Remote Sensing in Ecology and Conservation
Open Access

RESEARCH ARTICLE

An autonomous network of acoustic detectors to map tiger risk by eavesdropping on prey alarm calls

Arik Kershenbaum[1,2], Andrew Markham[3], Holly Root-Gutteridge[4], Bethany Smith[5], Casey Anderson[6], Riley McClaughry[6], Ramjan Chaudhary[7,8], Amogh Vishwakarma[1], Stephen Cummins[1] & Angela Dassow[9]

[1]Girton College, University of Cambridge, Cambridge, UK
[2]Department of Zoology, University of Cambridge, Cambridge, UK
[3]Department of Computer Science, Oxford University, Oxford, UK
[4]University of Lincoln, Lincolnshire, UK
[5]Institute of Zoology, Zoological Society of London, London, UK
[6]VisionHawk Films, Bozeman, Montana, USA
[7]Bardia Nature Conservation Club, Bheri, Nepal
[8]The Den Adventures, Thakurdwara, Nepal
[9]Department of Biology, Carthage College, Kenosha, Wisconsin, USA

Keywords
Alarm calls, automatic detection, distributed autonomous sensors, human-wildlife conflict, interspecific eavesdropping, tigers

Correspondence
Arik Kershenbaum, Girton College, University of Cambridge, Huntingdon Rd, Cambridge CB3 0JG, UK. Tel: +44 1223 760017; E-mail: elk10@cam.ac.uk

Editor: Dr. Vincent Lecours
Associate Editor: Dr. Christos Astaras

Received: 26 June 2025; Revised: 17 December 2025; Accepted: 22 December 2025

doi: 10.1002/rse2.70061

Abstract

Tiger (*Panthera tigris*) attacks are a frequent source of injuries and fatalities among villagers in Nepal, where many communities make extensive use of dense forests for foraging and grazing of livestock. As conservation efforts have boosted the tiger population in the country, a conflict exists between maintaining traditional practises whilst ensuring human safety and protecting endangered predators. Hence, there is a need for cost-effective management strategies that do not reduce habitat use by humans or wildlife. Passive acoustic monitoring (PAM) offers a promising approach to mapping tiger presence in real-time and providing a warning system for villagers. Although tigers vocalize infrequently, their presence triggers alarm calls from prey species, meaning these alarm calls could potentially act as a proxy for detecting tigers. To explore the potential for tracking tigers and other dangerous predators such as leopards using these alarm calls, we designed and tested a PAM system in the Terai region of southern Nepal. We implemented a TinyML low-memory convolutional neural network (~1000 parameters) for chital deer (*Axis axis*) automatic detection—a species that reliably produce loud predator-specific alarm calls—and deployed a distributed network of 10 autonomous interconnected sensors for continuous operation over 3 months. The network transmits chital deer alarm call events via a cellular-connected gateway to a remote base station to generate a heatmap of predator risk. Incidences of high predator risk can be used to alert local forest rangers, who can then inform nearby villagers of areas with a higher likelihood of predator presence. The neural net achieved an F1 score of 0.91 in training and 0.72 in the field. We suggest that this proof of concept indicates that automated PAM could be an effective tool for detecting and tracking tigers and other predators and a potentially valuable tool for facilitating human-wildlife co-existence.

Introduction

The conservation of Bengal tigers (*Panthera tigris*) has been a success story in southern Nepal, with as many as 100 animals in the area of Bardia National Park alone (Shah et al., 2024). Tigers are both a keystone species, maintaining prey populations and supporting biodiversity, and are also a significant source of income for local communities via ecotourism (Thapa et al., 2017). Nonetheless, tigers remain listed as Endangered throughout their range (Goodrich et al., 2022), and rising tiger populations in Nepal have escalated conflicts with humans, with 32 confirmed human fatalities between 2007 and 2014 (Dhungana et al., 2018). Local populations that are at most risk from tiger attacks are those that use the forest as a subsistence resource, but traditional beliefs of human-nature balance lead such communities to remain generally supportive of tiger conservation (Maiti, 2008). Tiger tourism can also bring significant benefits to the community (Dangaura, 2025).

One way to prevent injury from tiger attacks while maintaining traditional forestry practises is to provide local communities with a risk map of their local forests. By avoiding areas with higher predator risk, villagers can maintain access to forest resources more safely. However, tigers are difficult to locate and track, both because of their solitary nature and their large home ranges. GPS-collared tigers can be tracked with precision, but GPS collars are invasive and costly—requiring capturing and sedating individual tigers—cover only those captured individuals and cannot be applied realistically to large tiger populations, such as those of southern Nepal. Camera traps, especially those with automatic recognition of tigers in images, can also be used to identify areas of tiger activity (Linkie et al., 2010). However, camera traps only survey a small area in front of the camera, and so while useful for surveying (Riley et al., 2017), can easily miss detecting tigers when they are present in a specific place at a specific time. What is required is a non-invasive method that can monitor tiger presence reliably over large spatial scales and in close to real-time, which could allow communities living alongside tigers to make informed decisions about where and when it is safest to enter the forest.

Passive acoustic monitoring (PAM) is an important and growing field in wildlife research, and is a non-invasive way to gather large amounts of data remotely on animal behaviour and distribution (Sugai et al., 2019). Large numbers of inexpensive recording devices can be deployed over large areas and will record audio continuously to be recovered and analysed offline. PAM has been shown to be effective at monitoring landscape use, interspecific interactions and conservation priorities for a wide range of terrestrial species (Clink et al., 2017; Kershenbaum et al., 2019; Root-Gutteridge et al., 2024). However, to be useful for widespread monitoring of animal activity, acoustic devices need to be able to detect vocalizations of the focal species, and those vocalizations need to be made frequently enough for location and movement inferences to be made. Although many species, including social predators such as wolves (Harrington & Mech, 1979) vocalise regularly and at high volume such that PAM can be highly effective, ambush predators tend to remain silent when moving through their territory to avoid detection by their prey. Among these, tigers can vocalise loudly, but do so primarily in territorial contexts (Walsh et al., 2003) and so these loud roars are of limited use for tracking via PAM.

