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Review

Applications and advances in acoustic monitoring for infectious disease epidemiology

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Emerging infectious diseases continue to pose a significant burden on global public health, and there is a critical need to better understand transmission dynamics arising at the interface of human activity and wildlife habitats. Passive acoustic monitoring (PAM), more typically applied to questions of biodiversity and conservation, provides an opportunity to collect and analyse audio data in relative real time and at low cost. Acoustic methods are increasingly accessible, with the expansion of cloud-based computing, low-cost hardware, and machine learning approaches. Paired with purposeful experimental design, acoustic data can complement existing surveillance methods and provide a novel toolkit to investigate the key biological parameters and ecological interactions that underpin infectious disease epidemiology.

Highlights

Passive acoustic monitoring (PAM) provides new opportunities to characterise zoonotic and vector-borne disease dynamics in changing landscapes.

Acoustic data can inform our understanding of variables that drive transmission risk, including human and wildlife occupancy over space and time and changes in habitat quality.

With low-cost hardware, cloud-based computing, and open-source platforms, acoustic data collection and analysis methods are increasingly accessible to nonspecialist users.

Key considerations for epidemiologists include the availability of complementary data sources and the technical requirements for acoustic data storage and analysis.

Acoustic monitoring is a cost-effective, noninvasive tool which could be effectively combined with existing data to strengthen early warning systems and integrated disease surveillance.

Integrating acoustic monitoring into epidemiology

Bioacoustic (see Glossary) approaches are increasingly utilised by ecologists to characterise the distributions and behaviours of wildlife species and monitor environmental change. These ecological patterns and processes also determine transmission of many infectious diseases; however, acoustic monitoring is rarely incorporated into epidemiological studies. To conduct effective **surveillance** and predict or control **zoonotic** and vector-borne diseases, epidemiological studies must untangle the biotic relationships between host and vector species, humans, and their environment. Here, we identify opportunities to integrate acoustic monitoring technology and acoustic data into epidemiological studies and disease surveillance systems.

Understanding the transmission dynamics of complex multihost disease systems requires the integration of information across multiple spatial and temporal **scales**, and across distinct biological processes [1]. With the exception of a few well-studied pathogens, we still know little about the mechanisms through which disease processes manifest in risk to human health. Bioacoustics has the potential to answer core epidemiological questions, including (i) which species are present in an area, (ii) where and how key species move and behave across heterogeneous space, (iii) when species are active in a space, and (iv) whether there is spatial/temporal overlap between host species, vectors, and/or human movement. In answering these questions, classical field methods (i.e., transects, trapping, questionnaires) can provide important insight into small-scale social and ecological processes that underlie disease risk. However, being typically labour-intensive and expensive, classical methods are not always suitable for understanding patterns of risk at scale. Methods for surveying the environment, using sound recorders, including **PAM**, have advanced rapidly in the fields of terrestrial and aquatic ecology and conservation, and ecoacoustic data are used effectively in assessments of biodiversity and ecosystem health over broad spatial scales [2–5]. To this effect, acoustic monitoring offers a complementary, scalable tool that can provide extensive data to give new insights in the parameterisation of risk

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models and potentially address some outstanding assumptions about the processes driving disease risk in changing landscapes.

There are currently limited examples of acoustic data being harnessed to understand infectious disease. In conservation biology, acoustic surveys are typically used in the identification and monitoring of soniferous species, particularly those that are visually cryptic or found in densely vegetated landscapes [6–9]. In relation to human disease, some research has been conducted into using acoustic sensing in community-science-based mosquito surveillance [10]. Mobile phone devices can be adapted as acoustic sensors to track human–mosquito encounters and, notwithstanding some limitations in implementation, collect occurrence data without typical sampling biases to inform vector-borne disease control programmes [11–13]. In a laboratory context there are also examples of acoustic data used to understand mating behaviour of mosquito vectors [14]. Otherwise, existing applications almost exclusively relate to the study of wildlife disease ecology – primarily white-nose syndrome in bats, using ecoacoustic data to survey hibernation sites [15,16], monitor seasonal disease-related behavioural change [17], and assess the implications of climate change on disease progression [18]. There are also a few examples of acoustic monitoring of amphibian disease, discussed in relation to chytridiomycosis [19] and investigating changes in call patterns of infected frogs [20].

A number of biological and ecological processes can be examined using PAM survey data, as detailed by Gibb *et al*. [21]. Ostensibly, these answer many of the same questions that are critical for epidemiology and the study of disease transmission, relating to the occupancy, abundance, and detectability of species over space or time, or estimating spatiotemporal overlap of species. While there is no existing literature on the application of acoustic data to understand processes underlying disease transmission, Figure 1 (Key figure) provides examples of epidemiological variables that could be obtained from bioacoustics and their potential applications to the surveillance and control of infectious diseases. By offering a new tool to inform relevant parameters, acoustic surveys could be advantageous in studying a range of infectious disease systems, particularly those with sylvatic pathogen **reservoirs**. For instance, acoustic data could be used to detect changes in host location or behaviour that might enhance risk, such as wildlife ranging into livestock compounds [22] or human settlements [23], or host die-off indicative of an epizootic [24]. This includes, but is not limited to, diseases that have wildlife reservoirs in non-human primates (zoonotic malaria, yellow fever) [25,26]; canids and small mammals (rabies, trypanosomiasis) [27]; livestock and small ruminants (toxoplasmosis, Rift Valley fever) [28,29]; bats (Marburg virus, Ebola virus, Nipah virus, lyssaviruses) [30,31]; and wild birds (West Nile virus, Japanese encephalitis) [32,33].

