_test_matlab).

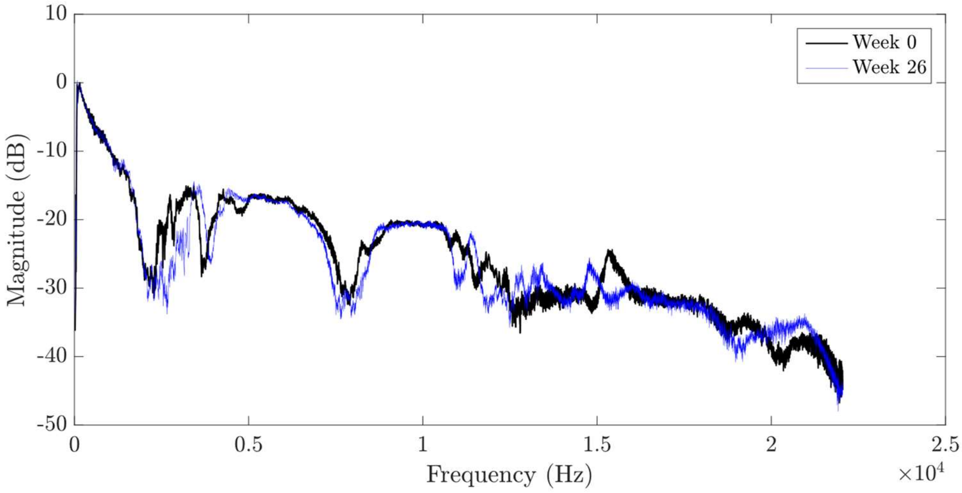

Figure 5: **Frequency response of microphone remains approximately constant over deployment time.** The frequency response of a brand-new microphone is measured before (in black) and after a 26-week deployment (in blue).

3.2 Time-lapse camera

Two time-lapse cameras deployed captured and transmitted over 8,300 images (approx. 24GB) combined during their deployment. Figure 6 shows a series of 15 images from the same autonomous time-lapse camera unit installed on the carbon flux tower, each taken one week apart. Whilst differing weather conditions caused automatic adjustments of the camera's exposure for each image, there is no visible degradation in the quality of the photos over this three month period.

Figure 6: **Time-lapse camera images over 15 weeks.** A time-lapse camera unit was installed on a 53m carbon flux tower; here 15 images are shown, each taken one week apart.

4 Discussion

In this study we have introduced an inexpensive method of continuous, autonomous ecosystem monitoring. The equipment has been shown to be robust and versatile through successful field testing in both tropical and temperate climates.

The volume of data collected through long term continuous ecosystem monitoring using such equipment requires consideration. Other studies have performed analyses directly on the monitoring device at the point of data capture as a way of reducing the volume of data being transmitted (Deniz et al., 2017). This reduces the data storage requirements of the device since only analysed statistics derived from the raw data are kept. However, discarding the raw data limits the use of the monitoring unit as a general tool as it does not allow re-analysis of the original data using ever-improving techniques.

For acoustic monitoring, employing the 24-hour recording schedule and VBR MP3 compression used in this study can lead to almost 700 GB of data being recorded per unit in one year. Whilst many commercial providers offer large data storage options, plans on this scale can prove costly. Furthermore, performing real-time analyses on such a large volume of data will either place constraints on the complexity of the techniques used, or will require significant computing resources to be employed. For the task of species identification from audio data, for example, it has been shown that selecting subsets of the acoustic data during known active calling hours can lead to representative results (Zwart et al., 2014). The open source code used in our system can be easily modified to accommodate for customised recording schedules, and thus reduce data storage requirements.

To help alleviate the issues associated with such large amounts of data we include a stage of data compression before remote transmission. However, when using lossy forms of compression, it is important to consider a potential degradation of the quality of the signal. For acoustic monitoring we use MP3 compression, which, like many other lossy compression schemes, employs perceptual coding to remove parts of the audio signal that are not audible to human ears (Brandenburg, 1999). Previous studies have shown that MP3 compression has little effect upon the ability of trained birders to discern calls in a recording, as compared to using the uncompressed WAV file format (Rempel et al., 2005). However, future studies could further investigate the effect of audio compression upon the accuracy of automated bio-acoustic analyses, potentially allowing for higher data compression rates to be used.

The automated data transmission component of our system uses a mobile network data connection, which constrains the potential locations at which the recording units can be deployed. The robust data-uploading scheme allows us to target areas with less reliable connections, but many remote sites will not have access to even this level of connectivity. Alternatives such as satellite internet (Saito et al., 2015) and long-distance radio frequency (RF) links (Aide et al., 2013) have previously been used to remotely transmit acoustic data from remote field sites. However, both of these would significantly add to both the cost and power requirements of our system, limiting its scalability. Mesh networks are an increasingly popular solution for low-power long-distance remote data transmission (Akyildiz and Wang, 2005; Dugas, 2005), and using such an approach would be a recommended addition to future iterations of this system.

