







HumBug – An Acoustic Mosquito Monitoring Tool for use on budget smartphones

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Abstract

1. Mosquito surveys are time-consuming, expensive and can provide a biased spatial sample of occurrence data—the data often representing the location of the surveys, not the occurrence of the mosquitoes.
2. We present the HumBug project, an acoustic system that can turn any Android smartphone into a mosquito sensor. Our sensor has the potential to significantly increase the quantity of mosquito occurrence data as well as access locations that are more difficult to survey by traditional means.
3. We describe our database of wild-captured mosquito flight tone audio data and outline our mosquito detection algorithms that these data train. We also present our MozzWear App, designed to work on budget smartphones, which, together with our HumBug Net (an adapted traditional bednet), facilitates data collection and allows the user to record and directly upload mosquito flight tones from any dwelling with a bednet in the field.
4. Our HumBug system has the potential to vastly increase our understanding of the distribution of mosquito species in space and time and greatly improve surveys needed to assess the success or failure of ongoing vector control measures. At a time when the WHO reports a plateauing in the decade-long decline in malaria mortality rates, this new technological solution for surveying mosquito vectors will provide a timely new resource.

KEYWORDS

citizen science, malaria, neural network, vector survey

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1 | INTRODUCTION

There are over 100 genera of mosquito in the world containing over 3,500 species and they are found on every continent except Antarctica (Harbach). Only one genus (*Anopheles*) contains species capable of transmitting the parasites responsible for human malaria. It contains over 475 formally recognised species (Harbach) of which, approximately 75 are vectors of human malaria and around 40 are considered truly dangerous (Service & Townson, 2002; Sinka et al., 2012). These 40 species are inadvertently responsible for more human deaths than any other creature (Coetzee, 2004). In 2018, for example, malaria caused around 228 million cases of disease across more than 100 countries resulting in an estimated 416,000 deaths (World Health Organization, 2019). It is imperative therefore to accurately locate and identify the few dangerous mosquito species among the many benign ones to achieve efficient mosquito control (Sinka et al., 2010, 2012).

Mosquito surveys are used to establish vector species' composition and abundance, human biting rates and thus the vectorial capacity (potential to transmit a pathogen). Traditional survey methods, such as human landing catches, which collect mosquitoes as they land on the exposed skin of a collector, can be time-consuming, expensive and are limited in the number of sites they can survey. They can also be subject to collector bias, either due to variability in the skill or experience of the collector or in their inherent attractiveness to local mosquito fauna. These surveys can also expose collectors to disease. Moreover, once the mosquitoes are collected, the specimens still need to undergo post-sampling processing for accurate species identification. Consequently, an affordable automated

survey method that detects, identifies and counts mosquitoes could generate unprecedented levels of urgently needed high-quality occurrence and abundance data over extensive spatial and temporal scales.

Mosquitoes are unique in the way they fly. They have a particularly short, truncated wing beat allowing them to flap their wings faster than any other insect of equivalent size—up to 1,000 beats per second (Bomphrey et al., 2017; Simoes et al., 2016). This produces their very distinct and identifiable flight tone and subsequently has sparked scientific interest in the biomechanics of flight tone (Arthur et al., 2014; Belton & Costello, 1979; Brogdon, 1998; Ogawa & Kanda, 1986; Potamitis & Rigakis, 2016), as well as seeking to use flight tone to survey (Kirsch et al., 2007; Kiskin et al., 2017; Li et al., 2017; Mukundarajan et al., 2017; Raman et al., 2007; Silva et al., 2014) or attract and kill them (Belton, 1994; Jakhete et al., 2017; Johnson & Ritchie, 2016; Kahn et al., 1945; Kahn & Offenhauser, 1949; Maxim, 1901).

The HumBug project (Figure 1) utilises this distinctive acoustic characteristic and explores the potential of using a budget smartphone to capture a mosquito's signature flight tone in the field and to provide real-time occurrence data. Here we describe our novel methodology for (a) passively capturing mosquito flight tones on a smartphone by exploiting the natural host-seeking behaviour of blood-feeding females, (b) incorporating these data into a web-based platform, (c) developing a mosquito flight tone database and (d) using this database to train machine learning algorithms to detect and identify wild mosquito species in sub-Saharan Africa. The outcome is a system in which any (Android) smartphone can become a mosquito sensor, potentially massively increasing the available

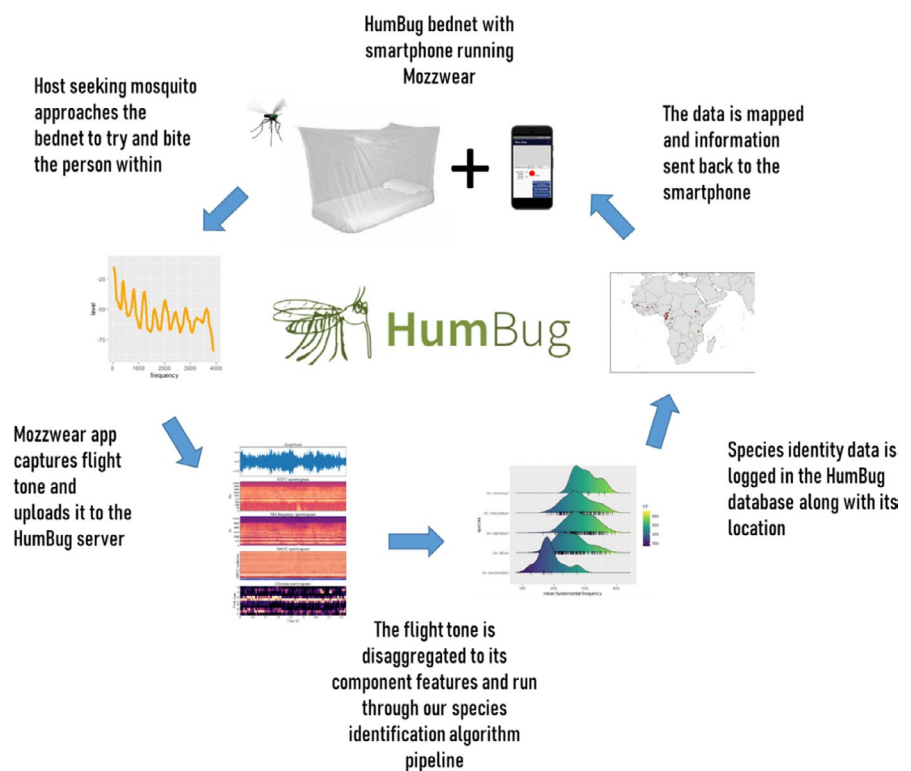


FIGURE 1 The HumBug project workflow. We deploy our sensor (a smartphone running our MozzWear App) into adapted bednets (HumBug Nets). The flight tone of the host-seeking mosquito is recorded as the mosquito tries to access the person inside the net. The acoustic data are uploaded to the HumBug server for processing where it is passed through an algorithm pipeline that removes sections of human speech and refines the mosquito detection

vector occurrence data and providing invaluable information for entomologists, biologists, vector-borne disease modellers and vector control programs.

The HumBug system has been designed with three user bases in mind. Firstly, as a tool to supplement and enhance ongoing mosquito monitoring programs to inform mosquito intervention policy. Secondly, for use by the vector research community and disease modellers, to generate long-term comparable multi-site mosquito abundance data, identify peak mosquito activity as well as identify spatial occurrence over many more locations than are feasible with traditional mosquito survey methodologies. Finally, as a system for citizen scientists across the malaria endemic world to gather and upload mosquito data to help fight the vector-borne diseases that continue to impact on their lives.