In some fields, PAM is already routinely used; here, the advantage for infectious disease research would be of applying existing workflows to epidemiological questions. One such target for extending existing acoustic methods to human epidemiology is bats. Certain species are known to host a melange of viral pathogens with existing or emergent zoonotic potential [30,31,34] and analysis of bioacoustic data is already a mainstay methodology in this field to investigate population dynamics and behavioural trends [35–38]. As an example, existing acoustic methods could be utilised to better understand the dispersion of nonhaematophagous bats and inform urban rabies surveillance and control [39]. In a well-studied, vocal species, acoustic data could also monitor behavioural signatures of disease risk: for example, there is evidence that peaks in human risk of Marburg virus correspond to breeding season for the Egyptian fruit bat *Rousettus aegyptiacus* [40]. Moreover, it has been shown that combining acoustic data with other high effort, high-quality data types (e.g., mark-recapture, point count surveys, GPS tagging) can produce superior models and better parameter estimation compared to using a single data

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source, reducing detection biases, and improving estimates of abundance and population size [41,42].

In other instances, acoustic data may present a novel opportunity to fill technological gaps in current infectious disease research. Remote sensing technologies such as satellite sensing, unmanned aerial vehicles (UAVs) and LiDAR (Light Detection and Ranging) data have emerged as key assets in collating spatial and environmental data and are increasingly being used to infer patterns in disease risk and model transmission [43]. However, while UAVs have been used successfully in aerial population surveys of livestock reservoirs [44,45] and in mapping mosquito vector breeding sites [46], this technology is best suited to large animals and features of open grassland landscapes.[i] Here, PAM could offer a significant advantage for monitoring the distribution and movement of species in forested or closed landscapes. Epidemiological studies unfamiliar with using acoustic technology, particularly those collecting data in remote areas, can benefit from the recent development of low-cost sensors or **autonomous recording units (ARUs)** that are optimised to work in such contexts. Improvements in wireless sensor technology have facilitated the use of PAM to collect continuous data on surrounding acoustic environments. Open-source acoustic sensors are now readily available, with microcomputer-based devices such as **AudioMoth** providing options that are cheap to manufacture and flexible for nonspecialist users. Depending on the research question (i.e., target species, spatiotemporal scale), users can adjust sampling rate, gain, sampling intervals (how frequently devices record audio), and sampling durations (length of recordings and recording schedule), with AudioMoth devices supporting sampling rates up to 384 kHz and sampling distances within radii of 50 m to 1500 m depending on the source [47]. Other more specialised recording devices are also available from commercial suppliers (e.g., Wildlife Acoustics[ii] or wider monitoring initiatives, Cornell Swift recorders).[iii]

Acoustic monitoring can also be used to collect data to inform epidemiological processes related to human movement and activity. We still know relatively little of the mechanisms through which pathogens spread across a human–wildlife–ecosystem interface. By collecting noninvasive, real-time data concerning human movement, PAM has the potential to bring new understanding of spatiotemporal spillover risks associated with land use change or certain indicators of human activity in complex systems [48]. For instance, being able to monitor interfaces between people and fruit bats would provide valuable data with which to parameterise more mechanistic models that integrate bat ecology and human behaviour. For mosquito-borne diseases such as malaria, detection of human movement could be used to indicate heightened transmission risk and prioritise vector control in regions nearing elimination [49]. An example of this application for malaria risk monitoring is illustrated in Figure 2. Increased human activity during key mosquito biting times contributes to the malaria receptivity of a given area [50]: by comparing detection frequency of human chainsaw use against bite rate for the main malaria vector in Sabah, *Anopheles balabacensis,* high-risk times for malaria transmission in this hypothetical population would be early evenings, which might inform future interventions.

Acoustic methods can provide new opportunities to integrate data at scale into risk modelling and long-term infectious disease surveillance. Acoustic data have already been used to assess the impact of human-modified landscapes on biodiversity [51–54] and to understanding the impact of climate change on species distributions [55], particularly salient given the rapidity of habitat loss and critical landscape change. Risks of disease emergence or transmission from wildlife to humans are also understood to be affected by changing climates, urbanisation, and landscape modification [56], and there has been considerable progress in incorporating meteorological and environmental information to improve surveillance and early warning systems (EWSs) for climate-sensitive infectious diseases [57–59]. In the same way, passive acoustic data can be

Glossary

Acoustic indices: statistics that summarise features of acoustic data from audio recordings.

AudioMoth: a small recording device that records audio data and stores metadata.

Autonomous recording unit (ARU): a self-contained audio recording device.

Bioacoustic: related to the field of study concerning sounds produced by living organisms.

Passive acoustic monitoring (PAM): survey methods for monitoring species or the environment using sounds recorders.

Reservoir: refers to the animal species (reservoir host), population of organisms (disease reservoir) or environment in which a pathogen reproduces and is sustained.

Scale: describing the distance (spatial scale) or time frame (temporal scale) over which biological processes occur.

Soundscapes: a combination of sounds that form a complete acoustic environment.

Surveillance: monitoring of a disease, or of risk factors that influence disease spread, to establish patterns of progression and predict or mitigate adverse events.

Zoonotic: refers to diseases that are transmitted between animals and humans.

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Key figure

Potential use cases and applications of acoustic data to characterise epidemiological variables to inform surveillance and control measures