Harnessing solar power during the daytime allows our autonomous recording units to perform uninterrupted 24 hour monitoring through the night and periods of inclement weather. However, the efficiency of solar panels suffers significantly if the panels are not exposed to direct sunlight. Undisturbed tropical rainforests typically have high closed canopies (Hardwick et al., 2015). This means that solar panels placed on the forest floor would most likely not be able to generate enough power to keep the recording unit operating continuously; we avoided this issue by installing the monitoring units in the canopy. Whilst canopy installation significantly increases the effort required for maintenance and retrieval of the units, our fully autonomous approach means that physical access should only be required in the case of an equipment malfunction, as the data is remotely transmitted. Furthermore, the modular design of the recording unit allows the flexibility to swap in alternative renewable power sources where solar power may not be an appropriate choice (e.g. at polar locations with limited sunlight hours).

Our autonomous monitoring device can be made from readily available equipment, for a fraction of the cost of comparable alternatives, especially in the case of acoustic monitoring. The affordability will allow automated ecosystem monitoring to be carried out on a finer spatial scale as more recording units can be deployed within the scope of one study. In addition, equipment deployed in wild habitats such as tropical rainforests is often damaged or destroyed by regular tree-falls, extreme weather conditions or animal interference. For this reason it is desirable to deploy equipment that is less costly to repair or replace when necessary. The modular design also allows for specific replacement of only the damaged components rather than the whole unit, saving on maintenance costs of the system.

5 Conclusion

In this study we have outlined the design and implementation of an open source robust autonomous ecosystem monitoring unit, which allows remote collection and transmission of field data over long time periods. The equipment can be built for significantly less expense than existing systems offering comparative functionality, allowing field studies to be designed at a larger scale than previously possible. In addition to the hardware design, we have open-sourced the code providing the reliable recording and upload mechanism, which should allow the broader scientific community to further develop this method of fully automated data collection.

Acknowledgements

We would like to thank the research assistants and staff at the SAFE project camp, in particular Unding Jami and the canopy access team. We would like to thank Henry Bernard for his collaboration. This project was supported by funding from the Sime Darby Foundation and the Natural Environment Research Council [NE/K007270/1]. Sarab Sethi is also supported by Natural Environment Research Council through the Science and Solutions for a Changing Planet DTP.

References

Acevedo, M.A., Villanueva-Rivera, L.J., 2006. From the Field: Using Automated Digital Recording Systems as Effective Tools for the Monitoring of Birds and Amphibians. Wildlife Society Bulletin 34, 211–214. https://doi.org/10.2193/0091-7648(2006)34[211:UADRSA]2.0.CO;2

Aide, T.M., Corrada-Bravo, C., Campos-Cerqueira, M., Milan, C., Vega, G., Alvarez, R., 2013. Real-time bioacoustics monitoring and automated species identification. PeerJ 1, e103. https://doi.org/10.7717/peerj.103

Akyildiz, I.F., Wang, X., 2005. A survey on wireless mesh networks. IEEE Communications Magazine 43, S23–S30. https://doi.org/10.1109/MCOM.2005.1509968

Brandenburg, K., 1999. MP3 and AAC Explained, in: Audio Engineering Society Conference: 17th International Conference: High-Quality Audio Coding.

Bravo, C.J.C., Berríos, R.Á., Aide, T.M., 2017. Species-specific audio detection: a comparison of three template-based detection algorithms using random forests. PeerJ Comput. Sci. 3, e113. https://doi.org/10.7717/peerj-cs.113

Briggs, F., Lakshminarayanan, B., Neal, L., Fern, X.Z., Raich, R., Hadley, S.J.K., Hadley, A.S., Betts, M.G., 2012. Acoustic classification of multiple simultaneous bird species: A multi-instance multi-label approach. The Journal of the Acoustical Society of America 131, 4640–4650. https://doi.org/10.1121/1.4707424

Cakir, E., Ozan, E.C., Virtanen, T., 2016. Filterbank learning for deep neural network based polyphonic sound event detection, in: 2016 International Joint Conference on Neural Networks (IJCNN). Presented at the 2016 International Joint Conference on Neural Networks (IJCNN), pp. 3399–3406. https://doi.org/10.1109/IJCNN.2016.7727634

