

Shazam for bats: Internet of Things for continuous real-time biodiversity monitoring

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Abstract

Biodiversity surveys are often required for development projects in cities that could affect protected species such as bats. Bats are important biodiversity indicators of the wider health of the environment and activity surveys of bat species are used to report on the performance of mitigation actions. Typically, sensors are used in the field to listen to the ultrasonic echolocation calls of bats or the audio data is recorded for post-processing to calculate the activity levels. Current methods rely on significant human input and therefore present an opportunity for continuous monitoring and in situ machine learning detection of bat calls in the field. Here, we show the results from a longitudinal study of 15 novel Internet connected bat sensors—Echo Boxes—in a large urban park. The study provided empirical evidence of how edge processing can reduce network traffic and storage demands by several orders of magnitude, making it possible to run continuous monitoring activities for many months including periods which traditionally would not be monitored. Our results demonstrate how the combination of artificial intelligence techniques and low-cost sensor networks can be used to create novel insights for ecologists and conservation decision-makers.

1 | INTRODUCTION

The Internet of Things (IoT) has emerged from manufacturing and permeated across industries [1, 2]. The proliferation of consumer products has driven an ever-increasing ecosystem of hardware and software which in turn has increased applications in new and emerging forms of connected environments. In combination with machine learning, either run in the cloud or increasingly locally on the thing itself, IoT and edge processing are making many once

manual tasks more automated, allowing us to shift focus and skills to those that require a human touch.

This paper presents the application of embedded machine learning in the ecological domain to investigate interventions made in the built environment to support and maintain biodiversity. The challenge was to take state-of-the-art deep learning based methods for monitoring bat activity [3] and integrate that with emerging IoT technologies to broaden access to that expertise. For example, the United Kingdom's Bat Conservation Trust has the longest running systematic bat

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monitoring programme in the world utilising a network of scientists and citizen volunteers [4]. However, it relies on a high level of human input and currently utilises an equipment that is financially beyond the means of citizen scientists. In section two, we develop further the importance of this work within the smart city sector. The goal of this research was to implement a low-cost technical platform to give ecologists a better insight into urban bat activity through continuous longitudinal monitoring.

Utilising a novel IoT System-on-a-Chip (SoC) platform the project involved the design and development of state-of-the-art intelligent bat sensors, called Echo Boxes (Figure 1), that combine the latest advances in edge computing and machine learning. Each Echo Box works like ‘shazam for bats’, capable of listening to audio from the environment and immediately determining if bats are present and what species they are based on their echolocation calls. The complex analytics (audio processing and detection) that was previously undertaken in the lab on a high-performance machine was optimised to run on a low power, resource-constrained IoT device. A key goal for the project was to conduct a longitudinal research to investigate the challenges of specifying, installing, testing and maintaining the infrastructure over many months [5, 6]. To answer research questions about long-term patterns of bat behaviour and the potential for the technology to support ecologists and other stakeholders, the real-world deployment is required to scale up in several ways. Multiple technically complex Echo Box devices were required to work robustly and reliably for an extended period of time unsupervised in an outdoor environment where the technology would be completely exposed to the elements. In addition to the scientific and technical requirements, a key stakeholder goal of the prototype was to support data-driven policy-making. The research was conducted as part of a Smart Sustainable District programme supported by the Mayor's office of a major capital

city. As such, we describe the outcomes of the stakeholder engagement that helped to map the problem domain, set of requirements for the smart bat sensing system, and where, under the guidance of ecologists, the devices were installed to monitor bat activity levels across a large urban park in the city.

Our contributions include (i) working with stakeholders to identify application requirements for an urban sensing platform, (ii) the application of state-of-the-art machine learning techniques on sensor nodes for the automatic detection and counting of bat activity, (iii) continuous unattended monitoring of wildlife activity in an urban environment over multiple years.

The rest of the paper is organised as follows. We start by discussing the related work and requirements for the project (Sections 2 and 3). We present the system itself including the Echo Box bat sensors and the visualisation tool (Section 4). We report the results from the initial deployment that spanned several months (Section 5). Finally, we provide a broader discussion around the lessons learnt from successfully deploying and running the technology longitudinally, how it has been used by the ecologists to explore new patterns of data collection, and how the data captured has been used by decision-makers in the park to validate their biodiversity mitigation plans (Section 6).

2 | BACKGROUND AND RELATED WORK

The project was devised to bring together environmental researchers, conservation organisations, ecological consultants/practitioners, computer scientists and technologists to develop an end-to-end open source system for monitoring bats. The core research question was ‘how can technology provide more granular bat activity data over time and support ecologists and stakeholders in long-term decision-making?’ This multi-disciplinary research builds on three areas: (1) ecology

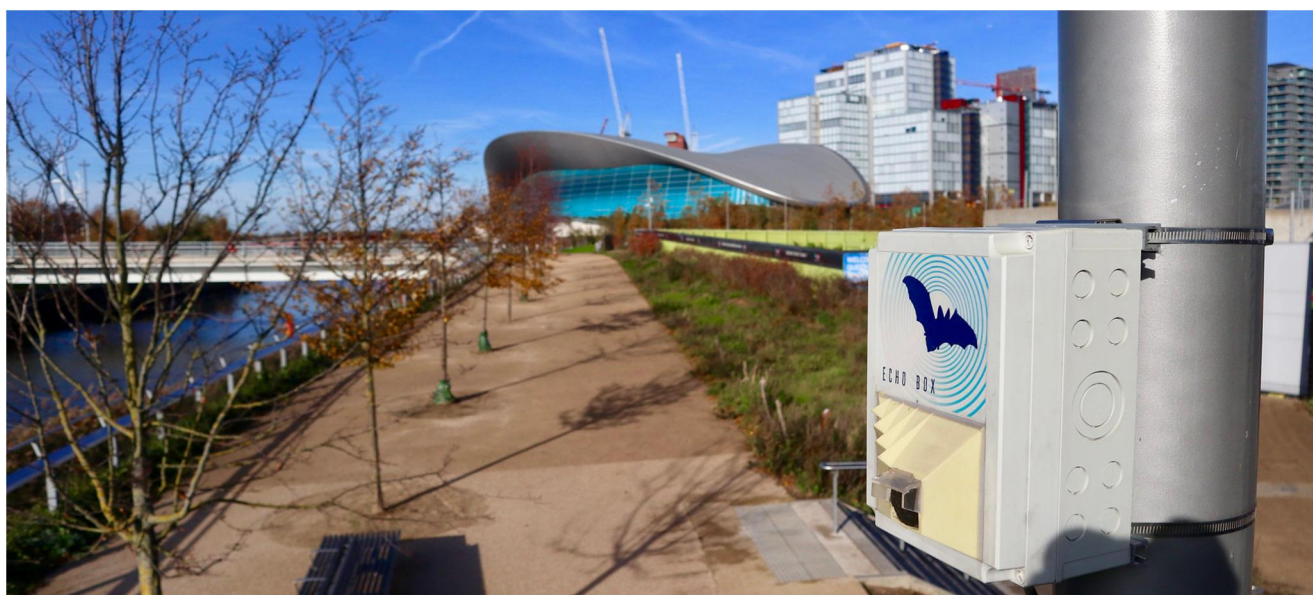


FIGURE 1 The smart bat sensor installed on the lamp column

practices for conducting bat surveys; (2) technology application in the field of ecology; and (3) latest advances in emerging technologies such as the IoT and edge processing.