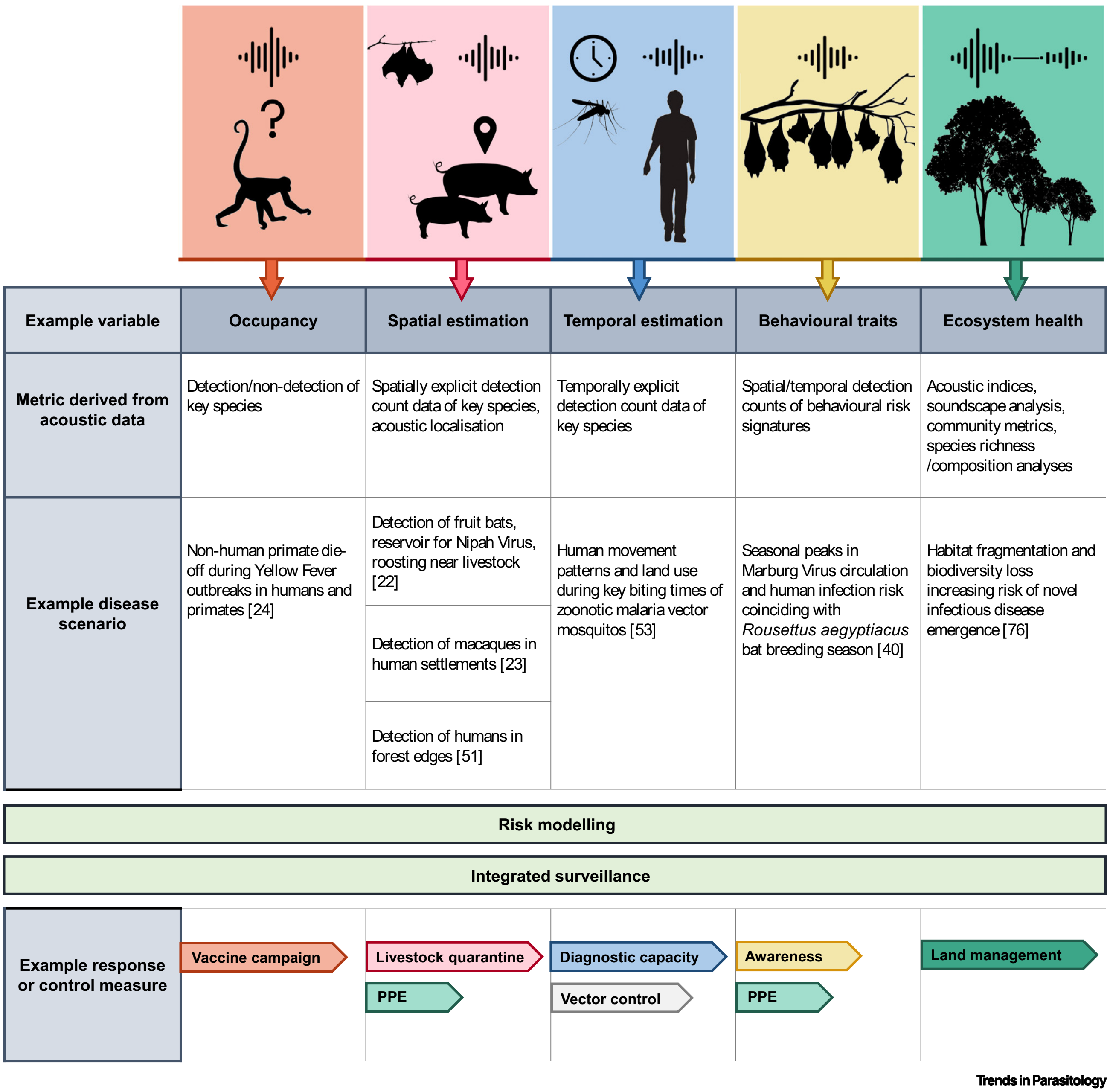

Figure 1. Key epidemiological variables are listed (dark grey boxes), below which metrics are given which could be informative to the specific variable and that can be derived from acoustic data. Examples provide disease scenarios where a particular epidemiological variable might be useful, listed within the table and illustrated above (coloured graphic boxes). All variables could contribute to risk modelling or integrated surveillance systems (green boxes). For each epidemiological variable and associated example disease scenario, example control measures are given (coloured arrows). Abbreviation: PPE, personal protective equipment.