2 | MATERIALS AND METHODS

2.1 | Capturing mosquito acoustic data on a smartphone

Mosquitoes are small insects and the physical movement of air caused by their beating wings creates the high-pitched whine of their flight tone. This quiet but distinctive sound can be difficult to detect even within moderate background noise. Thus, to ensure our smartphones record data, which is loud and clear enough for reliable mosquito detection and species identification, we needed to complete two steps. First, to develop an App (MozzWear) to record the mosquito's flight tone using the in-built microphone on a smartphone, and seamlessly stream the data to a central server. Second, to design a means to ensure that a mosquito flies close enough to the smartphone microphone to capture its flight tone (the HumBug Net).

2.1.1 | The MozzWear App

The App is written in the JAVA programming language and was developed for the Android platform, given that smartphone devices based on the Android operating systems can be found in wide distribution for as little as £30 per unit.

It has a simple, user-friendly interface (Figure 2) that allows the user to select whether they want to record on detection or manually activate the record function. The 'Record on Detection' option (prototype) uses the phone's hardware to detect mosquito sounds directly, and only these synchronise with the server. The 'Record' function records constantly on implementation. Here the App shows real-time plots of the mosquito detection output, based on the detection algorithm's predicted probabilities derived from the combination of audio features and a machine learning model (see Section 2.3.1). The App allows the user to adjust the recording length (minimum: 1 s, maximum: 1 hr). Recordings running longer than the set recording length produce multiple files, for example a two-and-a-half hour recording period, where the recording length

is set at 1 hr, produces three files, two 1-hr recordings and one 30-min recording. Limiting a single recording length to a maximum of 1 hr ensures that the recording device is able to process and record the data without errors. However, if the recording continues beyond 1 hr, multiple files are produced allowing the device to record for as long as is needed. The App is designed to operate without an active data connection and records to the phone's internal memory. Once a recording session is complete and upon an active data connection, the recorded files are uploaded to the HumBug server for further analysis (Section 2.3). For more details about the App functionality, please refer to (Li et al., 2017).

To transfer the recorded data from the smartphone to the HumBug server, the MozzWear App includes a synchronisation ('sync') function, which, once activated within range of Wi-Fi or a suitable mobile data network, makes an HTTP POST request to the server. This sends both the audio recording plus additional information detailing the recording time and device-specific identification data to a bespoke web application based on a Python web server, where it is received and stored in a MongoDB database. The database is subsequently searchable using queries. The stored data are accessible client-side via a dashboard which shows device recording ID as well as a visual representation of the audio. Future iterations will display mosquito detection outcomes and species classification probabilities.

2.1.2 | The HumBug Net

Many of the most dangerous malaria mosquito vectors are active during the night, entering people's houses to bite them while they are asleep and vulnerable. Insecticide-treated bednets are widely distributed by vector control programs and provide a barrier between the mosquito and the sleeping human (widespread insecticide resistance among mosquito populations has reduced the impact of the insecticide). We therefore deploy our sensor (a smartphone running our MozzWear app) into adapted bednets.

The HumBug Net (Figure 3) uses the inherent behaviour of host-seeking mosquitoes to make them fly close enough to the phone's internal microphone to passively record flight tone. Its design is based on traditional rectangular bednets found across the malaria endemic world. The bednet is adapted by the addition of a second outer canopy and a detachable pocket. The pocket is placed at the highest point of the outer canopy above the occupant's head and holds the smartphone running the MozzWear App (Section 2.1.1). The occupant switches on the App as they enter the bednet at night. Host-seeking mosquitoes are attracted to the CO₂ in the breath of the occupant and become trapped within the second canopy of the HumBug Net. Here they naturally migrate to the highest point of the net [a behaviour common among flying insects and exploited in insect trapping methods such as the malaise trap (Evans, 2016; Mississippi Entomological Museum Web Site: Malaise Traps)] where their flight tone is recorded by the MozzWear App. This design targets night-active mosquito species with a predilection to feed on

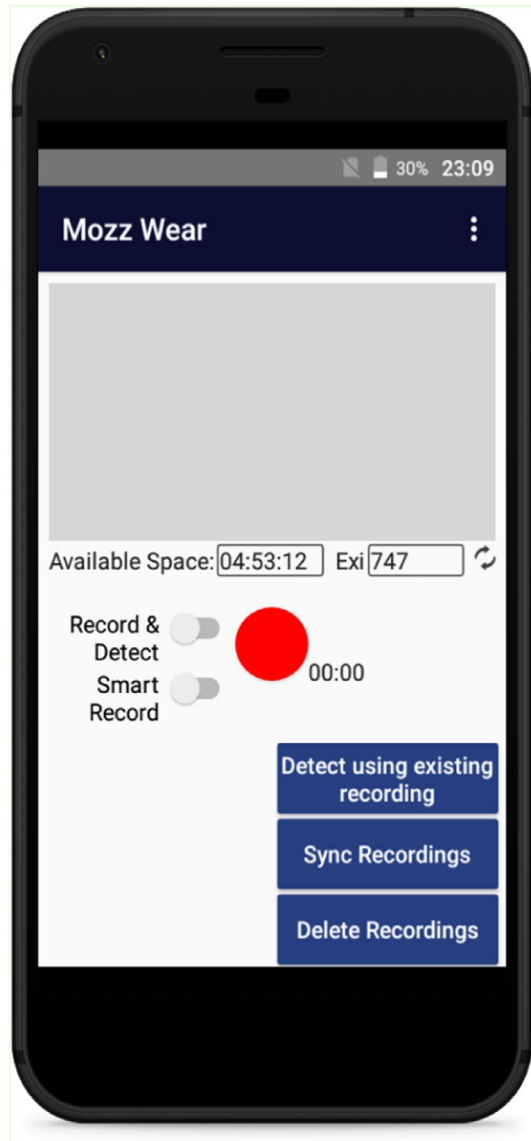


FIGURE 2 The MozzWear App interface is designed with simplicity in mind. Functionality includes detection triggered recording as well as options for synchronising data records with the server

humans—characteristics common among the dominant malaria vectors in sub-Saharan Africa that are the specific focus of the HumBug project.

2.1.3 | Addressing privacy and security concerns related to using MozzWear in a bednet

One of the key deployment targets for our MozzWear App is over-night recordings in the HumBug Net, capturing the night-active mosquitoes known to be the most effective vectors of malaria. However, these recordings can potentially pick up background sounds including speech. Not only do such background sounds make mosquito detection more difficult but they can also lead to privacy and security

concerns for the user. Therefore, voice activity needs to be detected and removed from the archived mosquito recordings. To facilitate this, we implemented a voice activity detection (VAD) pipeline (Ramirez et al., 2007). This pipeline operates as a binary classifier, detecting the presence and absence of a speech signal based on Google's WebRTC project, which is open-source, lightweight and reputed to be reasonably reliable and fast (Karrer, 2021). Sahoo (2018) tested the WebRTC VAD method over 396 hr of data, across multiple recording types. The approach was between 77% and 99.8% accurate. Although the method could perhaps be improved upon in the future, the WebRTC approach is robust and updates are supported by Google. The sections of recording with likely voice activity can be removed from subsequent analyses. This not only helps preserve privacy in our recordings but creates cleaner sections of data for more detailed mosquito analysis.