Many prey species, however, have evolved natural predator vigilance behaviours, including loud vocal alarm calls to alert conspecific group members in response to predator presence (Fichtel & Kappeler, 2002; Macedonia & Evans, 1993; Walton & Kershenbaum, 2019). In southern Nepal, chital deer (*Axis axis*), grey langurs (*Semnopithecus schistaceus*) and rhesus macaques (*Macaca mulatta*) issue loud alarm calls in response to predator presence, typically tigers and leopards (*Panthera pardus*) (Fugate et al., 2008; Newton, 1989). The chital deer alarm call (Newton, 1989) is loudest and most characteristic (Fig. 1a), being a strongly modulated narrowband chirp between 0.75 and 1.25 kHz. Rhesus macaque alarm calls (Fugate et al., 2008) (Fig. 1b) are noisy, broadband sequences lasting 1–5 s and given repeatedly. Each call is a series of short pulses (about 200 ms). Grey langurs produce shorter, single alarm calls (Newton, 1989) (Fig. 1c), each about 200 ms in length, very broadband (with significant energy well beyond the 8 kHz Nyquist limit of our recordings), but with a concentration of energy in a chirp at similar frequencies to the chital call.

Here we suggest that eavesdropping on these alarm vocalizations, as a proxy for predator presence, can be used to assess the risk of a tiger or leopard being present. In fact, local villagers, nature guides and forest rangers routinely listen for prey alarm calls to alert them to the presence of large predators (R. Chaudhary, pers. comm.). We therefore implemented a system to eavesdrop on the alarm calls of prey species and use their naturally evolved response to predators, automating and computerising detection, and translating this into a central digitised interface where predator risk can be visualised and conveyed to at-risk populations such as local villagers foraging in the forests. It should be noted that while the most dangerous predator for forest-going villagers is the tiger, leopards also cause injury, and so in this study we consider the risk of either as worth reporting.

Reliable automatic detection of animal calls is a well-developed technology (Kershenbaum et al., 2025), possible using large convolutional neural networks (CNNs), and has been demonstrated across a diverse range of species, for example, BirdNet (Kahl et al., 2021). However, such large neural networks require substantial amounts of microprocessor memory and consume large amounts of power and are therefore difficult to implement on small, low-powered edge devices. For example,

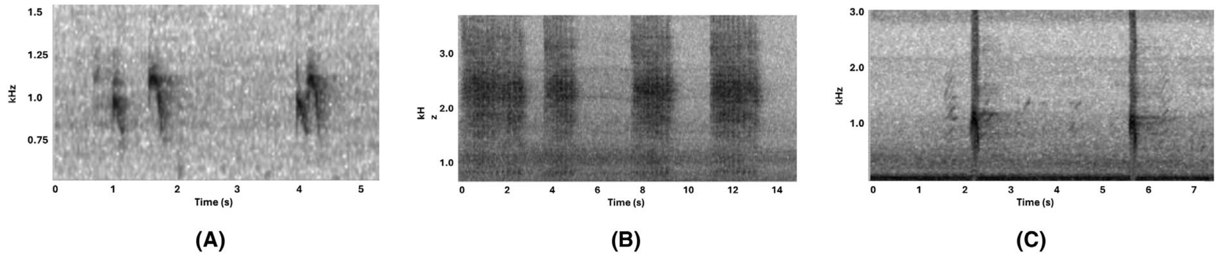

Figure 1. Spectrographic representation of alarm calls. (a) Chital deer alarm calls, showing their characteristic 0.75–1.25 kHz chirp. (b) Rhesus macaque alarm calls, being a series of short pulses, repeating in sets of 1–5 s length. (c) Langur alarm calls, very broadband short bursts.

the BirdNet CNN uses more than 27 million parameters, well beyond the capacity of the CARACAL's 128 kB RAM. Therefore, one of the main goals of this project was to test whether an ultra-small CNN (about 1000 parameters) could perform automatic detection with acceptable performance.

Before deploying a functional system, we needed to determine whether prey species alarm calls are reliably generated in response to tiger presence. To do this, we presented an artificial tiger model to chital deer, grey langurs, and rhesus macaques, and recorded their vocal responses, also monitoring the vocal activity of these species in the absence of tiger presence. As our results strongly suggested that chital deer alarm calls can be used as a reliable indicator of the prey species' perception of predator risk, we then deployed 10 sensor devices for 3 months in a community forest adjacent to the Bardia National Park buffer zone in southern Nepal.

In this study, we deployed PAM devices with onboard automatic detection of prey alarm calls in forests in the Terai region of southern Nepal, with a high occurrence of tiger-human conflict. The devices are based on the open-source CARACAL hardware (Wijers et al., 2021), but also include a LoRa sub-Gigahertz radio so that alarm notification events can be communicated to the outside world without the need to download and process audio recordings manually. The approach known as edge computing (Shi & Dustdar, 2016), in which complex processing is performed on peripheral devices to minimise communication overhead, has seen a rapid increase in popularity in recent years, including in the field of conservation technology (Raghav & Chauhan, 2025). Our remotely deployed acoustic sensors then communicate with a base station, which gathers alarm vocalisation events and generates a heat map indicating the likelihood of tiger presence, based on the frequency and intensity of alarm calls.

This study therefore had three goals: (a) to determine whether chital deer produce alarm calls reliably in response to model predator presentations, (b) to determine whether a very small (1000 parameter) CNN is sufficient to detect chital deer alarm calls automatically and (c) to test the feasibility of using a distributed mesh network of low-cost sensors to perform automatic detection and report to a remote monitoring station for generation of a predator risk map.

The experimental protocols were approved by IACUC #19102023, and carried out with a permit from the Nepal Department of Forests and Environment, #059/022.

Materials and Methods

Study site

The study was carried out in the Dalla (28.40421° N, 81.22958° E) and Khata (28.36813° N, 81.21630° E) community forests around Bardia National Park in southern Nepal (Fig. 2). Community forests are maintained by local trained rangers employed by the Nepal Division Forest Office and provide an opportunity for villagers to forage for food and firewood, as well as grazing livestock. Community forests are an important resource for traditional communities and maintain a productive balance in the natural ecosystem (Nagendra, 2002). However, working in these forests inevitably exposes villagers to injury from wildlife, including tigers as well as rhinoceroses (*Rhinocerous unicornis*), leopards and elephants (*Elephas maximus*) (Acharya et al., 2016). Community forest rangers are also tasked with monitoring for the presence of these potentially dangerous species. The vegetation in the forests is dominated by sal (*Shorea robusta*), silk cotton trees (*Bombax ceiba*) and kamala (*Mallotus philippensis*) (Joshi et al., 2019). In addition, various grass species (e.g. *Tripidium bengalense*) and edible and medicinal plants are collected by villagers for traditional uses (Bhattarai et al., 2011; Brown, 1998). The various aspects of the study took place during the dry season (December–March) with mean daily temperatures between 20°C and 30°C.