2.1 | Bat surveys

Bat surveys are important for conservation, for example, to understand if bats are inhabiting an area, or how proposed activities might affect them [7]. Bats are also considered to be good indicator species reflecting the general health of the surrounding natural environment [8]. Surveys are usually carried out by contracted ecologists who follow standard practices. Typically, a survey lasts for several days and may also be conducted periodically, perhaps every 6 months or more often as required. Bats are nocturnal animals and use a high-frequency system called echolocation to navigate their environment at night. Echolocation works in a similar way to sonar; bats make ultrasonic calls and listen to the returning echoes in order to build up a sonic picture of their environment. Ecologists will capture these ultrasonic calls during surveys, for example, to understand bat activity levels in an area. Methods and tools used differ based on the aim of the survey and the questions it should answer. Sometimes ecologists will visit the site at night with handheld bat detectors to observe and listen to bats in real-time or use handheld ultrasonic recording devices to capture audio for later lab analysis [4].

Other techniques involve static recording devices left on-site for nights at a time unsupervised or attaching ultrasonic recording devices to cars to capture recordings over larger areas [3]. Audio data from such devices is typically stored locally, for example, on SD cards, and then collected by ecologists for lab analysis at the end of the recording period. During lab analysis, software tools are commonly used to help extract bat calls from audio recordings and some solutions also incorporate machine learning models to help detect and classify bat species [9]. These systems are often closed-sourced commercial systems making it difficult to know how the algorithms work and their true accuracy.

Data collection and analysis practices are rather manual and time intensive. Depending on the duration and methods used, site surveys can result in several Gigabytes of audio data for analysis, from which knowledge must be extracted and decisions made [10]. This can often take many weeks or even months to complete for a single survey.

2.2 | Technology for ecology and conservation

Technology has long played a role in ecology and conservation, with audio-visual devices such as camera traps and acoustic monitors being commonplace [11–13]. However, emergent technologies are also being adopted for biodiversity conservation and ecological surveys [14]. Acoustics have been used to monitor a wide variety of species through their natural calls

ranging from infra-sonic frequencies through to ultra-sonic, including birds [15], whales [16], insects [17] and of course bats. As a consequence, intelligent audio analysis techniques using machine learning algorithms have been developed in order to process the sheer volumes of captured audio in the lab or on cloud platforms. For example, the Bat Detective project developed deep learning tools to automatically identify bat acoustic signals in recorded audio [18]. In fact, audio analysis is also being applied to anthropogenic sounds to monitor human activity across cities and identify significant events such as gunshots [19].

Remote imaging from satellites provides possibilities to monitor large numbers of animals across huge areas [20, 21]. In the Mediterranean, satellite images are being analysed by image recognition techniques to monitor the movement of jellyfish blooms [22]. Elsewhere, drones with on-board cameras are being used to automatically locate and count animals for survey and conservation purposes [23], and even to collect and analyse whale snot to determine the health of our oceans [24]. Latest camera technologies are also small and light enough to be attached to animals themselves, so researchers can see where they go and what they do, such as the routines and social interactions of domestic pets [25].

IoT sensors and real-time data are helping to protect wild rhinos from poachers in South Africa in a collaboration between Cisco and local companies [26, 27]. The sensors can track the animal's heart rate, with a sudden increase triggering an early warning that poachers might be giving chase. Small 5-g GPS trackers have also been attached to Cuckoos to monitor their migration paths across the world, with resulting data showing that their migration route was a key factor in their population decline [28].

2.3 | IoT and edge processing

The IoT has driven an explosion of Internet traffic and data coming from non-human connected things. In 2020, an estimated 11 billion connected things were pushing data and communicating via the Internet with 50 billion predicted for 2030 [29]. However, current innovation trends are pushing for the 'things' to become smarter by embedding more intelligence (e.g. machine learning models and data analytics) onto these edge devices. Prior to recent innovations in SoC technologies, this was not possible, but a new breed of SoC devices such as the Pi zero [30], Google AIY kit [31] and Aeon Up boards [32], now mean that entire operating systems and machine learning can be run on processing units smaller than a postage stamp.

This has opened the door to a next generation of IoT solutions that are moving away from the more traditional model of dumb sensor/actuator devices at the edge of the network [33]. New models of distributed intelligence are emerging across connected devices, and increased autonomy at the edges of the network, with machine learning being implemented on edge nodes themselves [34]. This move towards more intelligent 'things' with much greater processing power has been given many terms including Fog Computing, edge processing or edge intelligence [35].

The work presented here brings together the IoT, machine learning and edge computing in a novel sensing system for biodiversity bat monitoring and conservation. Continuous acoustic monitoring of bats provides an ideal use case to bring these three emergent technologies together. The longitudinal study provides insights into the challenges of running and managing high-tech prototypes in the field, how their adoption might impact on bat biodiversity monitoring and conservation decision-making, and also provides new insights on urban bat activity.

3 | PROJECT REQUIREMENTS

To further understand current ecology practices, the challenges faced and requirements that would inform the design and deployment of the IoT bat sensing system, a 1-day workshop was conducted with a variety of stakeholders.

3.1 | Understanding stakeholder requirements

Over 30 people attended the workshop from different sectors and backgrounds including ecologists, park owners, land managers and people who use the urban park. Workshop attendees were given an overview of the project vision plus initial outline plans for a novel bat sensing prototype, including possible capabilities and likely constraints. Attendees were then divided into interdisciplinary groups and a series of questions were used as prompts to drive group discussion around three main themes: (1) current challenges, (2) data and (3) impacts. During each round of discussions, comments were captured on post-it notes and analysed for recurring and emergent outcomes. These outcomes are described under each theme below.

3.1.1 | Theme 1—Current challenges

Stakeholders talked of a data paradox surrounding current biodiversity bat surveys. They described how after each survey they have too much data to process in a timely manner but still too little data over time and space to gain necessary insights or make informed long-term decisions. Surveys may last a few days but are typically only carried out once every 6 months, so although they produce huge amounts of data, the data only provides a very small snapshot of bat activity over time.

This emerged as particularly problematic for stakeholders when trying to determine if previous decisions and mitigation strategies are effective. Regardless of the huge effort required by ecologists to collect and analyse survey data, some referred to resulting decisions as being little more than guesswork. Several participants also stated that some survey data did not get analysed due to its sheer volume and lack of resources. Related to this, participants also talked of the challenges of

using such sparse data to advise other stakeholders. For example, consultant ecologists need to advise site managers on the best course of action to take from a biodiversity perspective with little or no evidence to prove whether their suggestions are working. This creates a trust issue between ecologists and stakeholders and the potential for mitigation measures to be overlooked or misinterpreted.

3.1.2 | Theme 2—Data

Across all stakeholders there was much enthusiasm about the potential for the bat sensing prototype to provide more real-time and granular streams of data. A key requirement from many was that such data would be presented in a spatial and temporal manner with interactive maps being the most common suggestion. Stakeholders also talked of putting the data into context by being able to overlay bat activity data with other data streams such as sound, temperature and light levels—all of which have a known impact on bat activity.