2.2 | Development of a mosquito sound database

There are a number of variables that influence a mosquito's flight tone including the size of the mosquito (Sane, 2003; Unwin & Corbet, 1984; Villarreal et al., 2017), its age (Belton, 1986; Brogdon, 1994; Ogawa & Kanda, 1986) and the air temperature (Unwin & Corbet, 1984) among others. Thus, in order to develop an algorithm to identify different mosquito species from their flight tone, a training dataset is needed that captures the natural variation within a population. We therefore built a database of wild-captured mosquito flight tones. Live mosquitoes were captured (using the traditional mosquito survey methodologies of human and cow-baited double nets) and recorded in Thailand (Pu Teuy Village, Sai Yok District, Kanchanaburi Province), South East Tanzania (multiple sites within Kilombero and Ulanga Districts) and the Democratic Republic of Congo (multiple sites within Kinshasa and Bandundu).

To record the mosquito sounds (for detailed methodology, see: HumBug Project Website), each captured mosquito was placed into a sample cup large enough for free flight and their flight tone was recorded using a high-specification field microphone (Telenga EM-23) as well as using locally available budget smartphones (LAVA, ITEL, Alcatel) running our MozzWear App (Section 2.1.1). Each individual specimen was identified to species using its morphological characteristics. A number of prominent mosquito vector species belong to groups ('species complexes') of closely related siblings that are taxonomically identical and can contain highly dangerous vectors alongside non-vector species. We therefore used standard PCR identification techniques (Scott et al., 1993) to fully identify mosquitoes from the *An. funestus* and *An. gambiae* species complexes.

Our database also holds flight tone data of multiple species recorded from laboratory cultures. These include recordings from the United States Army Medical Research Unit in Kenya (USAMRU-K), the Center for Disease Control (CDC) Atlanta and the London School of Tropical Medicine and Hygiene (LSTMH).

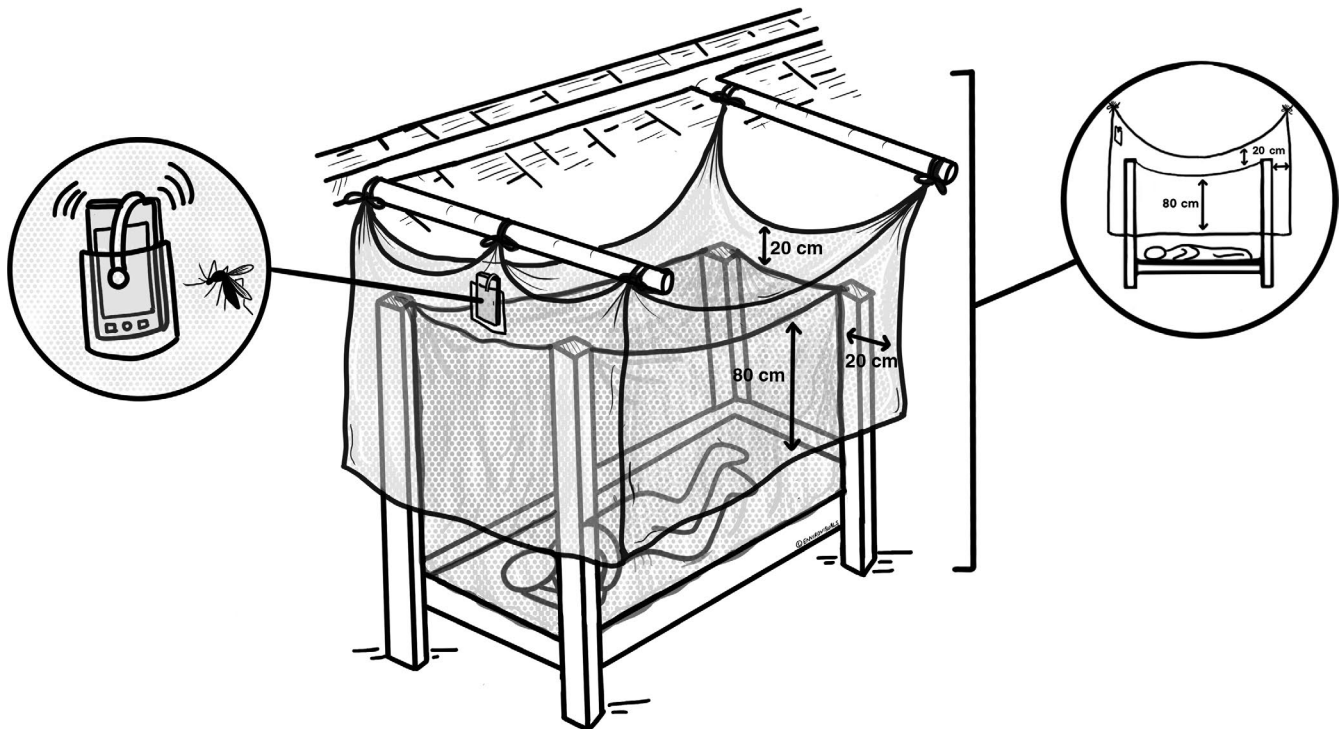


FIGURE 3 The HumBug Net showing the additional outer canopy with a pocket holding a budget smartphone placed above the occupant's head. The higher elevation of this section of canopy and the CO₂ from the occupant's breath attracts and funnels the mosquitoes towards the smartphone [Image: Illustration by EnviroVisuals (EnviroVisuals)]

2.3 | Identification of mosquito species by their sounds

There are many studies that distinguish between different mosquito species using the fundamental frequency of their flight tone (Table 1). The fundamental frequency, measured in Hertz, equates to the number of times the insect flaps its wings per second (Arthur et al., 2014; Belton & Costello, 1979; Williams & Galambos, 1950). However, fundamental frequency alone is not sufficient to differentiate between species (Chen et al., 2014) particularly when using datasets of wild-captured mosquitoes that exhibit natural variability (Figure 4). This led us to consider more data-driven approaches which can learn feature representations to maximally distinguish the various genera or species. Our previous work shows the possibility of distinguishing six species from data recorded in field studies in Thailand (Li et al., 2018). The HumBug workflow (Figure 1), therefore, makes use of both online and offline algorithms. Online, we perform functions critical to the discovery and recording of mosquitoes with our MozzWear smartphone App (see above). Our offline component, described below, is not limited by a phone's computational processing power, allowing more sophisticated modelling to be employed for the purpose of cleaning and preparing our audio data and for the final species identification.

2.3.1 | Mosquito detection

To identify mosquitoes according to their acoustic signature, we used our flight tone database to train a Bayesian convolutional

neural network (Krizhevsky et al., 2017) with Monte Carlo dropout, following a similar architecture to our previous convolutional neural network (Kiskin et al., 2020). The audio was transformed to the spectral domain, in the form of 128 log-mel frequency coefficients. Our choice of features follows the current trends in state-of-the-art algorithms on challenging, realistic datasets in the audio domain (Hershey et al., 2017; Purwins et al., 2019). The Bayesian nature of the algorithm is especially important for making predictions in the field, as we would like to accurately capture any uncertainty our model has of its operating conditions (as indeed our experimental results on latest field trial data from Section 3.4 confirm). To our knowledge, this is the first application which combines Bayesian and deep learning methods in this field, which gives us realistic uncertainty estimation, as well as strong performance in supervised classification.

Future versions of the pipeline will identify and log the species as well as allowing data and SMS messages to be sent to the smartphone, conveying information and reminding the user to charge the phone and deploy it into the bednet each night.