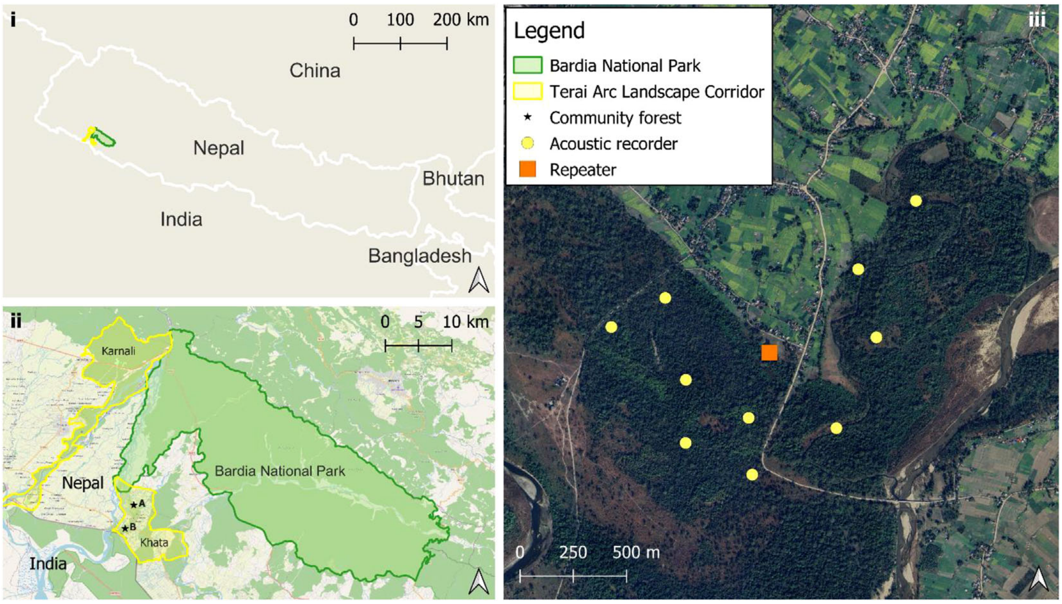

Figure 2. (i & ii) Location of the study area in Nepal, showing the Dalla Community Forest (A) and Khata Community Forest (B) within the Khata Terai Arc Landscape Corridor southwest of Bardia National Park. iii) Locations of the acoustic recorders and repeater during the 3-month deployment period in the Dalla Community Forest.

Tiger presentation

In the first phase of the project, we implemented an experimental protocol to determine whether prey alarm calls are reliable indicators of a response to tiger presence. Previous studies have shown that prey animals respond strongly to artificial predator models (Berthet et al., 2022; Book & Freeberg, 2015; Dassow, 2014). Therefore, we presented wild chital deer, rhesus macaques and grey langurs with a tiger model in the form of a faux tiger skin (Fig. 3) draped over one of the researchers. Once we had identified a group of the focal prey species who were showing normal (non-stressed) behaviour close to the side of the road, one of the researchers would then descend from the vehicle, typically at a distance of more than 50 m from the animals, and hide while putting on the faux tiger skin. The researcher would then slowly approach the animals through the forest, attempting to imitate the motion of a tiger. A presentation was considered successful if the animals did not bolt before seeing the tiger model. The predator presentation continued for 15 min, or until the prey animals had left the area. During this time, another researcher was recording the prey animal vocal responses on a DR-44WL handheld recording device (TASCAM, CA, USA) with an AT8035 shotgun condenser microphone (Audio-Technica, OH, USA). We also recorded this audio on CARACAL devices so that we could train an automatic detector based on the acoustic properties of the CARACAL devices. The tiger presentations were carried out both in the Dalla and Khata community forests. As a control, we also performed presentations to prey with the same human without the tiger costume, to ensure that the prey responses were due to the visual cue of the tiger skin, rather than olfactory. We carried out 7 successful predator presentations to chital deer, 5 to rhesus macaques, and 2 to grey langurs, and 14 presentations to chital deer with a human without the tiger costume, 10 to rhesus macaques, and 11 to grey langurs.

Automatic detection of alarm calls in situ

We deployed 10 CARACAL acoustic recording devices in the Dalla community forest from December 2024 to March 2025 (Fig. 2) at a mean distance of 160 m. CARACAL devices have been shown to detect dogs, coyotes and owls at distances of over 2000 m (Smith et al., 2021). Each CARACAL device was solar powered with a backup battery and required no maintenance during the 3-month deployment (Fig. 4). These devices are equipped with four solid-state microphones and integrated GPS clock synchronization (Wijers et al., 2021). Of the species tested, chital deer most often alarm called in response to the faux tiger presentation (see Results); hence, we implemented an automated PAM system based on detecting the alarm calls of this species only.

To do so, we implemented a lightweight (<1000 parameter) CNN for automatic detection of chital deer

Figure 3. Left: the faux tiger skin used as a predator model. Right: presentation of a faux tiger model to chital deer.

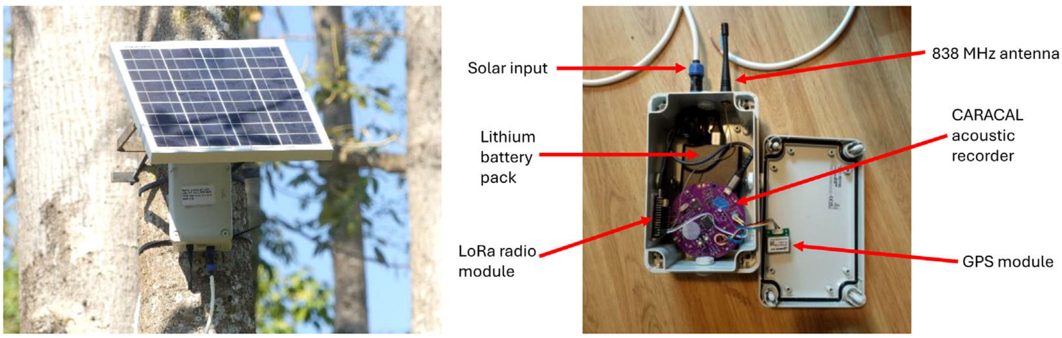

Figure 4. Left: A CARACAL acoustic recording device deployed in the Dalla community forest. Right: the inside of the device showing the various components.