The potential of having interactive maps driven by real-time data, or even static map-based visuals, also appealed to many attendees for influential reasons. They believed that more eye-catching images would make it easier to capture the attention and interest of senior management and decision-makers. As such, there was little appetite for data to be presented in more traditional forms such as spreadsheets or graphical reports. As one consultant stated, he typically had very little time to put his point across to seniors and other stakeholders and needed impactful visual support that would do the talking for him.

In a similar thread, many workshop attendees saw the potential of the prototype to make the data more publicly accessible, and how this could help boost awareness and interest in biodiversity and bats from the wider public. Example suggestions included using the data to create new experiences for park visitors, to improve outreach activities such as citizen science, to educate the public on the importance of bats and biodiversity, and to generally create more interest and buzz around the urban park.

3.1.3 | Theme 3—Impacts

Workshop attendees agreed that the proposed technology had the potential to disrupt the field of acoustic biodiversity monitoring and greatly change the current practice. However, this provoked many interesting questions and touch points. One of the most common was the question of data accuracy given the potential ‘black box’ nature of the bat sensing prototype incorporating machine learning algorithms, and how details of algorithmic confidence levels would be made transparent. Ecologists stated that they currently only use bat data with a confidence level of >85%.

The real-time potential of the proposed prototype was a surprise to many stakeholders. Current survey and data analysis practices can result in a latency of many weeks or months

between data collection and completed processing. The possibility to reduce this to seconds was a revelation to some. However, it highlighted a key point that true real-time streams of bat data were not necessary and that near real-time with some latency was perfectly acceptable.

In terms of impact potential, stakeholders were in agreement that the proposed prototype would finally give them a way of measuring the effectiveness of mitigation strategies. The unprecedented level of granular data across time and space would enable them to identify patterns and trends in bat activity levels that could indicate positive or negative results.

3.2 | Design requirements

The technical aim of this project was to develop a novel bat sensing system that could continuously monitor bat activity across a large urban area through audio capture and analysis. Based on this and the workshop outcomes, the following set of design requirements was identified.

3.2.1 | Robust and reliable

The developed technology was required to operate sufficiently well in order to allow ecologists to answer long-term questions about bat activity levels across the park and the usefulness of the novel technology. This meant that the Echo Boxes needed to operate and gather data for at least several months, and ideally as long as possible. In addition, there are financial costs associated with the installation of devices across the park which were covered by park stakeholders in this case. However, this meant that they were also keen to see long-term operation in return. It was unlikely that researchers would be able to physically access installed Echo Box devices after deployment, since the intended locations were 4 m above ground on lamp posts. Only certified engineers could access such heights with cherry-pickers and extra costs would be incurred if the devices needed to be retrieved for repairs or modifications.

As such, software systems needed to run indefinitely without crashing or running out of memory. Hardware components needed to operate reliably without overheating or becoming damaged, and therefore a weatherproof, protective enclosure was critical. However, since ultrasonic audio data was being captured from the environment, the enclosure still was required to allow the undistorted recording of sound waves while keeping internal instruments dry.

3.2.2 | Always on, always connected

The system needed to provide granular data over time to address key research questions on supporting ecologists and stakeholders in long-term decision-making and determining the efficacy of mitigation strategies. As such, it was desirable that the system would constantly monitor the environment for bat activity, pushing new results or data as and when available.

Therefore, the sensors needed to always be powered and connected to a network. A free park-wide WiFi network provided a solution for connectivity, plus lamp posts situated all across the park could provide high mounting points for the boxes and a constant power supply. However, the sensors needed to handle WiFi and power outages without major data loss or reconfiguration.

3.2.3 | Audio analysis

Bats use sound to navigate and communicate, and the calls they make can be used to determine their species and behaviour. The system was required to process audio data in order to reduce the manual burden on ecologists. However, as is typical when recording audio to identify bats, it was important that the sensors would capture the full spectrum of sound up to the very high ultrasonic frequencies that bats use to echolocate. This would mean dealing with very large amounts of high frequency audio data. If the sensors were to simply capture this data and push it all to the cloud it would put huge demands on network transfer and cloud storage.

As such, it was deemed more desirable to implement the concept of edge computing to do all processing of the audio on the sensor devices themselves. Using this concept in the bat sensors would result in only nominal results data being transferred across the network and stored in the cloud, thus greatly reducing demands. However, this would also mean that all audio processing would occur on the sensor devices themselves without the oversight of an expert. As such it was desirable that the algorithms could be configured to only return results with high confidence.

3.2.4 | Data visualisation

Developing and deploying the intelligent sensors and generating a live stream of bat data is unprecedented in the field of ecological monitoring. However, if there was no means to view the live data, the usefulness of the system and its potential impacts would be greatly diminished. As such, it was critical that the system also included a visualisation tool to display the data over time and space (as requested by workshop attendees). The tool was intended for a broad audience including park stakeholders, ecologists and the wider public as it was hoped that it could also help attract more volunteers and raise the agenda of urban bat life and conservation work.

4 | TECHNICAL DEPLOYMENT

The IoT bat sensing system has several component parts including 15 acoustic sensors called Echo Boxes, a backend data platform and APIs hosted by a third-party cloud service, and a visualisation website that shows live bat data streaming from all 15 sensors deployed across the Olympic Park. Figure 2a shows the overall system architecture.

4.1 | Echo Box acoustic sensor

The Echo Boxes are made from weatherproof enclosures housing an Intel Edison with Arduino breakout board, a Dodotronic Ultramic 192k microphone, plus other power supply components so they can run off lamp posts in the park (Figure 3).

To create the weatherproof enclosure, we adapted an IP-rated box that provided a tough, waterproof basis. A hole was cut in the front of the box to accommodate the long ultrasonic microphone and a custom-made insert was created through a three-step process of 3D printing, silicone mould-making and casting resin. Given the intended outdoor location of the enclosures, it was necessary to use a tough plastic resin that would not degrade over time, unlike 3D printing materials could. However, an initial 3D printed shape provided a flexible means to create the desired form for the silicon mould and resin cast.

The Echo Box sensors run on a mains power supply which is provided by the lamp posts on which they are mounted

across the park and to transmit data they connect to a free public WiFi network provided by the park owners. Figure 2b illustrates the internal architecture of each Echo Box sensor.

The Intel Edison provides a Linux environment on which the Echo Box software, written in Python source code, is run as a system service. A local MongoDB provides on-board storage in case an unexpected network or cloud platform outage means that bat data cannot be properly uploaded to cloud storage. The database provides enough local storage to handle up to one week's worth of bat data and automatic upload processes regularly attempt to upload any locally held data to the cloud platform. To identify bats and their species from audio, the following process flow happens on each Echo Box, as illustrated in Figure 4.