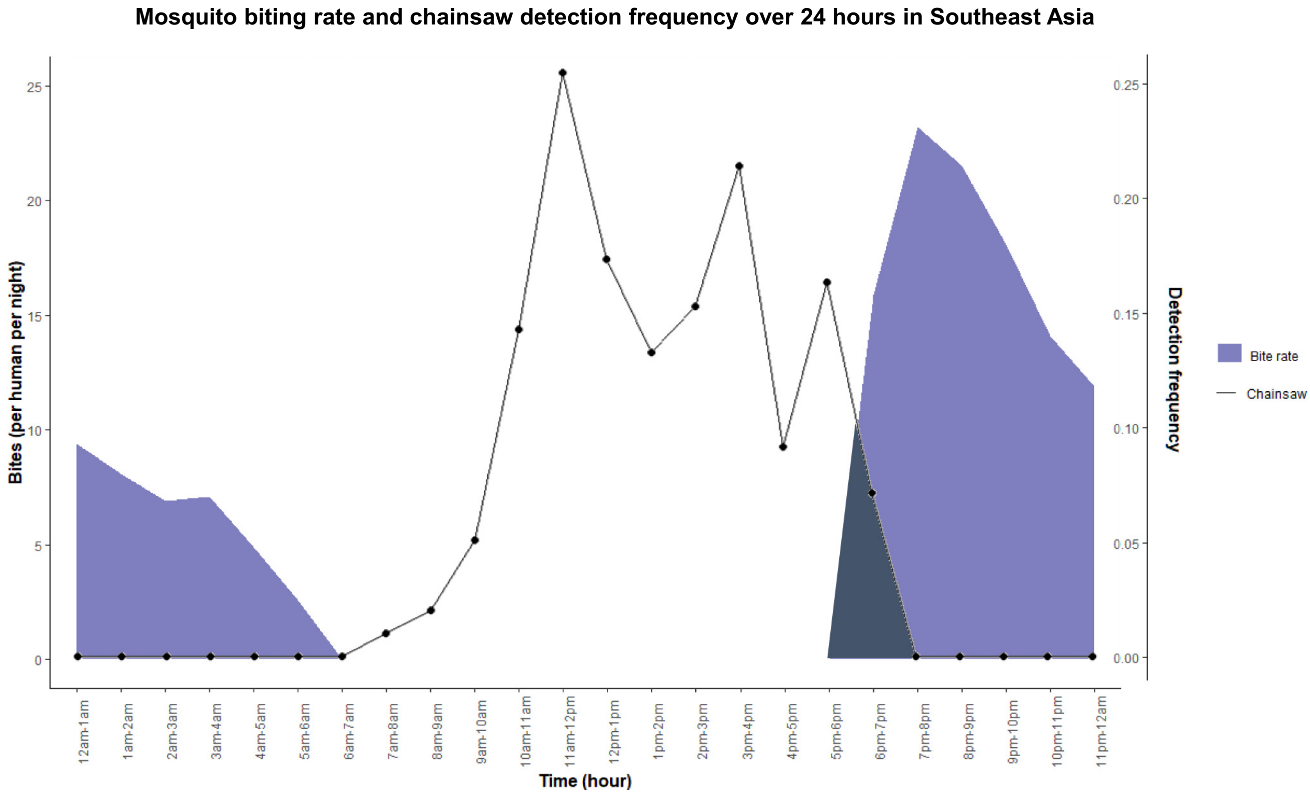

Figure 2. Hourly detection frequency of human activity against mosquito bite rate (per human per night). Hourly detection frequency of chainsaw activity in Sumatra, Indonesia (black line), superimposed with hourly mosquito biting rate in Sabah, Malaysia (blue shading). Dark blue shading indicates possible temporal overlap between human activity and mosquito biting.

collected and used to parameterise rapidly changing risk for disease spillover. With improvements in on-board analysis and cloud-based data processing, acoustic monitoring can now provide long-term monitoring and real-time alerts of human activity, including illegal logging and poaching [60]. Solar-powered devices that are associated with continuous and real-time detection capabilities can further facilitate long-term monitoring in remote ecosystems and tracking of ephemeral sounds. This presents a novel opportunity to incorporate longitudinal acoustic monitoring into infectious disease surveillance workflows.

Case study: acoustic survey design and practical considerations of ARUs

Optimal sampling design for epidemiological studies using PAM technology will depend on the target species and research objectives. The SENSOR Project was recently established to characterise transmission intensity of specific zoonotic and vector-borne diseases with a view to modelling spillover and transmission rates relative to certain land-management practices.[iv] Acoustic surveys will be used to parameterise the presence/absence of long-tailed macaques (*Macaca fascicularis*), a potential reservoir for zoonotic malaria and arboviruses, across landscapes at different stages of forest restoration [61]. Figure 3B illustrates set-up and deployment of AudioMoths during a pilot study to compare host species detection, positioned in a monitoring grid in and around forest restoration plots across a land use gradient in Kinabatangan, Sabah (Figure 3A). In a disease system that is undergoing rapid landscape change, spatially explicit sampling protocols are particularly important to collect representative data to characterise disease