alarm calls that ran on the CARACAL microcontroller using TensorFlow (Abadi et al., 2016) and using EdgeImpulse command line interface to generate embedded C code. Rather than using a full spectrogram image for classification, we instead used a small subset of the entire frequency range (typically from 600 to 1400 Hz) that were aggregated into 10 equally spaced frequency bins using a 512 point real FFT. A sliding window (typically with a stride of 1024 samples) was used to stack 10 of these frequency bins, yielding a 10 × 10 matrix which effectively is a low resolution spectral 'image' of the target call as shown in Fig. 5. This is then supplied to a small deep learning model (typically one or two CNN layers, followed by max pooling and subsequent dense connections) to output a binary classifier output. Based on a threshold, the class confidence is then used to indicate whether a call has been detected or not. To optimise the hyperparameters of the TinyML model, sweeps of various model configurations (number and size of different layers) were conducted to choose a model which showed a good F1-score, whilst being compact enough to run in real-time (typically taking 20 ms to process a 10 × 10 spectral image frame) on the ARM M4F microcontroller running at 80 MHz. A selected configuration is shown in Supplementary S1.

We trained the detector on 26 one-hour audio files, containing 992 chital deer alarm events, and the same number of randomly chosen non-alarm windows. Each of these recordings was collected from CARACAL devices in the Dalla and Khata areas, which were manually scanned for incidents of chital alarm calls. When the CARACAL CNN detects an alarm event, a message is sent to a 838 MHz LoRa radio transmitter (iLabs Challenger RP2040, Invector Labs, Tomelilla, Sweden) that transmits the alarm message once every 30 s.

The repeater device was installed on the edge of the forest at a point with cellular reception. This repeater also contained an RP2040 LoRa device, connected to a Raspberry Pi Zero 2 W single board computer, that monitored the LoRa radio messages and transmitted them via a cellular modem using the AWS SNS protocol. As this system is designed to be installed in forest and jungle areas with

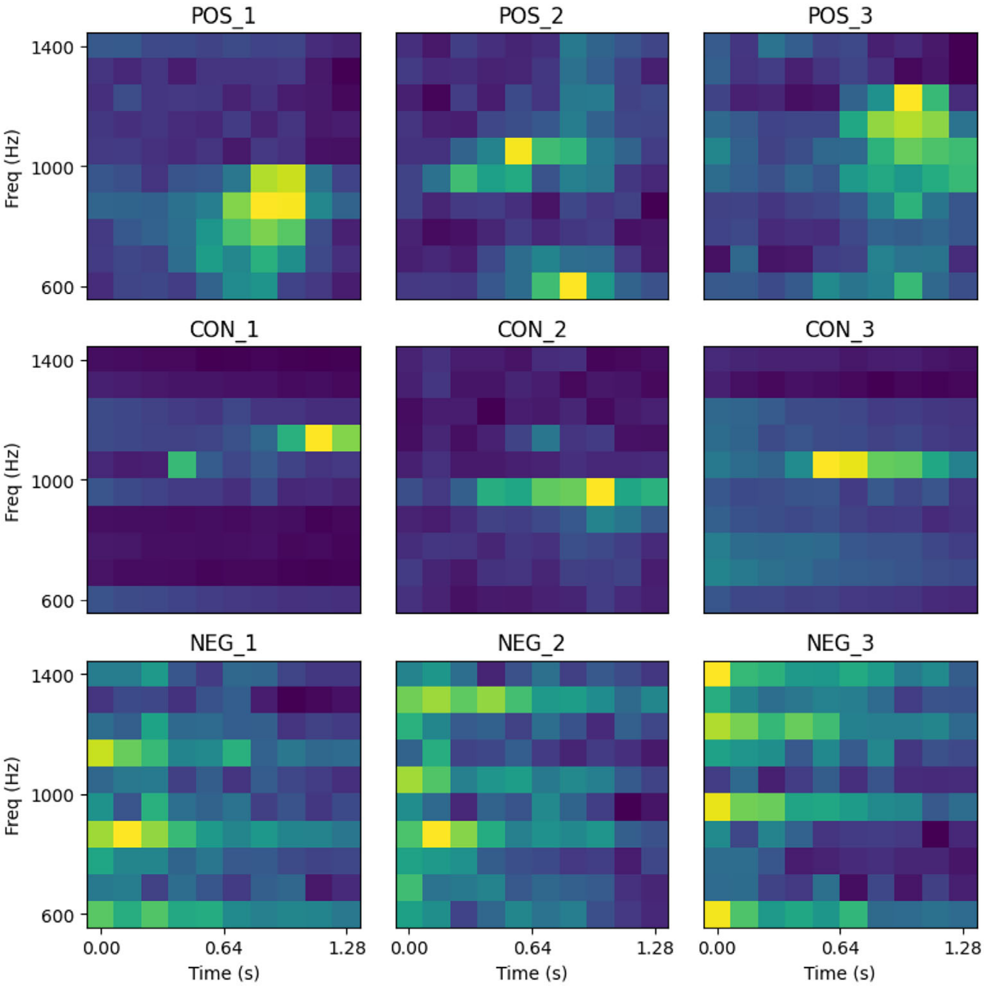

Figure 5. Figure showing the downsampled spectrogram matrices as input to the CNN. Top row: Positive (Chital deer) calls. Middle row: Confounding calls. Bottom row: Negative (background) samples.

no cellular reception, each CARACAL device was programmed to monitor the LoRa frequency and re-transmit any messages from other CARACAL devices, so that even messages from devices far from the cellular-enabled repeater could be transmitted onwards. This kind of mesh network allows information to be extracted from distributed devices, even if each individual device has no internet connectivity.

Once the 3-month deployment period (December 2024–March 2025) was concluded, we gathered all the recorded audio and detailed log files from the CARACAL devices for offline analysis of detection and false alarm rates. We examined the audio files manually to measure how well the system responded to chital deer alarm call presence. We randomly selected 10% of the daytime audio files and manually marked the occurrence of chital deer alarm calls using Raven Pro ('Raven Pro: Interactive Sound Analysis Software (Version 1.6.5)' 2024). We then calculated the false positive rate (FPR) and true positive rate (TPR) for a wide range of detection thresholds (0.5–1.0). These FPR–TPR values were plotted as a receiver operating characteristic plot for varying thresholds of CNN output.