Firstly, the ultrasonic microphone on each device captures all audio from the environment up to 96 kHz (the Nyquist frequency of the microphones). Most bats calls occur at frequencies above 20 kHz (the limit of human hearing) so are undetectable by the human ear or more traditional microphones. Secondly, the

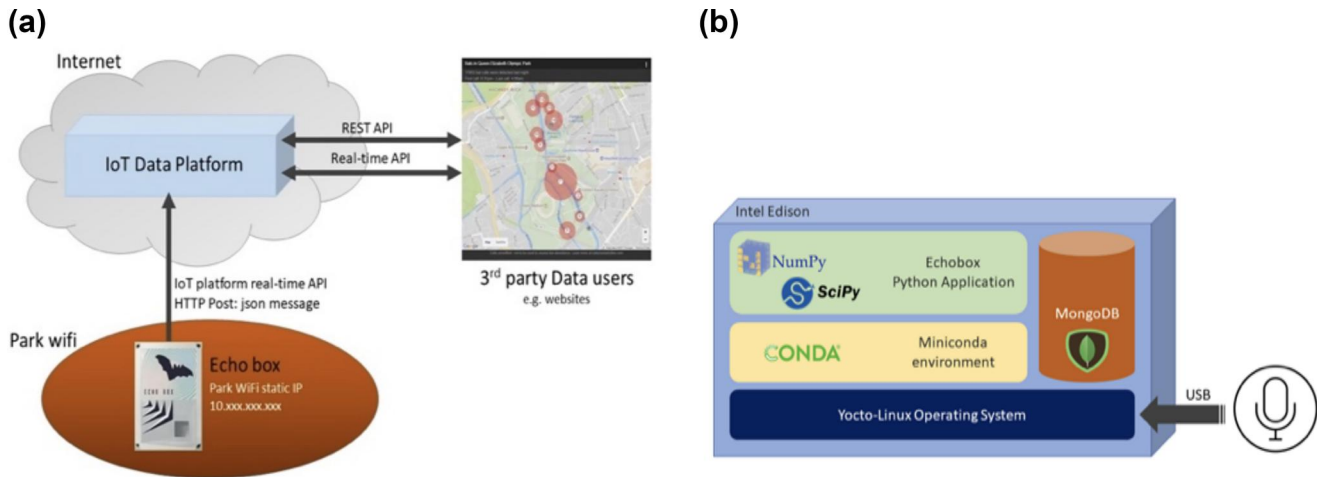


FIGURE 2 System architecture including the (a) overall system and (b) Echo Box architecture



FIGURE 3 Components inside an Echo Box

recorded audio is chunked into three-second samples and stored as a series of .wav files. Each three-second .wav file is 1.1 MB in size due to the large amount of full-spectrum audio it contains (everything up to 96 kHz). Thirdly, each three-second .wav file is converted into a spectrogram using the Discrete Fast Fourier Transform. The spectrogram allows one to visualise what sound looks like by showing the amplitude of sounds across frequencies over time. Bat calls can clearly be seen on the spectrogram as bright ‘hockey-stick’-shaped patterns (indicating a loud noise) at high frequencies (see Figure 5).

By converting the sound into a spectrogram image, we change the analysis challenge from a signal processing task to an image processing task. As such, we can then utilise deep learning modes typically used in computer vision, called Convolutional Neural Networks (CNNs), to process the image and classify patterns that resemble bat calls. Firstly, a CNN detection algorithm scans the spectrogram to identify individual bat calls. Only calls with a likelihood of 95% or more are logged as a detection and proceed to the next stage for species classification. Secondly, a species classification CNN is applied to individual bat calls to look at their shape in more detail and determine what species they most likely are [15]. Both detection and species classification algorithms have been trained on a database of over 50 k tagged bat calls and while high accuracies (95%+) are already achieved for detection, work continues to improve the more challenging species classification algorithm to similar levels of accuracy. Following bat detection

and species classification, results are immediately pushed to a cloud data platform for storage and open access, and the raw audio recording .wav file is deleted. The entire process flow takes 6 s to process a 3-s audio file on the Echo Box.

4.2 | Cloud data platform

A third-party hosted cloud data platform is used to collect and manage the results data from the Echo Box sensors. The platform provides MQTT [36] support for data upload from the sensors, and to enable external applications to register for bat detection notifications. A REST API is also available to handle data queries, for example, from visualisation websites. IoT communication security and API scalability are handled by the platform.

4.3 | Visualisation website

A visualisation website [37] was designed around an interactive map of the urban park that allows users to explore bat activity data across time and space (Figure 6). The location of each Echo Box is indicated on the map surrounded by a red circle to show how many bat calls were detected by that sensor during the previous night. Alternatively, if one were to view the website during the night, it is possible to watch bat calls being