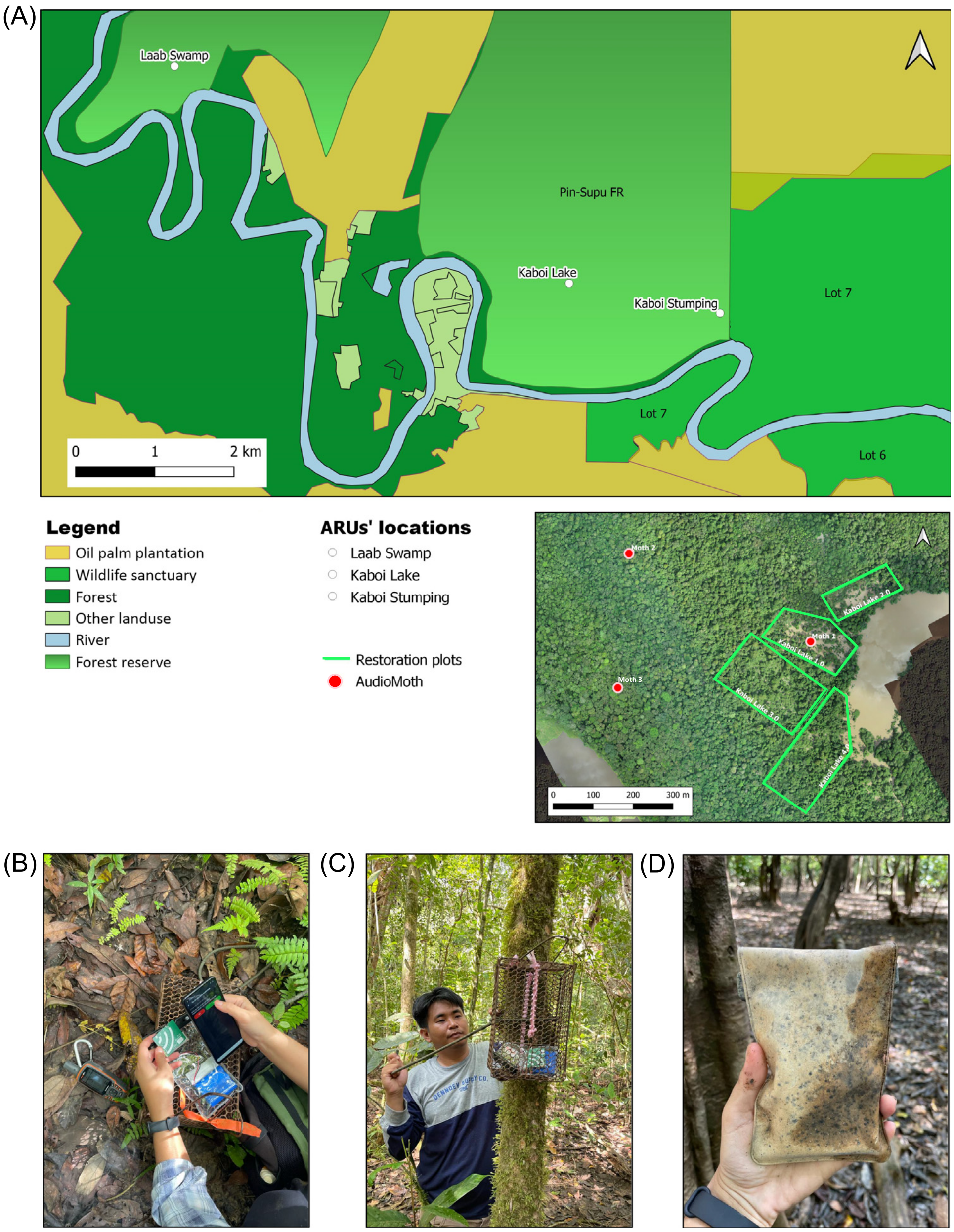

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Figure 3. Set-up and deployment of autonomous recording unit (ARU) in Sabah, Malaysia. (A) Map Kinabatangan floodplain. Inset photo illustrates AudioMoths (red) deployed in and near forest restoration plots (green lines) at Kaboi Lake. (B) Programming and setting up ARU. (C) Positioning ARU with battery pack in waterproof casing and protective wire cage. (D) ARU waterproof case after 10 days submerged in floodwater.

risk – for example, examining acoustic signatures from stratified land use types or habitat fragment sizes [62].

When deploying ARUs as part of a study or for long-term surveillance, it is important to understand the study area to ensure that potential biotic and abiotic disturbances that can hinder audio data collection are mitigated. For example, pilot studies have found that ARUs might attract animals such as monkeys, squirrels, birds, or ants, and extra measures may be needed to protect the ARUs from being disturbed or damaged. This might look like setting the ARUs inside a sturdy cage (Figure 3C) tightly secured to the chosen location, or, if using clear casing, covering light-emitting diodes (LEDs) with waterproof tape. Field researchers should also be familiar with the geography and meteorology of study sites; terrain and weather conditions should be carefully considered while designing your study. The AudioMoth in Figure 3D was positioned within the Lower Kinabatangan Wildlife Sanctuary (LKWS), which lies on a floodplain. Seasonal flooding in the study area resulted in one ARU being submerged for over 10 days. While the ARU and associated data were salvaged, deployment at a greater height would have mitigated against flood damage.

Bioacoustic data analysis for epidemiological studies

In most scenarios, analysis of ecoacoustic is primarily concerned with the deconstruction and interpretation of the audio collected to interpret the biological patterns and processes that occur; for epidemiological studies, this will give discrete information regarding disease ecosystems or host/human communities, populations, or individuals [63]. Typically, the first step in the workflow is detecting and classifying acoustic signals from sound files for specific sonotypes. During processing, waveforms are converted into spectrograms (time–frequency–amplitude visualisation), demonstrated for a call signature of the *R. aegyptiacus* fruit bat in Figure 4. Signals must first be detected, using thresholding or statistical methods, and then classified according to specific acoustic features of the sound [21]. Methods are continually evolving and improving to automate this [64], and there are a range of software that offer inbuilt template matching tools. An example application of this would be for *Plasmodium knowlesi*, a vector-borne zoonotic disease with a simian reservoir. Extensive deforestation and the proliferation of oil palm plantations in Malaysia is potentiating transmission, with changes in land use likely to be increasing contact between humans, mosquito vectors, and wildlife hosts [25]. To understand *P. knowlesi* epidemiology and institute control measures, studies require fine-scale data to characterise macaque movement across space and time. Using cloud-based computing and pattern-matching approaches implemented in a freely available web-based platform [65], acoustic data can be analysed to detect *M. fascicularis* presence across different habitats within areas endemic for *P. knowlesi* transmission (Figure 5). In addition to standalone sensors, the deployment of multisensor networks, microphones, and linked arrays can facilitate acoustic localisation of terrestrial species, using position estimation algorithms at later analysis stages [66]. New efforts are also being made to address potential sampling biases in existing study designs by standardising sensor calibrations and metadata collection, as well as quantifying sensor sensitivity in different environments [67].

Epidemiologists interested in analysing acoustic data at scale can take advantage of recent advances in machine learning for acoustic signal recognition, which are automating this process and reducing the time and labour requirements. Supervised learning algorithms (trained on prior manually labelled audio features) or unsupervised learning algorithms (only based on structural features within the data, i.e., clustering algorithms) then detect signals and generate scores that represent the predicted probability of presence for different classes. However, there often are deficits in species or geographic regions for which there is little/no training data, which might pose a particular problem for novel hosts or regions required for infectious disease research. Subsequently, there is a need to generate labelled data and training algorithms applicable to the use of acoustics in a disease context. More generally, issues of variable accuracy and sound quality can occur and hinder both detection and classification stages of analysis, affected by factors such as distance from sound, nontarget background noise, or signal masking. Deep-learning