3 | RESULTS AND DISCUSSION

3.1 | MozzWear App

We have now collected over 5,000 hr of uploaded acoustic data from 45 devices with MozzWear installed. The MozzWear App records the mosquito flight tone and the audio is uploaded to a

TABLE 1 Published, species-specific mosquito wing beat frequencies. Upper rows reproduced/adapted from Clements (Clements, 1999) with kind permission from CAB International, Wallingford, UK

Species	Age (days)	Temp (°C)	Wing beat Frequency		Source
			Males (Hz)	Females (Hz)	
<i>Aedes aegypti</i>	2–5	23	557–600	414–453	Clements (1999); Tischener and Schief (1955)
	1–10	22	750 ± 47	508 ± 66	Clements (1999); Moore et al. (1986)
	4	25	715	458	Clements (1999); Brogdon (1994)
	—	32.6 ± 0.5	975.08 ± 8.09	—	Cator et al. (2011)
	4	25	—	460	Brogdon (1994)
	7–28	23	711 ± 78	511 ± 46	Arthur et al. (2014)
<i>Aedes albopictus</i>	4	25	724	544	Clements (1999); Brogdon (1994)
	4	25	—	536	Brogdon (1994)
<i>Aedes diaantaeus</i>	—	24	538 ± 20	330 ± 13	Clements (1999); Tamarina et al., (1980)
	—	28	—	380 ± 22	Clements (1999); Tamarina et al. (1980)
	—	32	—	412 ± 22	Clements (1999); Tamarina et al. (1980)
<i>Aedes communis</i>	—	24	555 ± 14	350 ± 9	Clements (1999); Tamarina et al. (1980)
<i>Aedes punctator</i>	—	24	503 ± 17	308 ± 10	Clements (1999); Tamarina et al. (1980)
<i>Aedes triseriatus</i>	—	22	592 ± 47	388 ± 33	Clements, 1999; Moore et al. (1986)
<i>Aedes vexans</i>	—	21	—	300–350	Clements (1999); Belton and Costello (1979)
<i>Culex pipiens</i>	5	21	—	329–370	Clements (1999); Belton and Costello (1979)
<i>Culiseta inornata</i>	—	21	—	180–250	Clements (1999); Belton and Costello (1979)
<i>Anopheles earlei</i>	—	21	—	190–250	Clements (1999); Belton and Costello (1979)
<i>Anopheles subpictus</i>	—	28	520–580	330–385	Clements (1999); Tischner (1953)
<i>Anopheles arabiensis</i>	2 to >2	24–26	580–820	360–520	Clements (1999); Wekesa et al. (1998)
<i>Anopheles arabiensis</i>	1–2	25	703 ± 8.72	435 ± 4.88	Brogdon (1998)
<i>Anopheles gambiae</i>	2->2	24–26	660–900	420–600	Clements (1999); Wekesa et al. (1998)
<i>Anopheles gambiae</i>	1–2	25	789 ± 4.43	533 ± 6.99	Brogdon (1998)
<i>Anopheles melas</i>	1–2	25	571 ± 8	372 ± 4.62	Brogdon (1998)
<i>Anopheles merus</i>	1–2	25	586 ± 7.06	380 ± 7.15	Brogdon (1998)

central server for post-processing and analysis. It has been successfully tested on multiple Android devices, including those budget models commonly found in Europe (Alcatel) Tanzania (ITEL and LAVA) and DRC (ITEL). Indeed, Mukundarajan et al. (2017) compared a number of mobile phone models, including a 10-year old basic model, from a range of budgets and demonstrated that the microphones are able to record mosquito flight tone at close hand (50 mm) and generate acceptable recordings of tethered and free-flying laboratory mosquitoes.

The native sampling rate of these devices is 8 kHz, which we have shown to be sufficient for the purposes of detection (Kiskin et al., 2020). Audio is compressed to 32 kbps advanced audio codec (aac) format to facilitate data transfer in rural African areas. Furthermore, aac is natively supported in Android not requiring additional third part downloads to run the App. We have tested our algorithms to ensure no performance degradation has occurred due to compression. A thorough comparison is outside the scope of this paper but is part of ongoing work.

3.2 | HumBug Net

The HumBug Net has been assessed in a semi-field setting (publication in prep) to ensure optimal acoustic data collection with minimal impact on the comfort of the user. Two community trials are also currently underway. The first compares the efficacy of the HumBug system with accepted mosquito survey methodologies [Center for Disease Control light traps (CDC-LTs) and human-baited nets]. The second is looking at community acceptance and engagement, examining the willingness of community members to sleep under a HumBug Net and to oversee the charging and placing of the smartphone in the adapted net pocket and upload the audio data once per week. These data will demonstrate the potential for community members to generate much needed longitudinal mosquito survey data and how well they engage with the HumBug concept as a whole.

Preliminary data confirm observations from Thailand, that the HumBug Net successfully captures distinct recordings of host-seeking mosquitoes (Figure 5).