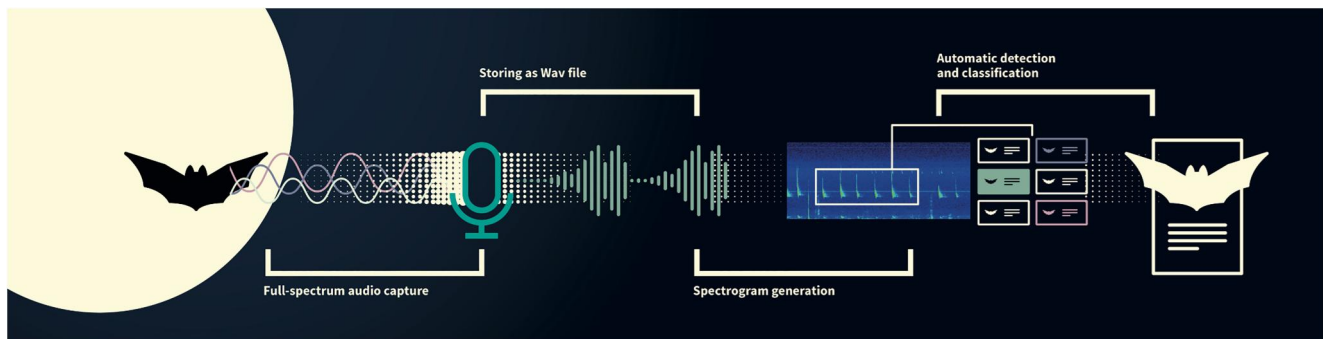


FIGURE 4 The Echo Box process flow

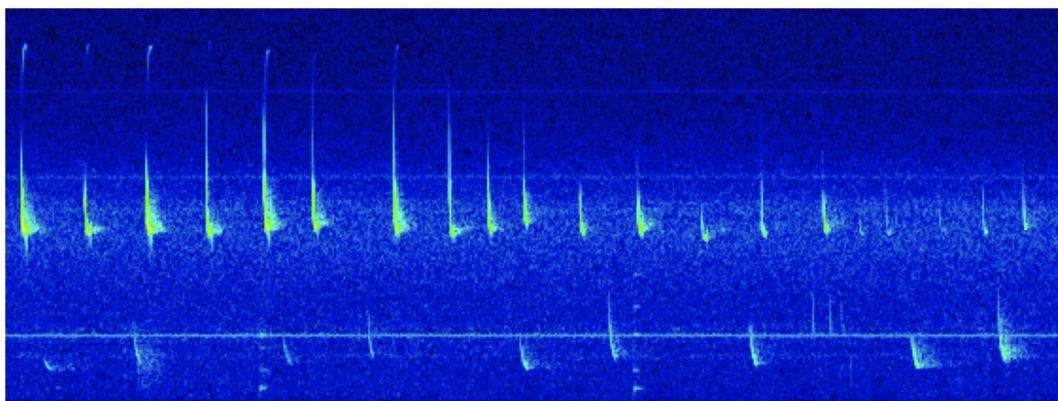


FIGURE 5 Spectrogram showing bat calls as bright ‘hockey-stick’ shapes

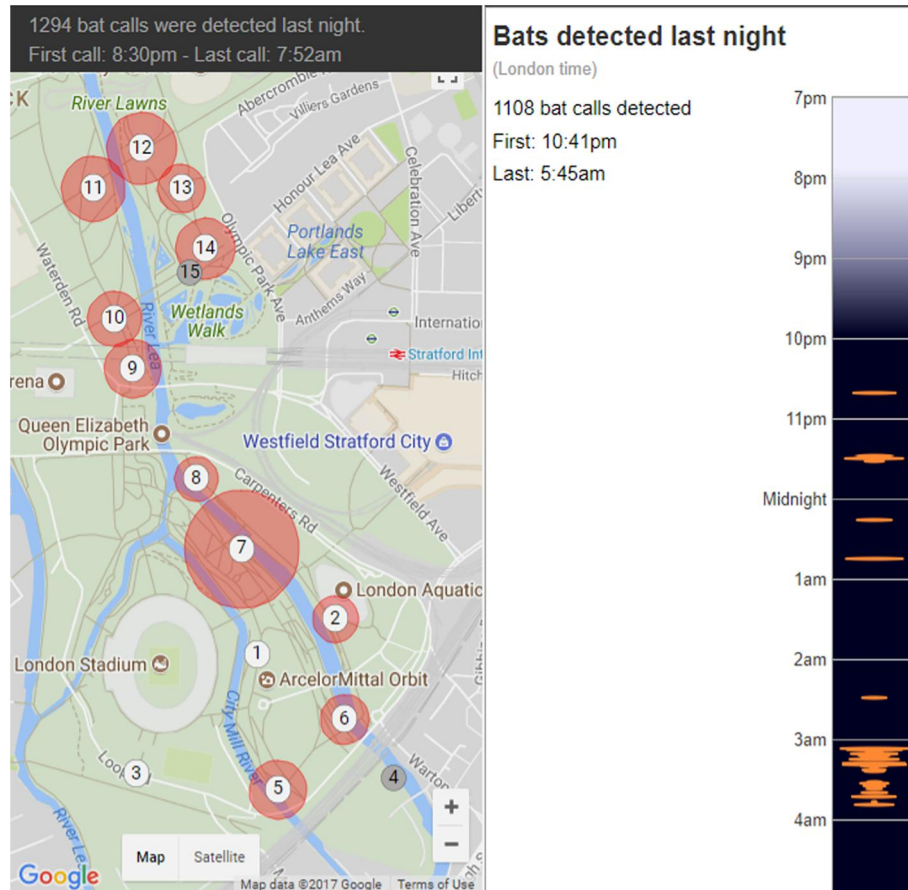


FIGURE 6 Screenshot of bat data visualisation website showing activity levels across the park and bat call detections at sensor 7 during the course of a night

detected in real time and the red circles growing accordingly. Additionally, the user can click on any sensor to see more details of recent bat detections along a timeline (shown in right-hand segment of Figure 6, width of the line shows number of calls within that minute), plus details of the sensor location and bat activity levels for the past 10 nights.

4.4 | Sensor deployment locations

The deployment locations of the sensors across the park were determined using a method called Random Stratified Sampling. This is a commonly used method for determining bat monitoring locations in surveys across large areas. The survey site is overlaid with a grid and classified into habitats. Then a random algorithm assigns monitoring locations across the site grid based on the percentage of each habitat that the site contains (Figure 7). For example, if the site contains a large amount of open water habitat then a greater number of monitoring sites will be randomly located in this habitat. When defining the location of the 15 Echo Box sensors in the park, the random algorithm sometimes assigned them to locations with no nearby lamp post for power supply. In such cases we located the sensor to an adjacent grid square with the same habitat and an available lamp post.

5 | RESULTS

Overall, the deployment of the bat sensing system has been insightful and successful, both in realising the design requirements outlined above and addressing the research questions it was intended to help answer. The sensors were originally installed in May 2017 with the initial intention of remaining for 3 months; however, they still remain operational and in situ over 4 years later at the request of park stakeholders due to unprecedented levels of continuous bat data.

There have been inevitable downtimes due to the scaled-up and integrated nature of the deployment, with the impact of public WiFi interruptions, power outages and third-party cloud service downtimes. As such, the results and trends presented in this section are analysed from the initial 4 months of the deployment using reliable continuous data from 12 out of 15 sensors (data from additional months are available and continue to be used for trend analysis).

These real-world complications and challenges provide practical lessons learned for ambitious technology field deployments. Most significantly, the importance of lab testing and emulating the deployment environment when attempting to recover from failures. For example, in the park, the Echo Box sensors were only physically accessible by certified engineers with cherry pickers and requiring them to do so would incur

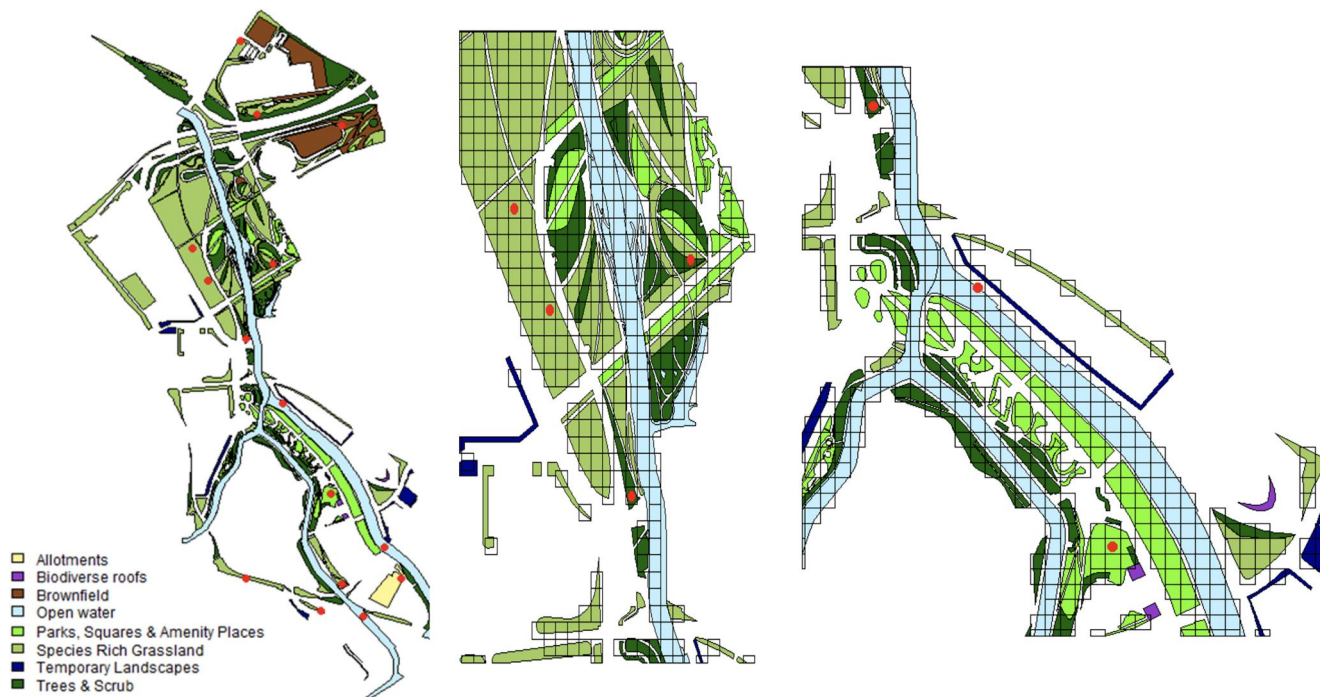


FIGURE 7 Random stratified sampling of the park with overlaid grid squares and algorithmically assigned sensor locations (red dots) based on habitat percentages