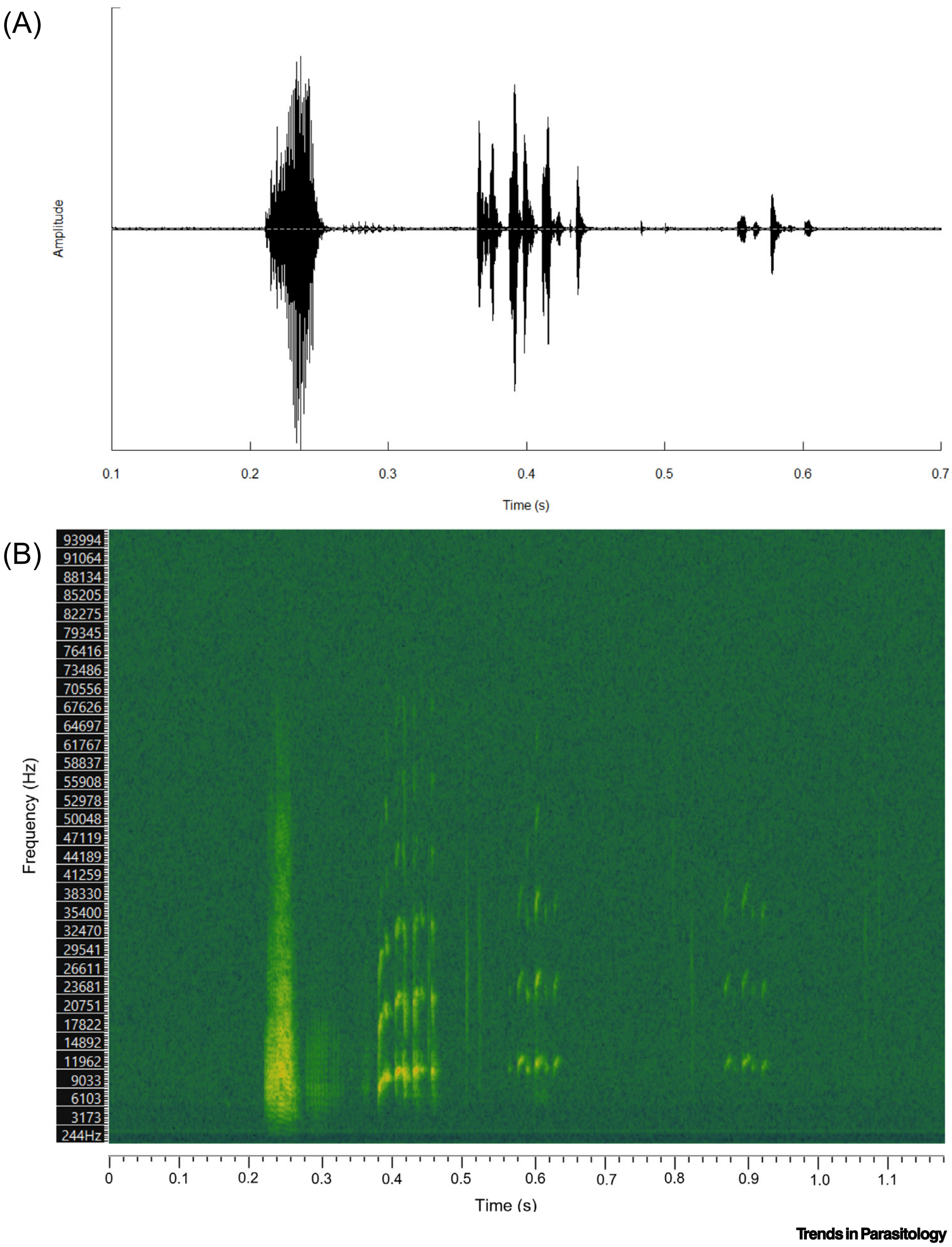

Figure 4. Example acoustic outputs. (A) Basic oscillogram waveform for Egyptian fruit bat (*Rousettus aegyptiacus*) vocalisation [36]. (B) Spectrogram (time–amplitude–frequency) for Egyptian fruit bat vocalisation.

models based on recurrent or convolutional neural networks (RNNs or CNNs) are evolving as a valuable new tool to address these challenges, bypassing the feature extraction stage and performing highly in classification tasks. Deep-learning algorithms can be applied to discerning anthropogenic sounds [68] as well as biotic features [69,70] in noisy datasets; indeed, deep-learning detection algorithms have been applied to identifying human vocal signatures [71], which, in a disease context, could be used to better understand spatial or temporal patterns of human activity in integrated surveillance systems.