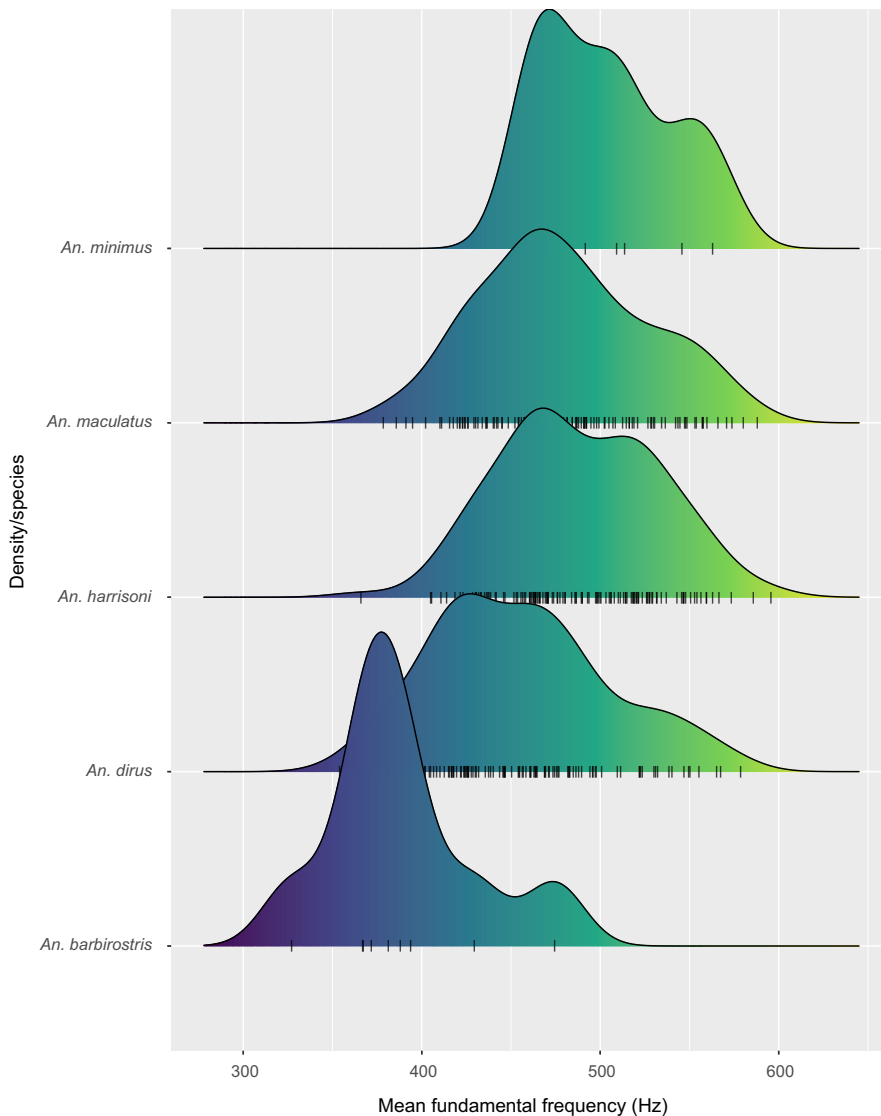


FIGURE 4 A ridgeline density plot of wild-captured mosquitoes (Kasetsart University vector field site near Pu Teuy Village, Sai Yok District, Kanchanaburi Province, Thailand) illustrating the significant overlap in fundamental frequency (FF) between five dominant vectors of human malaria. The mean FF was calculated for each individual sample (each sample represents a flight tone cup recording of a single unique mosquito specimen) from the FF of five non-overlapping randomly selected 0.5 s sections of the audio. The plot visualises the density/frequency of the FF values per species. The black ticks on the x-axis indicate the number of samples and their FF value used to make each plot

Over a six-night pre-trial collection, the mean number of mosquitoes captured by aspiration from within the outer canopy of the HumBug Net in a traditional village house (Igumbiro) was 83. Midway through the collection, a CDC-LT, run in the same house, collected 108 mosquitoes. Although crude, this preliminary evaluation of the ongoing study indicates concordance between the two methods. However, comparing mosquito survey methodologies is notoriously complex. Different methods can target different species (e.g. the species abundance and diversity captured in a CDC-LT can be different to that collected in a Human Baited Net Degefa et al., 2020; Tangena et al., 2015). Acoustic detection will also probably under-represent abundance and, as with all sampling methods, may over-represent certain species, for example those that are predisposed to aggressively seeking out a human host and are more active within the HumBug Net. This may also lead to potential double counting of single mosquitoes. However, the ability to deploy an automated system with minimal supervision and the potential for long-term data collection may outweigh these limitations.

3.3 | Database

Our current mosquito flight tone database, which is the largest and most comprehensive in the world, contains over 6,900 recordings of individual wild-captured mosquitoes from six genera (*Aedes*, *Anopheles*, *Armigeres*, *Coquilletidia*, *Culex* and *Mansonia*) and includes five dominant Asian malaria vector species (*An. barbirostris*, *An. dirus*, *An. harrisoni*, *An. maculatus* and *An. minimus*) as well as the African vectors *An. arabiensis*, *An. coluzzi*, *An. funestus* and *An. pharoensis* (Tables 2 and 3). Data collection is ongoing. The final database will include time-series acoustic data recorded from mosquito populations sampled throughout the rainy and dry seasons. Data collected during the deployment of the MozzWear App in the HumBug Net will continue to feedback into the database. All data will be available with open access via the HumBug Project website (<https://humbug.ox.ac.uk/>).

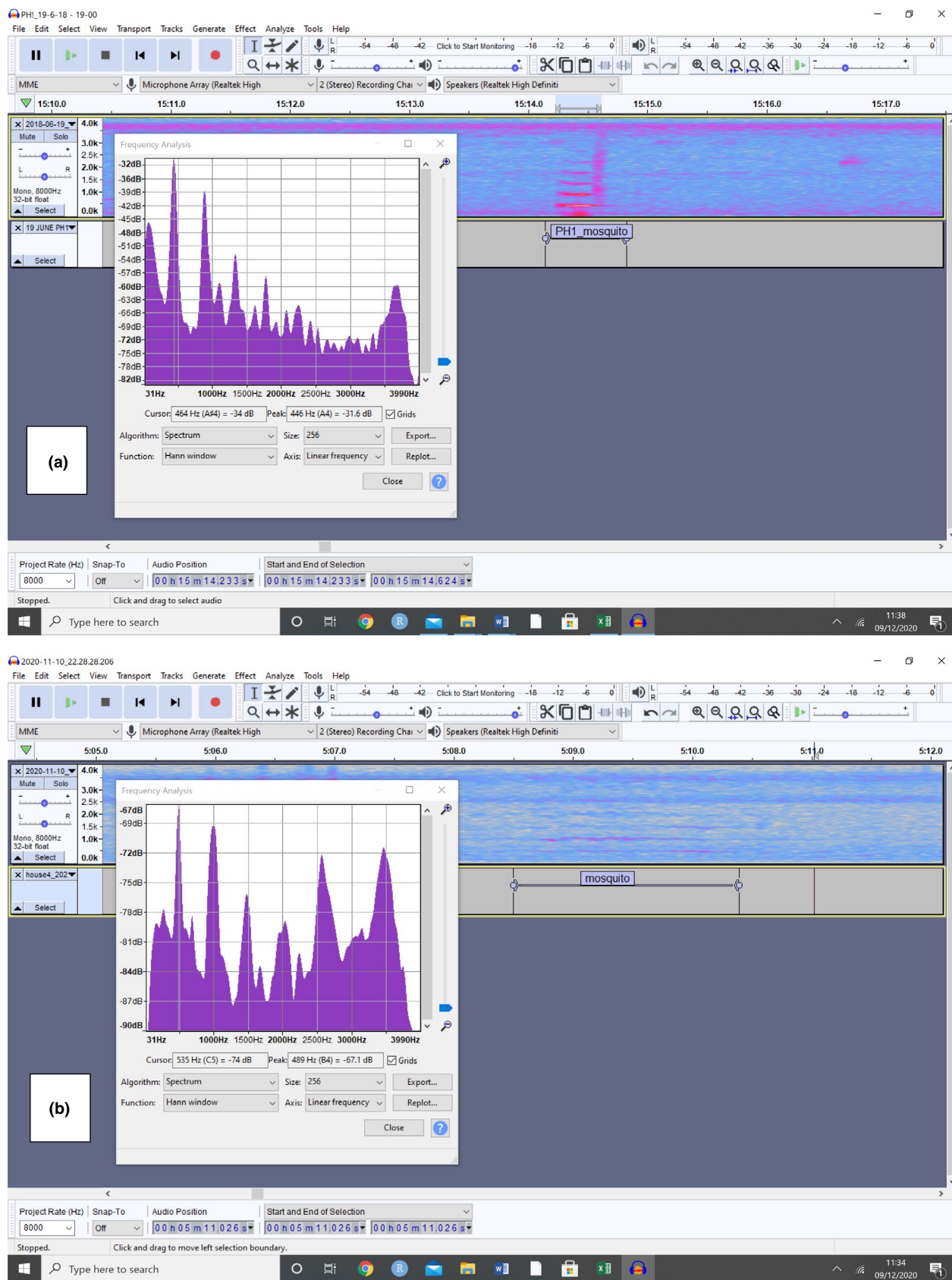


FIGURE 5 (a) Flight tone of 'An. dirus' - FF 446Hz' (Pu Teuy Village) and (b) 'An. arabiensis' - FF 489Hz' (Igumbiro village) captured passively using the HumBug Net

TABLE 2 Summary table of wild captured and recorded mosquitoes in Africa. Species complexes are listed in bold to indicate where additional PCR identification has been conducted with identified sibling species listed below