large financial costs. Therefore, once the sensors were installed it was undesirable for researchers to require physical access to them again. As one researcher commented, ‘we might as well be sending them to the moon’. Critical measures were put in place allowing researchers to access and control the sensors remotely via the SSH connection in line with the park’s WiFi security schemes. Researchers also followed a self-termed Apollo 13 strategy for recovery from failures during lab testing. Once a device failure occurred, the researchers tried to perform all necessary operations for recovery without physically touching the Echo Box or using any tools that would not be available to them in the park. As such, researchers refrained from plugging USB cables into serial ports to interact with devices or pushing hardware reset buttons, or power-cycling the boxes—all options that would not be available to them once the Echo Boxes were deployed in the park. This simple scheme proved to be extremely powerful for subsequent successful deployment and provided a bat sensing system that was robust enough and reliable enough to address scientific and stakeholder aims of the project.

5.1 | Bat activity levels

Over a period between June and October 2017, over 300,000 bat calls were detected across the 12 devices with an average of 7000 calls per evening and a peak of 20,000+ calls in one evening. Stakeholders are delighted that the data suggests a strong and healthy population of bats across the park, validating the financial investments made to reduce impacts from

the nearby construction and to create a positive, natural habitat in an urban space that fosters biodiversity.

In terms of data volumes, calculations across the same period showed that the 12 devices typically generated 180 GB of raw audio data every day. However, due to on-board machine learning and edge analysis of the raw audio data, this was reduced to only 2.1 MB of detection and species data sent to the cloud every day—providing huge savings in terms of network and storage demands.

Preliminary analysis of the detection and species data shows consistent patterns of bat activity in line with the expectations of ecology experts. These patterns occur when the bats emerge to hunt and when they are most active in different habitats during the night. The data also shows how bat activity levels drop significantly in bad weather and then peak soon after as hungry bats make up for the hunting time lost. Species detection is also in line with expected norms. The *Pipistrellus pipistrellus* is the most common British bat and species classification results over 4 months of data that strongly aligns with this across all habitats in the park (Figure 8).

The second most classified genus is *Nyctalus* which is also in line with ecologist expectations. However, species classification is more experimental and challenging due to less reliable tagged datasets. Work continues to optimise the CNN algorithms used in the Echo Boxes for species classification, and the bat sensing system of 15 Echo Box sensors deployed provides a real-world test bed in the ongoing research. In addition to expected results that help to confirm the validity of the audio analysis, the data has also presented several trends in bat activity that have given new and valuable insights to ecologists.

5.2 | Artificial roost usage

Bat activity levels detected by Echo Boxes have been good across different habitats in the park; however, sensor 7 consistently detected significantly more bat calls than all other sensors combined, typically registering 90% of nightly bat calls. This sensor is located beside water—a typical hunting ground for bats—but crucially it is also right next to a bridge with artificial bat roosts underneath. The roosts were installed by park operators with the intention to attract bats, however, it can often take bats a long time to find roosts and make use of them, if ever. Park ecologists were surprised by the high levels of activity at sensor 7 and believe it suggests that the artificial roosts under the bridge are well used. This is a brand new insight and a very positive outcome which again validates investments in fostering biodiversity (Figure 9).

As one senior ecologist commented:

These are simply incredible stats and so consistent on numbers by vicinity to give [a] clear view on [the] health of [the] bat population feeding/living in Lee valley. This tool will make such a

positive impact to support ecological surveys and studies for sensitive development, pre- and post-build monitoring and most importantly, measure [the] benefit of mitigation and enhancement actions.

5.3 | October activity levels

As the weather turns colder bat activity tends to reduce and hence ecologists are unlikely to perform surveys beyond September. However, the 12 sensors in the park detected a huge unexpected spike in activity levels during the month of October, as illustrated in Figure 10.

Ecologists have postulated that this spike is due to more vigorous hunting by bats to fill up on food just prior to hibernation. This increased activity prompts the question of whether the current bat survey practices should persist longer into the autumn months. Since surveys typically stop in September such activity spikes have not been captured before, however, with continuous monitoring, such as that provided by

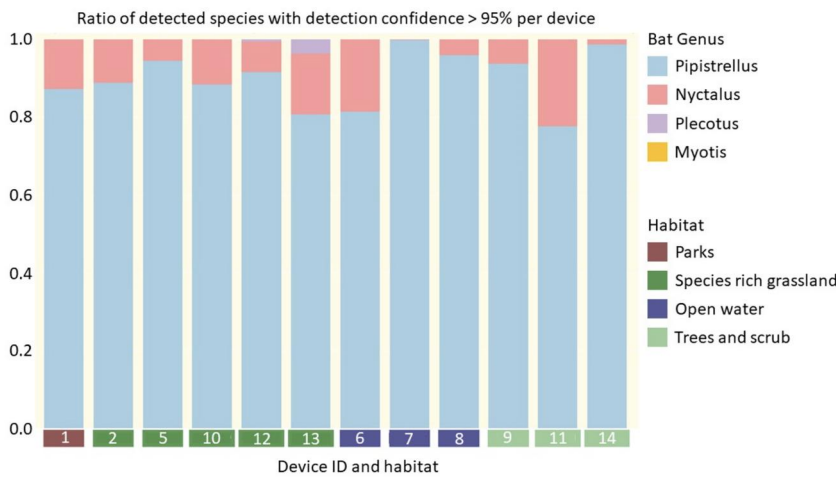


FIGURE 8 Detected species by sensor and habitat

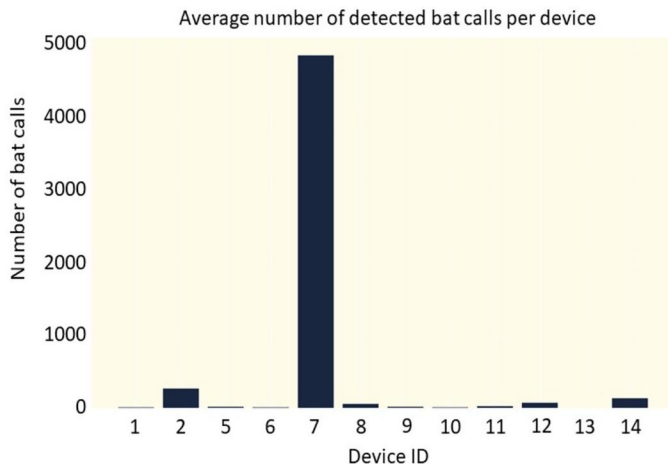


FIGURE 9 Graph of average bat detections per sensor, and artificial bat roosts under the park bridges