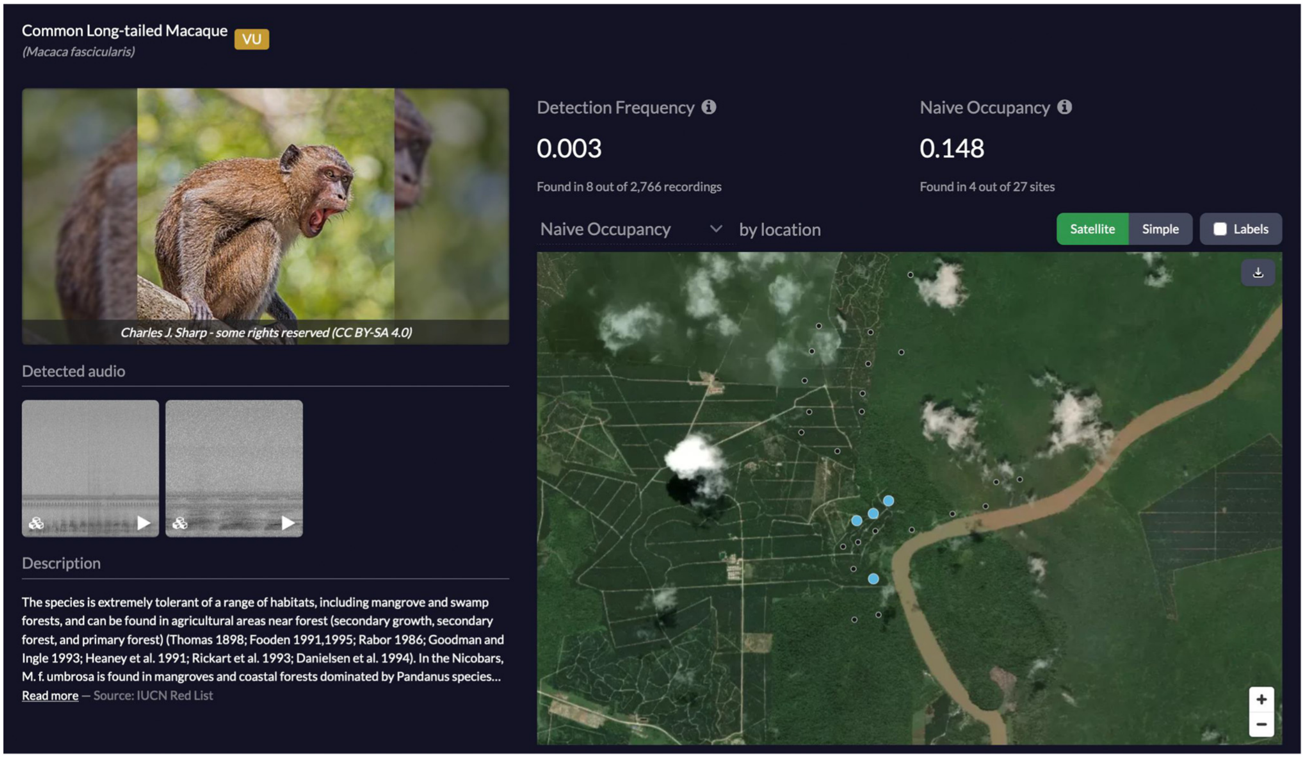

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Figure 5. Arbimon Insights user-interface dashboard summarizing results from acoustic analyses. The dashboard of Arbimon Insights [65] includes a map of detection points for the common long-tailed Macaque (*Macaca fascicularis*) in a study site in Sabah. Blue points indicate locations of acoustic sensors where long-tailed macaques were detected (four of 27 sites). Black points indicate monitoring sites where the species was not detected.

Another approach to extract useful ecological information from audio data is through **soundscape** analyses, where the focus moves away from individual species to characterising the entire acoustic environment. Soundscape analyses can be used to assess and compare animal richness thought time and space, which could be valuable in understanding altered disease transmission potential linked to changes in biodiversity or overall declines in ecosystem health [72,73]. For instance, species richness of insects, anurans, birds, and primates are strongly and positively correlated with the proportion of acoustic space used (ASU) in the neotropics [74] (Figure 6). Deep-learning approaches have also been successfully applied to soundscape analysis: by creating a universal acoustic feature space, CNNs can identify soundscape 'fingerprints' of biotic and anthropogenic sound that can be used to assess habitat quality and human activity across multiple spatial and temporal scales [75]. Habitat disturbance has been widely linked with increased disease outbreaks, suggesting that these metrics, identifying rapid changes in soundscapes, may be good proxies for future outbreaks. In other cases, this may provide valuable information to characterise habitats associated with different levels of disease risk.

Alternatively, abstraction can also be useful in interpretating audio data, deriving community information by means of **acoustic indices**. Acoustic indices reflect distinct attributes of a soundscape and calculate metrics with which to make inferences about overall ecosystem health, biodiversity indicators, or habitat function that could have useful applications to parameterising disease risk [76]. Indices such as acoustic complexity index (ACI) take features of the soundscape (amplitude, pitch, saturation) and simplify audio data into single numerical values. Acoustic

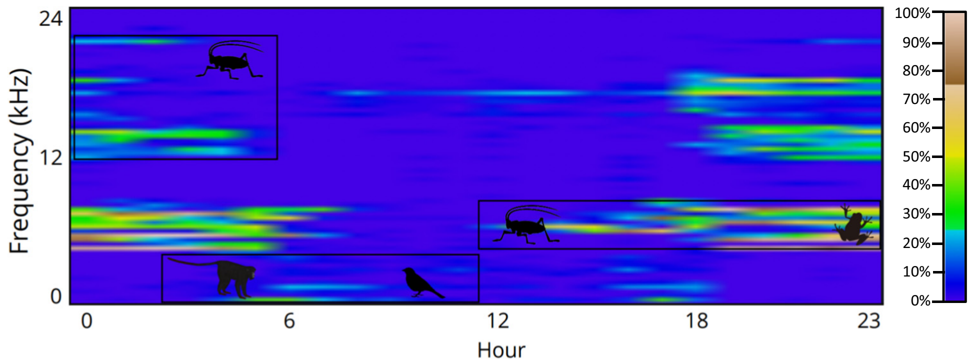

Figure 6. Visual representation of acoustic space use (ASU) from Barro Colorado Island (Panamá). The axes represent hour (x), frequency (y), and the proportion of observations. The figure includes a total of 3072 frequency–time bins (24 h × 128–172 Hz frequency bins). The black boxes indicate the main taxonomic groups contributing to the acoustic patterns observed in certain time–frequency periods.

indices have shown particular value in quantifying temporal changes in a soundscape, such as tracking diel patterns or seasonal shifts [77], or in identifying marked differences between the soundscapes of undisturbed and disturbed habitats [78] in areas undergoing substantial landscape change. However, caution is needed when using acoustic indices as proxies for biodiversity since recent meta-analyses have shown only a moderate positive relationship and inconsistent performance [79]. Utility of current acoustic indices for disease applications needs to be evaluated, and there is potential for the development of other indices or metrics to reflect disease risk.

Benefits of PAM in epidemiology

Zoonotic and vector-borne diseases tend to be strongly impacted by changes in climate, landscape, or habitat composition across multiple spatial scales. Acoustic monitoring provides a non-invasive method to collect data that are both spatially and temporally explicit, locally and at scale, without the logistical intensity that classical field ecology methods otherwise require. PAM has the potential to complement existing remote sensing methods (UAVs, LiDAR) in disease settings with dense vegetation, canopy cover, and challenging terrain, addressing conceptual gaps and providing detailed data on the spatiotemporal interactions between humans, vectors, and animal host species. By combining broad acoustic survey data with data that are high quality but sparse, expensive, or intensive to collect, acoustic monitoring can also strengthen existing datasets. Acoustic surveys are adaptable to user requirement and simple to deploy, creating the opportunity for epidemiological studies to collect data within specific frequencies with minimal input. Furthermore, there is ample scope to integrate acoustic monitoring into existing disease surveillance programmes to improve real-time estimation of disease risk [41,80]. With recent advances in open-source hardware and software, acoustic technology is widely accessible – with commercial unit costs for devices such as the AudioMoth as low as US$70 and with minimal training and maintenance requirements. These devices can use wireless communication, GSM (Global System for Mobile Communications) signal and satellite connection to send raw recordings or detection alerts to online platforms [81]. Satellite-connected devices can be equipped with processing power sufficient to conduct onboard computation and transmit real-time reporting via cloud-based platforms [60]. Potentially prohibitive technical barriers have also been lowered or removed at analysis stages, with user-friendly platform interfaces, inbuilt automated detection algorithms and acoustic call libraries in both open-source or free software (Arbimon [81], PAMGUARD, LDFCS, iBatsID [82], Tadarida [83]) and membership-based software (Kaleidoscope, Raven Pro, Avisoft).