Results

Predator presentations

In total, we made 79 attempted presentations to prey species groups. In 30 of these cases (38%), the animals spotted us preparing the experiment and fled without making any vocalizations, leading to the presentation being aborted. However, we succeeded in carrying out seven successful predator presentations to chital deer, five to rhesus macaques and two to grey langurs. In each of these successful cases (100%) where the animals saw the tiger model before bolting, they produced characteristic alarm calls.

In addition to predator model presentations, we performed 14 presentations to chital deer with a human without the tiger costume, 10 to rhesus macaques and 11 to grey langurs. In only one of these cases (3%) did the animals (chital deer) give a single, short alarm call in response to the humans.

CNN performance

After training the 1000 parameter CNN with a 60/40 training/testing split, the network achieved an F1 score—defined as the harmonic mean of precision and recall (Powers, 2020) —of 91%, 54 false negatives (out of 992 alarm calls) and 2068 false positives over the 26 h of training data. Deploying the system in the field, the CARACAL devices recorded c. 11,000 h of audio in total. Manually reviewing 10% of the daytime files from the field recordings, we found 360 chital alarm calls in 10 separate files out of the 1-h recordings. These 360 calls fell into 23 separate alarm calling bouts, where a bout was defined as a series of calls separated by at least 30 s of silence. Running those 10 files through the CNN offline, and varying the detection threshold from 0.5 to 1.0 (Fig. 6), the maximum F1 achieved was 0.72 at a detection threshold of 0.725, with the maximum true positive detection rate 0.87, that is, a maximum of 20 out of the 23 alarm bouts were detected. The maximum FPR was 4.1 per hour, and at the threshold with the maximum F1 score, the false alarm rate was 2.5 per hour.

Mesh network system

The system ran continuously over the 3 months of deployment (December–March), and alarm messages were received at the remote monitoring station in the United Kingdom throughout that period. Alarm incidents were displayed on a map (Fig. 7) using kernel density estimation with user-specified bandwidth, and allowing alarm signals to decay temporally with a user-specified decay constant. These parameters can be varied to allow time and space correlations between alarms to be investigated. The multi-hop mesh network was effective in allowing messages from distant units to reach the repeater by being retransmitted by intermediate detector units.

A number of technical challenges remain. For example, the repeater unit suffered from consistent daily downtime during the middle of the day, presumably due to overheating (Fig. 8). However, as the afternoon progressed, the repeater inevitably recommenced sending messages.

Discussion

Predator presentations

Alarm calls were initiated in the target prey species using a predator model, as has been shown in previous studies (Berthet et al., 2022; Book & Freeberg, 2015; Dassow, 2014). Our experiments indicated that the alarm calls appear to be specific to predator presence, as chital deer almost never alarm called in response to human presence without the faux tiger skin in our experiments. This is a strong indication that prey alarm calls can act as a proxy for inferring predator presence, as a form of interspecific eavesdropping. Furthermore, since local villagers make use of the forest for daily activities, it is important that any predator warning system distinguishes between human presence and true predator presence, to avoid false identification of high-risk areas. In more than a third of presentations, the deer fled without making any alarm calls. This could indicate either that the animals identified the researchers and fled silently with no need for an alarm call, or that the deer sometimes do flee identified tigers without giving any call. In the latter case, deer alarm calls would provide an underestimate of tiger risk; however, it is not possible to distinguish these two cases from our experiments.

Validation of tiger presence while prey species are alarm calling is unrealistic, as tiger presence is difficult to predict. However, the use of prey alarm calls by wildlife guides to direct tourists to tiger locations is an indication that prey do indeed alarm call in response to real tiger presence, as well as to artificial model presentations. Although many animal predator alarm calls are highly specific (Fichtel & Kappeler, 2002; Macedonia & Evans, 1993; Walton & Kershenbaum, 2019), leopards are another large feline predator common in the study area that also prey on both monkeys and deer. As such, it is not yet known whether the alarm calls are specific to tigers or predators, and it seems likely that prey animals would not distinguish in their alarm calls between different types of big cats. However, as leopards also pose a threat to humans working in the forest, we consider that listening for prey alarm calls, which could be a response to either tiger or leopard presence, is an advantage rather than a limitation of the system.

CNN performance

The CNN implemented within a very small memory footprint (1000 parameters) was remarkably successful in detecting chital deer alarm calls. Although detection vs. false alarms will inevitably not approach the performance of a full-size CNN, the system running on low-cost,