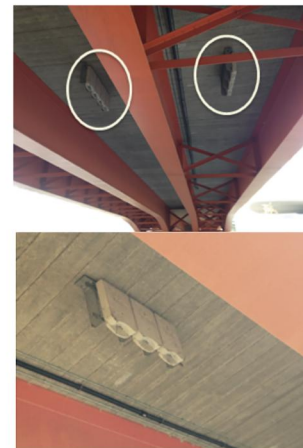
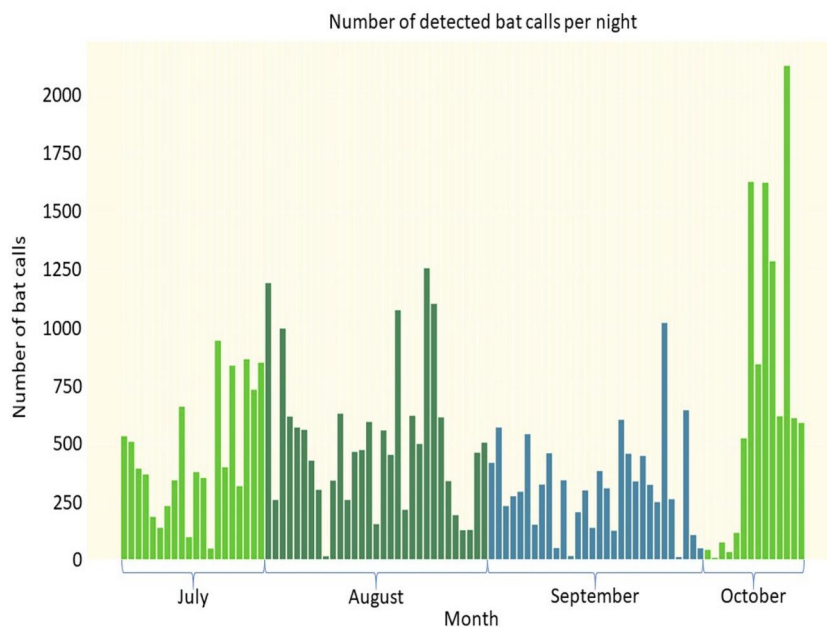


FIGURE 10 Graph of average bat calls per night from June to October 2017



the Echo Boxes, previously unseen activity data from throughout the year is now available.

6 | DISCUSSION

This project targeted to deliver on ambitious technical, scientific and stakeholder aims. Despite the technical complexity of the developed infrastructure the system has remained robust enough and reliable enough to answer scientific questions on bat activity and support stakeholder visions of future data-driven conservation. The longitudinal deployment of a novel bat sensing system with IoT, machine learning and edge computing enabled observations of bat activity is not typically seen by the research community. Since the network of devices was permanently deployed and the cost of running the system is minimal, the researchers were able to run observations during periods when they traditionally would not have monitored activity since it was either not cost effective or the anticipated value would have been minimal (e.g. no point in monitoring over winter since the bats will be hibernating). The continuous deployment meant that novel insights were observed during periods such as October when more bat activity was observed than anticipated.

The nature of the type of data collected and therefore the design of the system initially split the opinion amongst the researchers. Discussion centred on a bias towards keeping all raw data to validate results amongst the experienced bat research community, versus capturing the events only and, by implication, trusting in the classification algorithms. Whilst the functionality existed to capture and store all raw audio events, this was only used for debugging, testing of the classifications, and validating the performance of the system when updates to the classification algorithms were implemented. This shift from capturing and storing all data as audio files marked up with

meta-data to events only was critical to being able to technically deliver a platform that would handle high-frequency acoustic data and work over months of operation in the field. It still remains an open challenge to select the type of data to be discarded; however, since there will typically be outliers such as rare bat calls which would be useful for contribution into the legacy training database or for verification purpose such as legal requirements to verify the observed events.

The data visualisation tools developed supported the validation of the system by the ecologists. Fusing bat count data and environment data from the park in spatial and temporal domains enabled visualisations of activity over a longer than usual period for the ecologists and provided the tools for discussion around the behaviours being observed. This approach both supported communication between the ecologists and equally importantly with other non-specialist stakeholders in the project (e.g. developers responsible for investment in the bat roosts).

The ability to visualise the data easily also helped identify false positives in the data such as bat activity during daylight hours (when bats use their vision rather than echo location) and resulted in the observation of anomalies such as gardening equipment having similar, but distinctive, audio patterns. The ability to identify, refine and update the learning algorithms based on improved in situ knowledge is critical to the longer-term use of these techniques in different environments.

7 | CONCLUSIONS AND FUTURE WORK

A perfect storm of technology innovation has presented new opportunities for digital transformation across many industries. In this paper, we described how we brought together emergent technologies such as the IoT, deep machine learning and edge

computing to develop a novel system for continuously monitoring bats over a large urban area. The research addresses technical, scientific and stakeholder goals.

Technically, we have demonstrated the possibility to run complex signal processing and deep machine learning on SoC devices in a near real-time manner. We have also provided an empirical evidence of how edge processing can reduce network traffic and storage demands by orders of magnitude, making it possible to run continuous monitoring activities centred on capturing large volumes of raw acoustic (and possibly also visual) data.

The data and insights delivered by the IoT bat monitoring system have proved very useful to ecologists and other stakeholders alike. They have raised questions on whether bat surveys should continue further into the autumn months, and have helped to validate the financial investments made by park operators and developers alike for mitigation and enhancement. Additionally, from a scientific perspective, the sensors remain in the park at stakeholders' request as a real-world test-bed for the continued iterative improvement and validation of classification algorithms.

Finally, the deployment has brought to the fore many fundamental questions and discussions on data management, edge processing patterns, reliability and accountability. This ties to a broader rhetoric on the often 'black box' nature of machine learning. However, the deployment has also pressed many traditionalists to question initial assumptions that all raw data must be stored and persisted, and has opened more nuanced thinking and discussion on the benefits and trade-offs that emergent technologies bring.

Future work includes the development of more efficient deep networks to reduce the overall power draw of the system, more robust evaluation of the deep learning models in the context of species classification, investigation of the feasibility of using an open source hardware for example, Raspberry Pi, and application of the system for monitoring other taxonomic groups.