Species	
An. gambiae s.l.	2,242
An. arabiensis (Gambiae Complex)	y
An. gambiae (Gambiae Complex)	y
An. melas (Gambiae Complex)	y
An. coluzzi (Gambiae Complex)	y
An. funestus s.l.	1,067
An. funestus s.s. (Funestus Complex)	581
An. leesoni (Funestus Complex)	2
An. rivulorum (Funestus Complex)	9
An. paludis	291
An. ziemanni	13
An. coustani	130
An. squamosus	169
An. pharoensis	27
An. maculipalpis	116
Ae. aegypti	382
Ae. albopictus	211
Cx. quinquefasciatus	438
Cx. pipiens complex	801
Culex sp.	262
Culex duttoni	3
Culex tigripes	123
Ma. uniformis	372
Ma. africanus	140
Mansonia sp.	124
Coquillettia sp.	6
	6,917

TABLE 3 Summary table of wild captured and recorded mosquitoes in Thailand

Species	Number of recordings
Aedes sp.	259
An. barbirostris	10
An. dirus	133
An. harrisoni	163
An. maculatus	128
An. minimus	9
Armigeres sp.	285
Culex sp.	66
Mansonia sp.	19
Total	1,072

3.4 | Algorithms and detection capabilities

To build an offline detection algorithm, we train our model on a subset of data from our existing database, and test on a distinctly different subset, to help the generalisation of the algorithm to field data. Our detection algorithm correctly predicts noise with 97% accuracy, and mosquito with 89% on 7.1 hr of database data (Figure 6). Our probabilistic model allows us to both estimate the presence of a mosquito and quantify how certain our model is in its predictions. Here we showcase its effectiveness on field data collected from South East Tanzania. As the certainty threshold is tightened, a greater proportion of predictions are correct, at the expense of an increase in false negative detections. We vary the certainty threshold, the mutual information (Houlsby et al., 2011) from its maximum value of 1.0 through a series of discrete steps as given in Table 4. We calculate the quantity of positives that the model produces for those values and estimate the true positive and negative rates by manually screening the detections for mosquito sound. We note that the dataset is heavily imbalanced, consisting overwhelmingly of noise. This results in the very high true negative rates, which were a strong point of the algorithm on out-of-sample testing, as evidenced by the confusion matrix (Figure 6). Our key result is that the model correctly understands its uncertainty, as the true positive rate increases monotonically with the tightening of the uncertainty threshold. Using a certainty threshold of 0.02 with probability of detection set to 0.7 or greater, Figure 7 shows audio with the 'mosquito' tag that was automatically extracted. The algorithm successfully finds a high-quality, diverse mix of mosquito audio (corresponding to the hand labels which were added upon screening the algorithm output). Following detection of mosquito audio, we can then further classify into species, which we have shown possible in our earlier work (Li et al., 2018) which is an ongoing part of our current research.

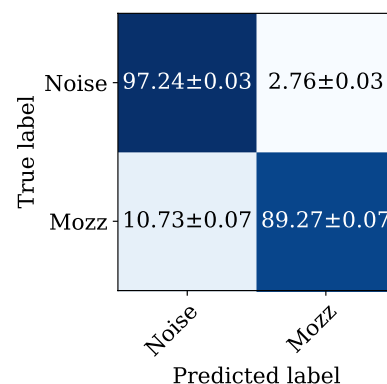


FIGURE 6 Confusion matrix showcasing classification accuracy on out-of-sample mosquito prediction on the data in our extensive database

4 | CONCLUSIONS

Our HumBug project comes at a time when the World Health Organization's (WHO) 2019 World Malaria Report states that the decade-long decrease in malaria mortality rates has 'slowed dramatically' (World Health Organization, 2019) suggesting that our malaria control programs are beginning to fail.

Alongside decreasing levels of investment assigned to fight malaria (in 2019, total funding reached US \$3 billion, a shortfall of \$2.6 billion against the global target of \$5.6 billion), increasing emergence of insecticide resistance is having a big impact. It is now, therefore, more imperative than ever to monitor the presence, abundance and species composition of vectors in areas of endemic malaria transmission as well as those locations closer to their malaria elimination goals. A more in-depth knowledge of the ecology and behaviours (changing or inherent) of the mosquito fauna is vital to tailoring vector control regimes to minimise the emergence of insecticide resistance. As such, HumBug is an extremely timely new tool, one that could be revolutionary in providing a cheap and effective way to monitor vector presence in real time as well as provide high quantities of high quality, environmentally linked,

species-specific data providing unparalleled levels of information about these disease bearing insects. Only by targeting the few dangerous species among the many benign ones can we maintain effective mosquito control and finally eliminate many of the preventable diseases they carry.

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AUTHORS' CONTRIBUTIONS

S.R. and K.J.W. conceived the original project and S.R., K.J.W. and M.E.S. secured the funding; M.E.S. and D.Z. conceived the manuscript; M.E.S. wrote the manuscript with contributions from all the authors. All the authors contributed critically to the drafts and gave final approval for publication; M.E.S. designed the field data collection methods and oversaw the data collections; D.Z., Y.L., D.K. and H.C. developed the app and D.Z. developed the online infrastructure; L.W. designed the database; W.R., I.K. and B.G. developed the offline algorithms; E.H.-M. and H.P. assisted in the data collections and processing.

TABLE 4 Effect of mutual information thresholding on the true positive and true negative rates (TPR and TNR). Positives: duration of audio which was predicted as positive. Mosquito recovered: duration of the mosquito audio which was recovered from all the data, determined by TPR \times Positives

Certainty threshold	TNR	TPR	Positives	Mosquito recovered
1.0	≥ 98	12	18 hr 1 min	2 hr
0.1	≥ 99	30	5 hr 30 min	1 hr 39 min
0.05	≥ 99	54	1 hr 39 min	53 min
0.02	≥ 99.9	58	38 min	22 min
0.01	≥ 99.99	60	20 min	12 min
0.005	≥ 99.99	99	5 min	5 min

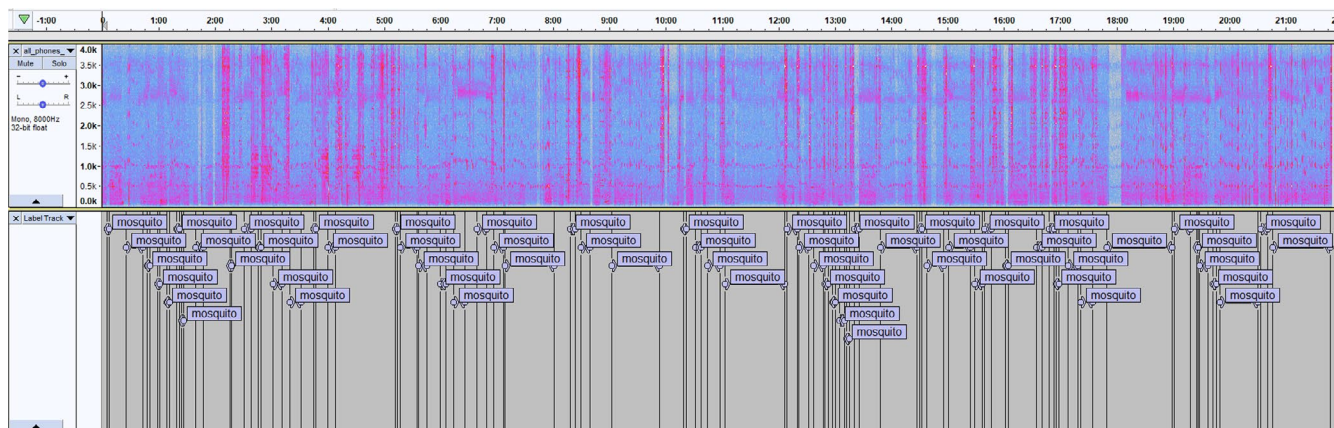


FIGURE 7 Audio with the flag of 'mosquito' automatically extracted and concatenated by the detection algorithm on unlabelled field data (top). The corresponding hand labels added after prediction illustrate the high proportion of correct classifications

PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1111/2041-210X.13663>.