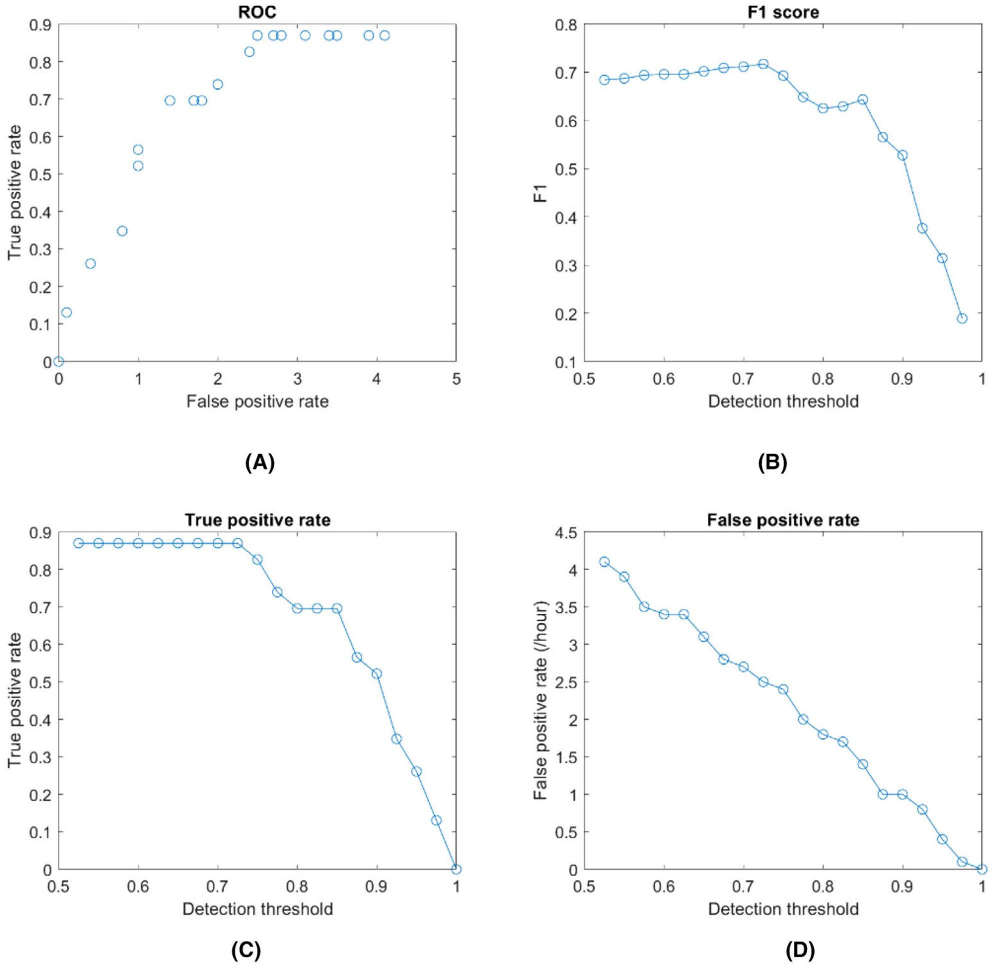

Figure 6. (a) Receiver Operator Characteristic curve, showing false positive rate against true positive rate, for varying alarm detection thresholds. Points closest to the upper-left corner show the best performance. (b) F1 statistic plotted against detection threshold. (c) True positive rate (proportion) against detection threshold. (d) False positive rate (number of false alarms per hour) against detection threshold.

low-power edge devices still detected alarm calls reliably. Reduction in the false alarm rate is essential to the long-term operation of an automated system, to prevent alarm fatigue in operators. Although further studies would be necessary to determine an acceptable alarm rate, it should be noted that community rangers are present patrolling the forests throughout much of the day, and the system would mostly fulfil the role of directing them to areas of concern. One principle of edge computing is that further analysis is always possible at the remote station, and in this case, it would be possible to reduce false alarm rates even further by looking for temporal and spatial correlation between CNN alarms (Kershenbaum et al., 2025), that is, to trigger an alarm only when multiple calls are detected, or only when calls are detected simultaneously on adjacent devices. In our system, we provided a limited form of such post-analysis by allowing the user to configure the spatial and temporal smoothing of the alarm maps, but further work is required to find optimal criteria for alerting local populations of predator risk. The ability of the CARACAL device to localise the sound source using time difference of arrival (Smith et al., 2021; Wijers et al., 2021) would provide additional validation via spatial correlation between devices.

Mesh network system

Effective edge computing systems require communication with a remote base station, and cellular reception is both power-intensive and not always available at remote locations. We have conclusively demonstrated the effectiveness of using a mesh network of detector devices equipped with short range, low-power wireless communication, routing messages from one device to another until

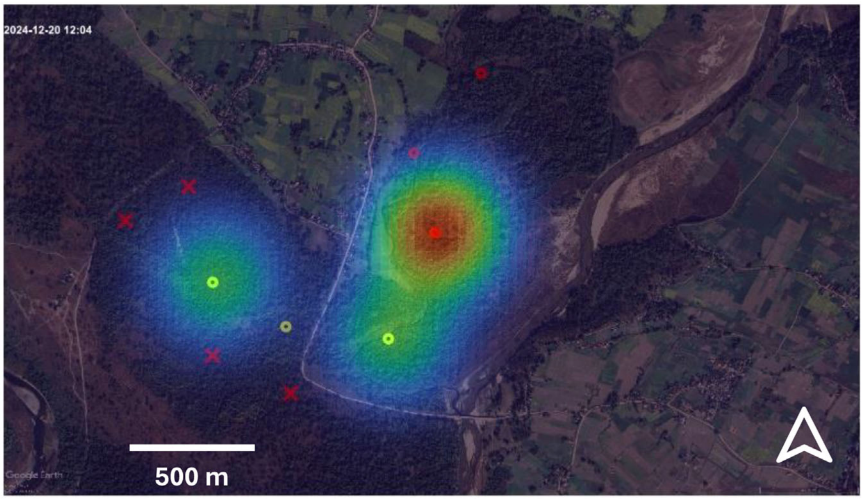

Figure 7. An example alarm map as generated at the remote base station, using a kernel bandwidth of 100 m. Older alarms decay in intensity according to user-defined parameters, as can be seen in the southern and western alarms, whereas the northern alarm is more recent.

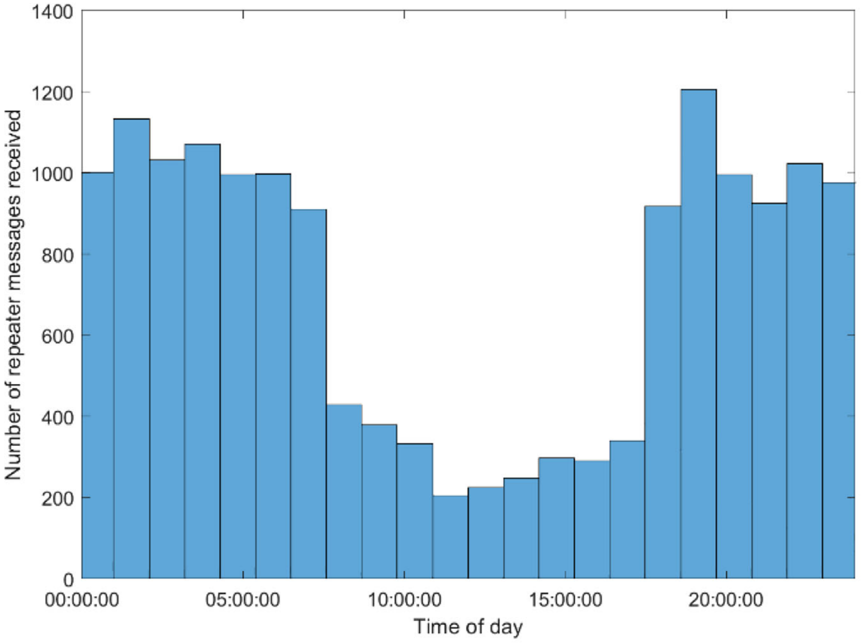

Figure 8. Number of messages received from the repeater as a function of time of day. The reduced number of messages in the middle of the day represents times when the repeater shut itself down unexpectedly.

they reach a single repeater device, equipped with cellular connection to the internet. The ability to monitor from across the world the precise CNN output from devices deep in the forest shows the power and potential of the edge computing paradigm. Power consumption did not seem to be a problem: modest 20 W solar panels with backup batteries were sufficient for both the CARACAL units and the repeater.