Limitations of acoustic monitoring approaches in epidemiology

While PAM presents new opportunities in epidemiological investigations, there are some limitations. One key limitation in this context is that use is restricted to disease hosts/vectors that produce audible sound. This precludes reservoir species that are nonvocal. Practically, whilst field placement of ARUs is reasonably straightforward, adequate resourcing and personnel are still required for the initial field deployment to set up the devices, which may create additional resource demands depending on the scale of the epidemiological study. Likewise, the scale of the survey will determine unit costs and maintenance costs, though technical requirements such as batteries may soon be superseded by solar-powered devices. For disease programmes looking to collect continuous data, it should be noted that the files generated by continuous passive monitoring comprise a notable data load; being computationally intensive to store and analyse, this necessitates computers with sufficient processing specifications, network connectivity, and cloud infrastructure that is not always available in remote field conditions.

While collection of PAM data is relatively intuitive, there may be initial barriers in the analysis and interpretation of acoustic data by nonspecialist users. Manual processing of audio data remains the most accurate but is time-intensive and subject to bias, while automation and machine learning is faster and scalable but requires the technical expertise to create models and large quantities of reliable datasets. For novel geographic areas or species that are of epidemiological interest but not typically the subject of acoustic surveys, a paucity of training data can limit the usability of supervised learning algorithms for species detection and monitoring. Despite recent advancements, there are still challenges in generating accurate estimations of density and abundance from acoustic recordings. Certain detection uncertainties are inherent to acoustic data, including imperfect detection due to call distances and local environmental factors (i.e., rain, anthropogenic noise) [67] and statistical nonindependence of vocalisations that are close in space or time. Given that species distribution parameters are likely to be some of the most useful for epidemiological studies to infer wildlife/human presence in certain locations or time frames, robust statistical methods should be applied to address these uncertainties. Examples include patch occupancy models that incorporate detection probability parameters [84] or Bayesian inference frameworks [85].

Concluding remarks

To design disease control strategies and implement effective surveillance, detailed understanding of how key biological systems interact is required. PAM offers a valuable addition to existing epidemiological tools used to monitor zoonotic and vector-borne disease but does not replace existing field-based methods. PAM is likely best used in combination with existing methods and data sources. Identifying optimal strategies for integrating these methods and evaluating their utility is a key priority for future research (see Outstanding questions). For epidemiologists looking to apply this technology, technical and logistical requirements will need to be considered when implementing acoustic surveys into a study. While PAM data collection is automated, field deployment in remote terrains necessitates a degree of time and financial cost to account for. To obtain useful and usable acoustic data, field surveys should be designed cognisant of the data requirements and appropriate sampling strategy. Purpose of data collection, target species and the required spatial and temporal scale should inform the recording specifications (i.e., sampling rate, recording schedule, duration of audio collection), the number and geometry of sensors, and whether other sensors or methods are used in tandem (i.e., thermal sensors, camera traps, entomological surveys). In regions of interest with fragmented ‘patchy’ landscapes, Earth Observation (EO)-derived environmental data might inform strategic ARU placement or stratified sampling that ensures environmentally representative acoustic data are collected [86]. Hardware (sensors and microphone specifications, microSD cards) and software are at user

Outstanding questions

Which acoustic metrics and acoustic monitoring survey designs are best able to generate meaningful data across wide spatial and temporal scales?

How can acoustic monitoring be combined with environmental and human or animal health data most effectively to inform infectious disease surveillance?

How does the cost–benefit trade-off of acoustic monitoring compare to other methods used to characterise disease systems?

How can data and metrics derived from acoustic monitoring be best evaluated specifically for their utility to health systems?

What are the barriers to implementation and interpretation of acoustic data by disease control practitioners?

discretion, but must be sufficient to match detection requirements and computational load of the analysis. As with any human epidemiological study, there are also ethical considerations around the collection, analysis, and storage of human audio data so appropriate ethical clearance should be sought from local stakeholders.

Acoustic monitoring provides novel opportunities for the field of human epidemiology, offering a new tool to address practical and theoretical shortfalls in current assumptions of spatiotemporal risk for emerging infectious diseases. As an emerging application of this technology, there are currently few examples of the use of acoustic data in epidemiology. Consequently, there remain knowledge gaps in how these technologies can be practically deployed, evaluated, and how analysis pathways can be adapted for disease-specific applications. To overcome potential barriers for the adoption of these technologies by in-country stakeholders, workflows for integrating acoustic data into research studies or disease control programmes need to be developed further. Guidelines and infrastructure need to be created for implementation of this technology in low-resource settings, including trainings that are specific to epidemiologists and applied disease management practitioners. Furthermore, improved evaluation of acoustic metrics and data analysis pathways will also be required that is specific to the use of acoustic data in the context of health management and disease surveillance. PAM can be cost-effective and straightforward to implement in epidemiological studies, and with purposeful sampling design acoustic surveys can be scaled up to collect extensive data on meaningful metrics of disease risk over wide geographic areas. Overall, acoustic monitoring is an emerging field which presents a valuable addition to epidemiological toolkits and an opportunity to improve the study and surveillance of complex emerging infectious disease systems, with considerable potential for important public health impact.

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Declaration of interests

The authors declare no competing interests.

Resources

[i]www.zooniverse.org/projects/rfv-drones/rift-valley-fever-drones/about/research

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