DATA AVAILABILITY STATEMENT

All data generated by the HumBug Project are open access and available via Zenodo <https://zenodo.org/record/4904800> (Kiskin et al., 2021). As acoustic data will be continually generated throughout this project, the database will continue to grow as we curate and add labelled flight tone recordings. Metadata for the database and detailed tutorial code training state-of-the-art baseline Bayesian neural network models are available via Github <https://github.com/HumBug-Mosquito/HumBugDB>.

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REFERENCES

- Arthur, B. J., Emr, K. S., Wyttenbach, R. A., & Hoy, R. R. (2014). Mosquito (*Aedes aegypti*) flight tones: Frequency, harmonicity, spherical spreading, and phase relationships. *Journal of the Acoustical Society of America*, 135, 933–941.
- Belton, P. (1986). Sounds of insects in flight. In W. Danthanatayana (Ed.), *Insect flight: Dispersal and migration* (pp. 60–70). Springer-Verlag.
- Belton, P. (1994). Attraction of male mosquitoes to sound. *Journal of the American Mosquito Control Association*, 10, 297–301.
- Belton, P., & Costello, R. A. (1979). Flight sounds of the females of some mosquitos of western Canada. *Entomologia Experimentalis et Applicata*, 26, 105–114.
- Bomphrey, R. J., Nakata, T., Phillips, N., & Walker, S. M. (2017). Smart wing rotation and trailing-edge vortices enable high frequency mosquito flight. *Nature*, 544, 92–95. <https://doi.org/10.1038/nature21727>
- Brogdon, W. G. (1994). Measurement of flight tone differences between female *Aedes aegypti* and *A. albopictus* (Diptera: Culicidae). *Journal of Medical Entomology*, 31, 700–703. <https://doi.org/10.1093/jmedent/31.5.700>
- Brogdon, W. G. (1998). Measurement of flight tone differentiates among members of the *Anopheles gambiae* species complex (Diptera: Culicidae). *Journal of Medical Entomology*, 35, 681–684. <https://doi.org/10.1093/jmedent/35.5.681>
- Cator, L. J., Arthur, B. J., Ponlawat, A., & Harrington, L. C. (2011). Behavioral observations and sound recordings of free-flight mating swarms of *Ae. aegypti* (Diptera: Culicidae) in Thailand. *Journal of Medical Entomology*, 48, 941–946. <https://doi.org/10.1603/ME11019>
- Chen, Y., Why, A., Batista, G., Mafra-Neto, A., & Keogh, E. (2014). Flying insect detection and classification with inexpensive sensors. *Journal of Visualized Experiments*, e52111. <https://doi.org/10.3791/52111>
- Clements, A. N. (1999). Flight. *The biology of mosquitoes* (pp. 287–332). CABI Publishing.
- Coetzee, M. (2004). Distribution of the African malaria vectors of the *Anopheles gambiae* complex. *American Journal of Tropical Medicine and Hygiene*, 70, 103–104. <https://doi.org/10.4269/ajtmh.2004.70.103>
- Degefa, T., Yewhalaw, D., Zhou, G., Atieli, H., Githeko, A. K., & Yan, G. (2020). Evaluation of human-baited double net trap and human-odour-baited CDC light trap for outdoor host-seeking malaria vector surveillance in Kenya and Ethiopia. *Malaria Journal*, 19, 174. <https://doi.org/10.1186/s12936-020-03244-2>
- EnviroVisuals. <https://www.enviro-visuals.co.uk/>
- Evans, A. (2016). Invertebrates: Malaise trapping. *Inventory and monitoring toolbox: Invertebrates*. Department of Conservation.
- Harbach, R. E. Mosquito taxonomic inventory. <https://mosquito-taxonomic-inventory.info/valid-species-list>
- Hershey, S., Chaudhuri, S., Ellis, D., Gemmeke, F., Jansen, A., Moore, R., Plakal, M., Platt, D., Saurous, R., Seybold, B., & Slaney, M. (2017). CNN architectures for large-scale audio classification. *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 131–135). Institute of Electrical and Electronics Engineers (IEEE).
- Houlsby, N., Huszár, F., Ghahramani, Z., & Lengyel, M. (2011). Bayesian active learning for classification and preference learning. *Preprint arXiv:1112.5745*.
- HumBug Project Website. <https://humbug.ox.ac.uk/sound>
- Jakhete, S. S., Allan, S. A., & Mankin, R. W. (2017). Wingbeat frequency-sweep and visual stimuli for trapping male *Aedes aegypti* (Diptera: Culicidae). *Journal of Medical Entomology*, 54, 1415–1419. <https://doi.org/10.1093/jme/tjx074>
- Johnson, B. J., & Ritchie, S. A. (2016). The Siren's song: Exploitation of female flight tones to passively capture male *Aedes aegypti* (Diptera: Culicidae). *Journal of Medical Entomology*, 53, 245–248.
- Kahn, M. C., Celestin, W., & Offenhauser, W. (1945). Recording of sounds produced by certain disease-carrying mosquitoes. *Science*, 101, 335–336. <https://doi.org/10.1126/science.101.2622.335>
- Kahn, M. C., & Offenhauser, W. Jr (1949). The first field tests of recorded mosquito sounds used for mosquito destruction. *American Journal of Tropical Medicine and Hygiene*, 29, 811–825.
- Karrer, R. (2021). Google WebRTC Voice Activity Detection (VAD) module. GitHub.
- Kirsch, P., McLaughlin, J., Czokajlo, D., & Moore, A. (2007). *Automated detection and recording of mosquitoes – Recorded in the eaves of an African hut*. American Society of Tropical Medicine and Hygiene, AGM.
- Kiskin, I., Pérez Orozco, B., Windebank, T., Zilli, D., Sinka, M. E., Willis, K. J., & Roberts, S. (2017). Mosquito detection with neural networks: The buzz of deep learning. *arXiv*, 1705.05180.
- Kiskin, I., Wang, L., Sinka, M., Willis, K., Cobb, A. D., Gutteridge, B., Zilli, D., Rafique, W., Dam, R., Marinos, T., Li, Y., Killeen, G., Msaky, D., Kaindoa, E., & Roberts, S. J. (2021). HumBugDB: A large-scale acoustic mosquito dataset (Version 0.0.1). *Zenodo*. <https://zenodo.org/record/4904800>
- Kiskin, I., Zilli, D., Li, Y., Sinka, M., Willis, K., & Roberts, S. (2020). Bioacoustic detection with wavelet-conditioned convolutional neural networks. *Neural Computing and Applications*, 32, 915–927. <https://doi.org/10.1007/s00521-018-3626-7>
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet Classification with deep convolutional neural networks. *Communications of the ACM*, 60, 84–90. <https://doi.org/10.1145/3065386>
- Li, Y., Kiskin, I., Sinka, M., Zilli, D., Chan, H., Herreros-Moya, E., Chareonviriyaphap, T., Tisgratog, R., Willis, K., & Roberts, S. (2018). Fast mosquito acoustic detection with field cup recordings: An initial investigation. *Proceedings of Detection and Classification of Acoustic Scenes and Events 2018 Workshop (DCASE2018)*. Tampere University of Technology.
- Li, Y., Zilli, D., Chan, H., Kiskin, I., Sinka, M., Roberts, S., & Willis, K. (2017). Mosquito detection with low-cost smartphones: Data acquisition for malaria research. *NIPS 2017 workshop on machine learning for the developing world*. <https://arxiv.org/abs/1711.06346>
- Maxim, H. S. (1901). Mosquitoes and musical notes. *The Times (letter)*, 11. October 28.
- Mississippi Entomological Museum Web Site: Malaise Traps. Mississippi State University. <https://mississippientomologicalmuseum.org.msstate.edu/collecting.preparation.methods/Malaise.traps.htm>
- Moore, A., Miller, J. R., Tabashnik, B. E., & Gage, S. H. (1986). Automated identification of flying insects by analysis of wingbeat frequencies.