Some technical challenges inevitably remain. In particular, temperature control is problematic in hot climates without active dissipation technologies, which would require substantially increased power supply. The environmental extremes of the monsoon season may cause additional challenges. Our team is currently working on addressing these challenges. A future version of the system could use camera traps with automatic predator recognition both to validate the system and to improve detection.

Conclusions

We have demonstrated a proof of concept large predator risk monitoring system, based on eavesdropping on the alarm calls of prey species. We successfully implemented automatic detection software on low-cost ($60), low-power edge devices, which communicated alarm events via a wireless mesh network to a repeater device, and then via cellular to the internet. Such a system can be used to monitor predator movement and alert local populations to avoid high-risk areas of the forest. Despite the challenges of validating a monitoring system based on eavesdropping alone as a proxy for predator presence, we are currently investigating the possibility of using the small number of GPS-collared tigers as a reference sample. The next step is creating a scalable, practical system for protecting vulnerable villagers by reducing false positives and establishing robust reporting and alerting protocols that are accessible to populations in high-risk areas.

Acknowledgements

We are very thankful to the Big Cat Initiative of the Great Plains Foundation for their generous ongoing support in funding this project. Dinesh Neupane and Abarta Pandey from ZSL Nepal helped greatly with arranging permits. The Nepal Forestry Department, and especially Shabnam Thapak, has been very supportive in allowing access to the community forests, and we would particularly like to thank the local rangers, Thengchu and Sukhna, who helped us to deploy the equipment and kept us safe from real tigers. Thanks also to Suman, the proprietor of Freedom Bar.

Author Contributions

Arik Kershenbaum: Conceptualization; investigation; funding acquisition; writing – original draft; writing – review and editing; visualization; validation; methodology; software; formal analysis; project administration; resources; supervision; data curation. **Andrew Markham:** Conceptualization; methodology; software; validation; resources; writing – review and editing; investigation. **Holly Root-Gutteridge:** Conceptualization; methodology; validation; funding acquisition; project administration; writing – review and editing. **Bethany Smith:** Conceptualization; methodology; validation; funding acquisition; project administration; writing – review and editing. **Casey Anderson:** Conceptualization; funding acquisition; investigation; writing – review and editing; resources; supervision; methodology; visualization. **Riley McClaughry:** Investigation; writing – review and editing; resources; methodology; visualization. **Ramjan Chaudhary:** Conceptualization; methodology; investigation; supervision; resources; project administration; writing – review and editing. **Amogh Vishwakarma:** Methodology; software; investigation; validation; formal analysis; writing – review and editing. **Stephen Cummins:** Supervision; methodology; conceptualization; software; validation; project administration; writing – review and editing. **Angela Dassow:** Conceptualization; methodology; software; data curation; supervision; formal analysis; validation; investigation; funding acquisition; writing – original draft; writing – review and editing; visualization; project administration; resources.

Data Availability Statement

The source code for the CNN can be found here https://github.com/amoghvk21/CaracalChitalDetector/tree/main. The raw audio recordings amount to 1.5 Tb and are available on request.

References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M. et al. (2016) {TensorFlow}: a system for {large-scale} machine learning. 265–283. https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi.

Acharya, K.P., Paudel, P.K., Neupane, P.R. & Köhl, M. (2016) Human-wildlife conflicts in Nepal: patterns of human fatalities and injuries caused by large mammals. *PLoS One*, **11**(9), e0161717. https://doi.org/10.1371/journal.pone.0161717

Berthet, M., Mesbahi, G., Cäsar, C. & Zuberbühler, K. (2022) Impact of predator model presentation paradigms on Titi monkey alarm sequences. *Behavioral Ecology and Sociobiology*, **76**(11), 143. https://doi.org/10.1007/s00265-022-03250-1

Bhattarai, S., Pant, B. & Upadhyaya, C.P. (2011) Dependency of Tharu communities on wild plants: a case study of Shankarpur, Kanchanpur District. *Banko Janakari*, **21**(1), 35–40. https://doi.org/10.3126/banko.v21i1.9062

Book, D.L. & Freeberg, T.M. (2015) Titmouse calling and foraging are affected by head and body orientation of cat predator models and possible experience with real cats. *Animal Cognition*, **18**(5), 1155–1164. https://doi.org/10.1007/s10071-015-0888-7

Brown, K. (1998) The political ecology of biodiversity, conservation and development in Nepal's Terai: confused meanings, means and ends. *Ecological Economics*, **24**(1), 73–87. https://doi.org/10.1016/S0921-8009(97)00587-9

Clink, D.J., Bernard, H., Crofoot, M.C. & Marshall, A.J. (2017) Investigating individual vocal signatures and small-scale patterns of geographic variation in female Bornean gibbon (*Hylobates muelleri*) great calls. *International Journal of Primatology*, **38**(4), 656–671. https://doi.org/10.1007/s10764-017-9972-y

Dangaura, M. (2025) Eco-tourism and associate lives across Tharu-inhabited region of India-Nepal border. *Literary Studies*, **38**(1), 70–79. https://doi.org/10.3126/litstud.v38i1.75937

Dassow, A. (2014) Exploring the interior structure of white-handed Gibbon and rat vocal communication – ProQuest. PhD, University of Wisconsin, Madison. https://www.proquest.com/openview/40b690edf5d6cc38431a0bc50bef07a8/1?pq-origsite=gscholar&cbl=18750.

Dhungana, R., Savini, T., Karki, J.B., Dhakal, M., Lamichhane, B.R. & Bumrungsri, S. (2018) Living with tigers *Panthera tigris*: patterns, correlates, and contexts of human–Tiger conflict in Chitwan National Park, Nepal. *Oryx*, **52**(1), 55–65. https://doi.org/10.1017/S0030605316001587

Fichtel, C. & Kappeler, P.M. (2002) Anti-predator behavior of group-living Malagasy primates: mixed evidence for a referential alarm call system. *Behavioral Ecology and Sociobiology*, **51**(3), 262–275. https://doi.org/10.1007/s00265-001-0436-0

Fugate, J.M.B., Gouzoules, H. & Nygaard, L.C. (2008) Recognition of rhesus macaque (*Macaca mulatta*) Noisy screams: evidence from conspecifics and human listeners. *American Journal of Primatology*, **70**(6), 594–604. https://doi.org/10.1002/ajp.20533

Goodrich, J, Wibisono, H, Miquelle, D, Lynam, A.J., Sanderson, E, Chapman, S et al. (2022) *Panthera tigris*. The IUCN red list of threatened species. https://doi.org/10.2305/IUCN.UK.2022-1.RLTS.T15955A214862019.en.