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CONFLICT OF INTEREST

The authors declare no conflict of interests.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

- Madakam, S., Ramaswamy, R., Tripathi, S.: Internet of Things (IoT): a literature review. *J. Comput. Commun.* 3, 164–173 (2015). <https://doi.org/10.4236/jcc.2015.35021>
- Al-Fuqaha, A., et al.: Internet of Things: a survey on enabling technologies, protocols, and applications. *IEEE Commun. Surv. Tutor.* 17(4), 2347–2376 (2015). <https://doi.org/10.1109/COMST.2015.2444095>
- Jones, K.E., et al.: Indicator Bats Program: a system for the global acoustic monitoring of bats. In: Collen, B., et al. (eds.) *Biodiversity Monitoring and Conservation. Bridging the Gap between Global Commitment and Local Action*, pp. 211–247. Wiley-Blackwell (2013). <https://doi.org/10.1002/9781118490747.ch10>
- Barlow, K.E., et al.: Citizen science reveals trends in bat populations: The National Bat Monitoring Programme in Great Britain. *Biol. Conserv.* 182, 14–26. (2015). <https://doi.org/10.1016/j.biocon.2014.11.022>
- Jackson, G., et al.: Tales from the wild: lessons learned from creating a living lab. In: Eskicioglu, R., et al. (ed.) *Proceedings of the First ACM International Workshop on the Engineering of Reliable, Robust, and Secure Embedded Wireless Sensing Systems (FAILSAFE'17)*, pp. 62–68. ACM, New York. (2017). <https://doi.org/10.1145/3143337.3143342>
- Langendoen, K., Baggio, A., Visser, O.: Murphy loves potatoes: experiences from a pilot sensor network deployment in precision agriculture. In: *Proceedings of the 14th International Workshop on Parallel and Distributed Real-Time Systems (WPDRTS 06)* (2006)
- Bats: Surveys and Mitigation for Development Projects. 2015. Retrieved 27 Nov 2018 from <https://www.gov.uk/guidance/bats-surveys-and-mitigation-for-development-projects>
- Jones, G., et al.: Carpe noctem: the importance of bats as bioindicators. *Endang. Species Res.* 8, 93–115. <https://doi.org/10.3354/esr00182>
- Walters, C.L., et al.: A continental-scale tool for acoustic identification of European bats. *J. Appl. Ecol.* 49, 1064–1074 (2012). <https://doi.org/10.1111/j.1365-2664.2012.02182.x>
- Walters, C.L., et al.: Challenges of using bioacoustics to globally monitor bats. In: Adams, R., Pedersen, S. (eds.) *Bat Evolution, Ecology, and Conservation*, pp. 479–499. Springer. (2013). <https://doi.org/10.1007/978-1-4614-7397-8-23>
- Gibb, R., et al.: Emerging opportunities and challenges for passive acoustics in ecological assessment and monitoring. *Methods Ecol. Evol.* 10(2), 169–185 (2019)
- Sugai, L.S.M., et al.: Terrestrial passive acoustic monitoring: review and perspectives. *BioScience.* 69(1), 15–25 (2019)
- Mcloughlin, M.P., Stewart, R., McElligott, A.G.: Automated bioacoustics: methods in ecology and conservation and their potential for animal welfare monitoring. *J. R. Soc. Interface.* 16(155), 20190225 (2019)
- Pimm, S.L., et al.: Emerging technologies to conserve biodiversity. *Trends Ecol. Evol.* 30(11), 685–696, ISSN 0169-5347. (2015). <https://doi.org/10.1016/j.tree.2015.08.008>
- Stowell, D., et al.: Automatic acoustic detection of birds through deep learning: The first bird audio detection challenge. *Methods Ecol. Evol.* 00, 1–380. (2018). <https://doi.org/10.1111/2041-210X.13103>
- Zimmer, W.M.X., et al.: Passive acoustic detection of deep – diving beaked whales. *J. Acoust. Soc. Am.* 124(5), 2823–2832 (2008). <https://doi.org/10.1121/1.2988277>
- Phung, Q.V., et al.: Automated Insect detection using acoustic features based on sound generated from insect activities. *Acoust. Aust.* 45, 445–451 (2017). <https://doi.org/10.1007/s40857-017-0095-6>
- Mac Aodha, O., et al.: Bat Detective – deep learning tools for bat acoustic signal detection. *bioRxiv*, 156869. <https://doi.org/10.1101/156869>
- Miranda, F., et al.: Urban pulse: capturing the rhythm of cities. *IEEE Trans. Vis. Comput. Graph.* 23(1), 791–800 (2017). <https://doi.org/10.1109/TVCG.2016.2598585>
- Mairota, P., et al.: Challenges and opportunities in harnessing satellite remote-sensing for biodiversity monitoring. *Ecol. Inf.* 30, 207–214. ISSN 1574-9541. (2015). <https://doi.org/10.1016/j.ecoinf.2015.08.006>
- Marvin, D.C., et al.: Integrating technologies for scalable ecology and conservation. *Glob. Ecol. Conserv.* 7, 262–275. ISSN 2351-9894. (2016). <https://doi.org/10.1016/j.gecco.2016.07.002>
- Albajes-Eizaguirre, A., et al.: Jellyfish prediction of occurrence from remote sensing data and a non-linear pattern recognition approach. In: *Proceedings of SPIE 8174, Remote Sensing for Agriculture, Ecosystems, and Hydrology*, 7 October, vol. XIII, 817418. (2011)

23. van Gemert, J.C., et al.: Nature conservation drones for automatic localization and counting of animals. In: Agapito, L., Bronstein, M., Rother, C. (eds.) *Computer Vision – ECCV 2014 Workshops. ECCV 2014. Lecture Notes in Computer Science*, vol. 8925. Springer (2015)
24. Bennett, A., et al.: Autonomous vehicles for remote sample collection: Enabling marine research, pp. 1–8. *OCEANS 2015, Genova*. (2015). <https://doi.org/10.1109/OCEANS-Genova.2015.7271621>
25. Loyd, K.A.T., et al.: Quantifying free-roaming domestic cat predation using animal-borne video cameras, *Biol. Conserv.* 160, 183–189, ISSN 0006-3207. (2013). <https://doi.org/10.1016/j.biocon.2013.01.008>
26. Connected Tech Aims to Protect Rhinos from Poaching. (2016). Retrieved 27 Nov 2018 from <https://www.bbc.co.uk/news/technology-36105738>
27. Connected Conservation: 3 Things We’re Doing Differently to Create a Safe Haven for Rhino. (2018). Retrieved 27 Nov 2018 from <https://www.dimensiondata.com/globalblog/connected-conservation-3-things-were-doing-differently>
28. Hewson, C.M., et al.: Population decline is linked to migration route in the Common Cuckoo. *Nat Commun.* 7, 12296 (2016)
29. Webb, W., Hatton, M.: *The Internet of Things Myth*. (2020)
30. Pi Zero product page. (2018). Retrieved 27 Nov 2018 from <https://www.raspberrypi.org/products/raspberry-pi-zero/>
31. Google AIY kit. (2018). Retrieved 27 Nov 2018 from. <https://aiyprojects.withgoogle.com>
32. Up Boards product page. (2018). Retrieved 27 Nov 2018 from <https://up-board.org/>
33. Hudson-Smith, A., et al.: Urban IoT: advances, challenges, and opportunities for mass data collection, analysis, and visualization. In: Shi, W., et al. (eds.) *Urban Informatics. The Urban Book Series*. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-8983-6_38
34. Lin, J., et al.: A survey on Internet of Things: architecture, enabling technologies, security and privacy, and applications. *IEEE Internet Things J.* 4(5), 1125–1142 (2017). <https://doi.org/10.1109/JIOT.2017.2683200>
35. Hudson-Smith, A., et al.: *Little Book of Connected Environments and the Internet of Things*. Imagination Lancaster, Lancaster University, UK (2019)
36. Message Queue Telemetry Transport. Retrieved 27 Nov 2018 from <https://mqtt.org>
37. Live bat data website. (2018). Retrieved 27 Nov 2018 from <https://www.batslondon.com>

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