Darras, K., Pütz, P., Fahrurrozi, Rembold, K., Tscharntke, T., 2016. Measuring sound detection spaces for acoustic animal sampling and monitoring. Biological Conservation 201, 29–37. https://doi.org/10.1016/j.biocon.2016.06.021

Deniz, N.N., Chelotti, J.O., Galli, J.R., Planisich, A.M., Larripa, M.J., Leonardo Rufiner, H., Giovanini, L.L., 2017. Embedded system for real-time monitoring of foraging behavior of grazing cattle using acoustic signals. Computers and Electronics in Agriculture 138, 167–174. https://doi.org/10.1016/j.compag.2017.04.024

Dugas, C., 2005. Configuring and managing a large-scale monitoring network: solving real world challenges for ultra-low-powered and long-range wireless mesh networks. Int. J. Network Mgmt. 15, 269–282. https://doi.org/10.1002/nem.573

Ewers, R.M., Didham, R.K., Fahrig, L., Ferraz, G., Hector, A., Holt, R.D., Kapos, V., Reynolds, G., Sinun, W., Snaddon, J.L., Turner, E.C., 2011. A large-scale forest fragmentation experiment: the Stability of Altered Forest Ecosystems Project. Philosophical Transactions of the Royal Society of London B: Biological Sciences 366, 3292–3302. https://doi.org/10.1098/rstb.2011.0049

Foster, R.J., Harmsen, B.J., 2012. A critique of density estimation from camera-trap data. The Journal of Wildlife Management 76, 224–236. https://doi.org/10.1002/jwmg.275

Gibson, L., Lee, T.M., Koh, L.P., Brook, B.W., Gardner, T.A., Barlow, J., Peres, C.A., Bradshaw, C.J.A., Laurance, W.F., Lovejoy, T.E., Sodhi, N.S., 2011. Primary forests are irreplaceable for sustaining tropical biodiversity. Nature 478, 378–381. https://doi.org/10.1038/nature10425

Gotelli, N.J., Colwell, R.K., 2001. Quantifying biodiversity: procedures and pitfalls in the measurement and comparison of species richness. Ecology Letters 4, 379–391. https://doi.org/10.1046/j.1461-0248.2001.00230.x

Hardwick, S.R., Toumi, R., Pfeifer, M., Turner, E.C., Nilus, R., Ewers, R.M., 2015. The relationship between leaf area index and microclimate in tropical forest and oil palm plantation: Forest disturbance drives changes in microclimate. Agricultural and Forest Meteorology 201, 187–195. https://doi.org/10.1016/j.agrformet.2014.11.010

Heinicke, S., Kalan, A.K., Wagner, O.J.J., Mundry, R., Lukashevich, H., Kühl, H.S., 2015. Assessing the performance of a semi-automated acoustic monitoring system for primates. Methods Ecol Evol 6, 753–763. https://doi.org/10.1111/2041-210X.12384

Leach, E.C., Burwell, C.J., Ashton, L.A., Jones, D.N., Kitching, R.L., 2016. Comparison of point counts and automated acoustic monitoring: detecting birds in a rainforest biodiversity survey. Emu - Austral Ornithology 116, 305–309. https://doi.org/10.1071/MU15097

Lee, C.H., Hsu, S.B., Shih, J.L., Chou, C.H., 2013. Continuous Birdsong Recognition Using Gaussian Mixture Modeling of Image Shape Features. IEEE Transactions on Multimedia 15, 454–464. https://doi.org/10.1109/TMM.2012.2229969

Magurran, A.E., Baillie, S.R., Buckland, S.T., Dick, J.M., Elston, D.A., Scott, E.M., Smith, R.I., Somerfield, P.J., Watt, A.D., 2010. Long-term datasets in biodiversity research and monitoring: assessing change in ecological communities through time. Trends in Ecology & Evolution 25, 574–582. https://doi.org/10.1016/j.tree.2010.06.016

Maina, C. wa, Muchiri, D., Njoroge, P., 2016. Cost Effective Acoustic Monitoring of Biodiversity and Bird Populations in Kenya. bioRxiv 72546. https://doi.org/10.1101/072546

Newson, S.E., Bas, Y., Murray, A., Gillings, S., 2017. Potential for coupling the monitoring of bush-crickets with established large-scale acoustic monitoring of bats. Methods Ecol Evol 8, 1051–1062. https://doi.org/10.1111/2041-210X.12720

Piczak, K.J., 2015. Environmental sound classification with convolutional neural networks, in: 2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP). Presented at the 2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP), pp. 1–6. https://doi.org/10.1109/MLSP.2015.7324337