Harrington, F.H. & Mech, L.D. (1979) Wolf howling and its role in territory maintenance. *Behaviour*, **68**, 207–249. https://doi.org/10.1163/156853979X00322

Joshi, R., Chhetri, R. & Yadav, K. (2019) Vegetation analysis in community forests of Terai region, Nepal. *International Journal of Environment*, **8**(3), 68–82. https://doi.org/10.3126/ije.v8i3.26667

Kahl, S., Wood, C.M., Eibl, M. & Klinck, H. (2021) BirdNET: a deep learning solution for avian diversity monitoring. *Ecological Informatics*, **61**, 101236. https://doi.org/10.1016/j.ecoinf.2021.101236

Kershenbaum, A., Akçay, Ç., Babu-Saheer, L., Barnhill, A., Best, P., Cauzinille, J. et al. (2025) Automatic detection for bioacoustic research: a practical guide from and for biologists and computer scientists. *Biological Reviews*, **100**(2), 620–646. https://doi.org/10.1111/brv.13155

Kershenbaum, A., Owens, J.L. & Waller, S. (2019) Tracking cryptic animals using acoustic Multilateration: a system for long-range wolf detection. *The Journal of the Acoustical Society of America*, **145**(3), 1619–1628. https://doi.org/10.1121/1.5092973

Linkie, M., Guillera-Arroita, G., Smith, J. & Rayan, D.M. (2010) Monitoring tigers with confidence. *Integrative Zoology*, **5**(4), 342–350. https://doi.org/10.1111/j.1749-4877.2010.00215.x

Macedonia, J.M. & Evans, C.S. (1993) Essay on contemporary issues in ethology: variation among mammalian alarm call systems and the problem of meaning in animal signals. *Ethology*, **93**(3), 177–197. https://doi.org/10.1111/j.1439-0310.1993.tb00988.x

Maiti, S. (2008) Supernatural and religious world of the Tharu. *The Oriental Anthropologist: A Bi-annual International Journal of the Science of Man*, **8**(1–2), 189–198. https://doi.org/10.1177/0976343020080113

Nagendra, H. (2002) Tenure and forest conditions: community forestry in the Nepal Terai. *Environmental Conservation*, **29**(4), 530–539. https://doi.org/10.1017/S0376892902000383

Newton, P.N. (1989) Associations between langur monkeys (*Presbytis entellus*) and chital deer (*Axis axis*): chance encounters or a mutualism? *Ethology*, **83**(2), 89–120. https://doi.org/10.1111/j.1439-0310.1989.tb00522.x

Powers, D.M.W. (2020) Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. ArXiv. https://doi.org/10.48550/arXiv.2010.16061

Raghav, Y.Y. & Chauhan, A. (2025) Tech for the wild: leveraging IoT and cloud computing in wildlife conservation. In: *AI and machine learning techniques for wildlife conservation*. New York, NY: IGI Global Scientific Publishing, pp. 49–64. https://doi.org/10.4018/979-8-3693-6935-7.ch003

Raven Pro: Interactive Sound Analysis Software (Version 1.6.5). (2024) K. Lisa Yang Center for Conservation Bioacoustics at the Cornell Lab of Ornithology. https://www.ravensoundsoftware.com/.

Riley, M., Soutyrina, S., Miquelle, D., Hayward, G., Goodrich, J. & Buskirk, S. (2017) Comparison of methods for estimating Amur Tiger abundance. *Wildlife Biology*, **2017**(1), wlb.00253. https://doi.org/10.2981/wlb.00253

Root-Gutteridge Holly Smith Bethany Kershenbaum Arik Butkiewicz Hannah Fontaine Amy Owens Jessica et al. (2024) Not afraid of the big bad wolf: calls from large predators do not silence mesopredators. January. https://www.repository.cam.ac.uk/handle/1810/362859

Shah, S.K., Karki, J.B., Bhatta, B., Subedi, N., Lamichhane, B.R., Bahadur, K.C.R. et al. (2024) Recovery of tigers (*Panthera tigris*): assessing ecological carrying capacity in Bardia-Banke complex, Nepal. *Global Ecology and Conservation*, **56**, e03326. https://doi.org/10.1016/j.gecco.2024.e03326

Shi, W. & Dustdar, S. (2016) The promise of edge computing. *Computer*, **49**(5), 78–81. https://doi.org/10.1109/MC.2016.145

Smith, B.R., Root-Gutteridge, H., Butkiewicz, H., Dassow, A., Fontaine, A.C., Markham, A. et al. (2021) Acoustic localisation of wildlife with low-cost equipment: lower sensitivity, but No loss of precision. *Wildlife Research*, **49**(4), 372–381. https://doi.org/10.1071/WR21089

Sugai, L.S.M., Silva, T.S.F., Ribeiro, J.W., Jr. & Llusia, D. (2019) Terrestrial passive acoustic monitoring: review and perspectives. *Bioscience*, **69**(1), 15–25. https://doi.org/10.1093/biosci/biy147

Thapa, B., Aryal, A., Roth, M. & Morley, C. (2017) The contribution of wildlife tourism to Tiger conservation (*Panthera tigris* Tigris). *Biodiversity*, **18**(4), 168–174. https://doi.org/10.1080/14888386.2017.1410443

Walsh, E., Wang, L., Armstrong, D., Curro, T., Simmons, L. & McGee, J.A. (2003) *Acoustic communication in Panthera tigris: a study of tiger vocalization and auditory receptivity*. Lincoln, NE: Durham School of Architectural Engineering and Construction: Faculty Publications. https://digitalcommons.unl.edu/archengfacpub/38

Walton, B. & Kershenbaum, A. (2019) Heterospecific recognition of referential alarm calls in two species of lemur. *Bioacoustics*, **28**(6), 592–603. https://doi.org/10.1080/09524622.2018.1509375

Wijers, M., Loveridge, A., Macdonald, D.W. & Markham, A. (2021) CARACAL: a versatile passive acoustic monitoring tool for wildlife research and conservation. *Bioacoustics*, **30**(1), 41–57. https://doi.org/10.1080/09524622.2019.1685408

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1.