- Journal of Economic Entomology*, 79, 1703–1706. <https://doi.org/10.1093/jee/79.6.1703>
- Mukundarajan, H., Hol, F. J. H., Castillo, E. A., Newby, C., & Prakash, M. (2017). Using mobile phones as acoustic sensors for high-throughput mosquito surveillance. *eLife*, 6. <https://doi.org/10.7554/eLife.27854>
- Ogawa, K., & Kanda, T. (1986). Wingbeat frequency of some Anopheline mosquitoes of East Asia (Diptera: Culicidae). *Applied Entomology and Zoology*, 21, 430–435.
- Potamitis, I., & Rigakis, I. (2016). Measuring the fundamental frequency and the harmonic properties of the wingbeat of a large number of mosquitoes in flight using 2D optoacoustic sensors. *Applied Acoustics*, 109, 54–60. <https://doi.org/10.1016/j.apacoust.2016.03.005>
- Purwins, H., Li, B., Virtanen, T., Schluter, J., Chang, S. Y., & Sainath, T. (2019). Deep learning for audio signal processing. *IEEE Journal of Selected Topics in Signal Processing*, 13, 206–219. <https://doi.org/10.1109/JSTSP.2019.2908700>
- Raman, D. R., Gerhardt, R. R., & Wilkerson, J. B. (2007). Detecting insect flight sounds in the field: Implications for acoustical counting of mosquitoes. *Transactions of the ASABE*, 50, 1481–1485. <https://doi.org/10.13031/2013.23606>
- Ramirez, J., Gorriz, J. M., & Segura, J. C. (2007). Voice activity detection. In M. Grimm, & K. Kroschel (Eds.), *Fundamentals and speech recognition system robustness, robust speech recognition and understanding*. IntechOpen. <https://doi.org/10.5772/4740>
- Sahoo, A. (2018). Voice activity detection for low-resource settings. CS230: *Deep learning*. Stanford University.
- Sane, S. P. (2003). The aerodynamics of insect flight. *Journal of Experimental Biology*, 206, 4191–4208. <https://doi.org/10.1242/jeb.00663>
- Scott, J. A., Brogdon, W. G., & Collins, F. H. (1993). Identification of single specimens of the *Anopheles gambiae* complex by the polymerase chain reaction. *American Journal of Tropical Medicine and Hygiene*, 49, 520–529. <https://doi.org/10.4269/ajtmh.1993.49.520>
- Service, M. W., & Townson, H. (2002). The *Anopheles* vector. In H. M. Gilles & D. A. Warrell (Eds.), *Essential malariology* (pp. 59–84). Arnold.
- Silva, D. F., Souza, V. M. A., Ellis, D. P. W., Keogh, E. J., & Batista, G. E. A. P. A. (2014). Exploring low cost laser sensors to identify flying insect species. *Journal of Intelligent & Robotic Systems*. <https://doi.org/10.1007/s10846-014-0168-9>
- Simoës, P. M. V., Ingham, R. A., Gibson, G., & Russell, I. J. (2016). A role for acoustic distortion in novel rapid frequency modulation behaviour in free-flying male mosquitoes. *Journal of Experimental Biology*, 219, 2039–2047. <https://doi.org/10.1242/jeb.135293>
- Sinka, M. E., Bangs, M. J., Manguin, S., Coetzee, M., Mbogo, C. M., Hemingway, J., Patil, A. P., Temperley, W. H., Gething, P. W., Kabaria, C. W., Okara, R. M., Van Boeckel, T., Godfray, H. C., Harbach, R. E., & Hay, S. I. (2010). The dominant *Anopheles* vectors of human malaria in Africa, Europe and the Middle East: Occurrence data, distribution maps and bionomic precis. *Parasit Vectors*, 3, 117.
- Sinka, M. E., Bangs, M. J., Manguin, S., Rubio-Palis, Y., Chareonviriyaphap, T., Coetzee, M., Mbogo, C. M., Hemingway, J., Patil, A. P., Temperley, W. H., Gething, P. W., Kabaria, C. W., Burkot, T. R., Harbach, R. E., & Hay, S. I. (2012). A global map of dominant malaria vectors. *Parasit Vectors*, 5, 69. <https://doi.org/10.1186/1756-3305-5-69>
- Tamarina, N. A., Zhantiev, R. D., & Fedorova, M. V. (1980). Frequency characteristics of flight sounds and Johnston's organs of sympatric mosquitoes of the genus *Aedes* (Culicidae). [In Russian]. *Parazitologiya*, 14, 398–402.
- Tangena, J. A., Thammavong, P., Hiscox, A., Lindsay, S. W., & Brey, P. T. (2015). The human-baited double net trap: An alternative to human landing catches for collecting outdoor biting mosquitoes in Lao PDR. *PLoS ONE*, 10, e0138735. <https://doi.org/10.1371/journal.pone.0138735>
- Tischener, H., & Schief, A. (1955). Fluggeräusch und Schallwahrnehmung bei *Aedes aegypti* L. (Culicidae). *Zoologischer Anzeiger*, 18(Suppl), 453–460.
- Tischner, H. (1953). Über den Gehörsinn von Stechmücken. *Acustica*, 3, 335–343.
- Unwin, D. M., & Corbet, S. A. (1984). Wingbeat frequency, temperature and body size in bees and flies. *Physiological Entomology*, 9, 115–121. <https://doi.org/10.1111/j.1365-3032.1984.tb00687.x>
- Villarreal, S. M., Winokur, O., & Harrington, L. (2017). The impact of temperature and body size on fundamental flight tone variation in the mosquito vector *Aedes aegypti* (Diptera: Culicidae): Implications for acoustic lures. *Journal of Medical Entomology*. <https://doi.org/10.1093/jme/tjx079>
- Wekesa, J. W., Brogdon, W. G., Hawley, W. A., & Besansky, N. J. (1998). Flight tone of field-collected populations of *Anopheles gambiae* and *An. arabiensis* (Diptera: Culicidae). *Physiological Entomology*, 23, 289–294.
- Williams, C. M., & Galambos, R. (1950). Oscilloscopic and stroboscopic analysis of the flight sounds of drosophila. *Biological Bulletin*, 99, 300–307. <https://doi.org/10.2307/1538745>
- World Health Organization. (2019). *World malaria report*. WHO.

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