Pijanowski, B.C., Villanueva-Rivera, L.J., Dumyahn, S.L., Farina, A., Krause, B.L., Napoletano, B.M., Gage, S.H., Pieretti, N., 2011. Soundscape Ecology: The Science of Sound in the Landscape. BioScience 61, 203–216. https://doi.org/10.1525/bio.2011.61.3.6

Rempel, R.S., Hobson, K.A., Holborn, G., Van Wilgenburg, S.L., Elliott, J., 2005. Bioacoustic monitoring of forest songbirds: interpreter variability and effects of configuration and digital processing methods in the laboratory. Journal of Field Ornithology 76, 1–11. https://doi.org/10.1648/0273-8570-76.1.1

Saito, K., Nakamura, K., Ueta, M., Kurosawa, R., Fujiwara, A., Kobayashi, H.H., Nakayama, M., Toko, A., Nagahama, K., 2015. Utilizing the Cyberforest live sound system with social media to remotely conduct woodland bird censuses in Central Japan. Ambio 44, 572–583. https://doi.org/10.1007/s13280-015-0708-y

Sala, O.E., Chapin, F.S., Iii, Armesto, J.J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L.F., Jackson, R.B., Kinzig, A., Leemans, R., Lodge, D.M., Mooney, H.A., Oesterheld, M., Poff, N.L., Sykes, M.T., Walker, B.H., Walker, M., Wall, D.H., 2000. Global Biodiversity Scenarios for the Year 2100. Science 287, 1770–1774. https://doi.org/10.1126/science.287.5459.1770

Salamon, J., Bello, J.P., 2016. Deep Convolutional Neural Networks and Data Augmentation for Environmental Sound Classification. arXiv:1608.04363 [cs].

Salamon, J., Bello, J.P., Farnsworth, A., Robbins, M., Keen, S., Klinck, H., Kelling, S., 2016. Towards the Automatic Classification of Avian Flight Calls for Bioacoustic Monitoring. PLOS ONE 11, e0166866. https://doi.org/10.1371/journal.pone.0166866

Sodhi, N.S., Koh, L.P., Brook, B.W., Ng, P.K.L., 2004. Southeast Asian biodiversity: an impending disaster. Trends in Ecology & Evolution 19, 654–660. https://doi.org/10.1016/j.tree.2004.09.006

Stowell, D., Plumbley, M.D., 2014. Automatic large-scale classification of bird sounds is strongly improved by unsupervised feature learning. PeerJ 2, e488. https://doi.org/10.7717/peerj.488

Towsey, M., Zhang, L., Cottman-Fields, M., Wimmer, J., Zhang, J., Roe, P., 2014. Visualization of Long-duration Acoustic Recordings of the Environment. Procedia Computer Science, 2014 International Conference on Computational Science 29, 703–712. https://doi.org/10.1016/j.procs.2014.05.063

Ventura, T.M., de Oliveira, A.G., Ganchev, T.D., de Figueiredo, J.M., Jahn, O., Marques, M.I., Schuchmann, K.-L., 2015. Audio parameterization with robust frame selection for improved bird identification. Expert Systems with Applications 42, 8463–8471. https://doi.org/10.1016/j.eswa.2015.07.002

Villanueva-Rivera, L.J., Pijanowski, B.C., Doucette, J., Pekin, B., 2011. A primer of acoustic analysis for landscape ecologists. Landscape Ecol 26, 1233. https://doi.org/10.1007/s10980-011-9636-9

Whytock, R.C., Christie, J., 2016. Solo: an open source, customizable and inexpensive audio recorder for bioacoustic research. Methods Ecol Evol n/a-n/a. https://doi.org/10.1111/2041-210X.12678

Wilson, R.J., Thomas, C.D., Fox, R., Roy, D.B., Kunin, W.E., 2004. Spatial patterns in species distributions reveal biodiversity change. Nature 432, 393–396. https://doi.org/10.1038/nature03031

Wrege, P.H., Rowland, E.D., Keen, S., Shiu, Y., 2017. Acoustic monitoring for conservation in tropical forests: examples from forest elephants. Methods Ecol Evol n/a-n/a. https://doi.org/10.1111/2041-210X.12730

Zhao, Z., Zhang, S., Xu, Z., Bellisario, K., Dai, N., Omrani, H., Pijanowski, B.C., 2017. Automated bird acoustic event detection and robust species classification. Ecological Informatics 39, 99–108. https://doi.org/10.1016/j.ecoinf.2017.04.003

Zwart, M.C., Baker, A., McGowan, P.J.K., Whittingham, M.J., 2014. The Use of Automated Bioacoustic Recorders to Replace Human Wildlife Surveys: An Example Using Nightjars. PLOS ONE 9, e102770. https://doi.org/10.1371/journal.pone.0102770