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Research Article

Passive Acoustic Monitoring of Asian Hornbill: A Case Study of Oriental Pied Hornbill (*Anthracoceros albirostris convexus*) in the Lower Kinabatangan Wildlife Sanctuary, Sabah

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ABSTRACT

Asian hornbills are keystone species in tropical forests for their various ecological functions. However, they are faced with threats including poaching, habitat loss, and habitat degradation, highlighting the need for effective monitoring of these iconic birds. This case study of the Oriental Pied Hornbill (*Anthracoceros albirostris convexus*) demonstrates the application of passive acoustic monitoring with a deep learning model in hornbill monitoring, comparing its efficacy to manual surveys. We also compare operational costs in data collection for both approaches. The study took place in Lot 6 of the Lower Kinabatangan Wildlife Sanctuary, Sabah, Borneo. We utilized AudioMoth Dev 1.0.0 combined with manual surveys to evaluate hornbill occurrence across 23 monitoring stations within a 5 km^2 study area. A Bayesian multi-method occupancy model was utilized to estimate detection probability and site occupancy, integrating data from visual, aural, and PAM-based surveys. *A. albirostris* demonstrated a high posterior probability of occupancy estimate across sites ($\psi = 0.743$). Posterior probabilities of detection were $\theta = 0.893$ for manual surveys and $\theta = 0.670$ for PAM. Assessment of the BirdNET deep learning model for automated identification of *A. albirostris* indicated a high precision of 0.96 with recall and F1 score of 0.46 and 0.62, respectively. Furthermore, PAM reduced monitoring expenses by 71% relative to manual surveys, mostly owing to decreased personnel and logistical demands. Our research indicates that PAM, enhanced by convolutional neural networks such as BirdNET, provides a scalable and economical approach for future monitoring of Asian hornbills.

Keywords: BirdNET; bioacoustics; Borneo; Bucerotidae; machine learning.

INTRODUCTION

Passive acoustic monitoring (PAM) is an increasingly popular approach used in terrestrial ecology research and monitoring (Sugai et al., 2019). Its growing popularity is mainly driven by the reduction in cost of the autonomous recording units (ARUs) (Hill et al., 2018), together with advances in data storage, battery lifespan, and flexible device configurations (Aide et al., 2013; Baumgartner et al., 2013). ARUs are currently available at various prices with affordable options, such as AudioMoth (Hill et al., 2018), SwiftOne (Cornell Lab of Ornithology, NY, USA), Song Meter (Wildlife Acoustics, MA, USA), and BAR-LT (Frontier Labs, QSD, Australia).

PAM has been applied across a wide range of scientific studies, including behavioural and movement ecology (Sanders & Mennill 2014; Gayk & Van Doren, 2025). More recently, it was applied beyond presence-absence studies (see examples in Duchac et al., 2020 and Hack et al., 2024), specifically in addressing population-level questions such as abundance and density. A variety of methods have been proposed such as using soundscape indices (Orben et al., 2019; Bradfer-Lawrence et al., 2020); sound pressure level-based distance estimation (Sebastián-González et al., 2018); triangulation-based spatial localization (Yip et al., 2020; Theuerkauf et al., 2025); and analyzing acoustic metrics like cue and vocal activity rate across recordings (Pérez-Granados et al., 2021). While these approaches vary in assumptions, they collectively illustrate the expanding application of PAM in wildlife ecology.

In addition, the field of ecology has also seen a dramatic shift with machine learning integration in data processing and analysis, particularly in its ability to automatically detect species directly from raw recordings collected with PAM (Stowell, 2022). The development of an open access deep learning model like BirdNET (Kahl et al., 2021), for example, has improved bioacoustics studies by significantly reducing the resources associated with manual approach in data processing and analysis, which include time, money, and personnel. BirdNET (v2.4) is currently trained on over 6,000 species with birds making up most of the species (Kahl et al., 2021).

Despite the popularity of PAM and the continuous advancement in automated approaches, distance sampling techniques (Buckland et al., 1993) remain a standard in Asian hornbill studies (Raman et al., 2024). These techniques include two primary methodologies: the line transect method (Burnham et al., 1980) and the point transect method (Reynolds et al., 1980), which often require significant investment in labour, time, and financial resources. For example, Buckland et al. (1993) propose a minimum of 60–80 detections for reliable fitting of a detection function, but Marsden (1999) contends that species such as hornbills may want up to 2,000 detections for accurate density estimations. Obtaining such amount of data (detections) in hornbill studies surely requires substantial resources especially in challenging field environments (Mudappa & Raman, 2009).

The Oriental Pied Hornbill (*Anthracoceros albirostris*) consists of two subspecies: *Anthracoceros albirostris albirostris*, which occurs in the Oriental region extending southward to southern Thailand and the northern region of Peninsula Malaysia, and *Anthracoceros albirostris convexus*, found throughout the Sundaic region of Peninsular Malaysia, Sumatera, and Borneo (Poonswad et al., 2013; Kemp & Boesman, 2020). It is listed as Least Concern on the IUCN Red List, but the Oriental Pied Hornbill (hereafter *A. albirostris*) is a protected species across its distribution in Borneo (see Table 1). *A. albirostris* is distinguished for its black-and-white plumage and its protruding cream-coloured keratin casque with a black marking on the anterior portion (Fig. 1). Due to its high adaptability, this species is widespread throughout vast range of degraded and modified landscapes, and can easily be identified by its loud calls (Rahman et al. 2019; Yahya et al., 2024). Its wide distribution and vocal behaviour make it a suitable species for this case study.

Table 1: Different laws protecting *A. albirostris* across countries in Borneo.

Jurisdiction	Main law & legal listing	Key provisions
Sabah, Malaysia	Wildlife Conservation Enactment 1997, [Schedule 2, Section 2, Section 25(2), Part 1]	Protected species with limited hunting and collection under license
Sarawak, Malaysia	Wild Life Protection Ordinance 1998, [First Schedule, Section 2 (1), Part 1]	Totally protected species
Brunei	Wild Life Protection Act 1984, [First Schedule, Sections 2, 7, 8 and 9, Part A]	Totally protected species
Indonesia	Law No. 5 of 1990 Concerning Conservation of Living Resources and their Ecosystems [with supporting regulation from Ministry of Environment and Forestry Regulation No. P. 106/MENLHK/SETJEN/KUM. 1/12/2018]	Totally protected species

This study has three primary objectives: 1) to conduct a baseline comparison of detection probabilities between manual surveys and passive acoustic monitoring (PAM) using a Bayesian multi-method occupancy model on *A. albirostris* as a case study in Borneo; 2) to evaluate the performance of BirdNET for automated hornbill detection using *A. albirostris* as a species-specific example; and 3) to compare the costs associated with manual and PAM-based surveys in conducting hornbill monitoring. This study seeks to evaluate the feasibility and efficiency of integrating PAM and machine learning for hornbill monitoring, while also addressing practical considerations for large-scale or long-term studies.

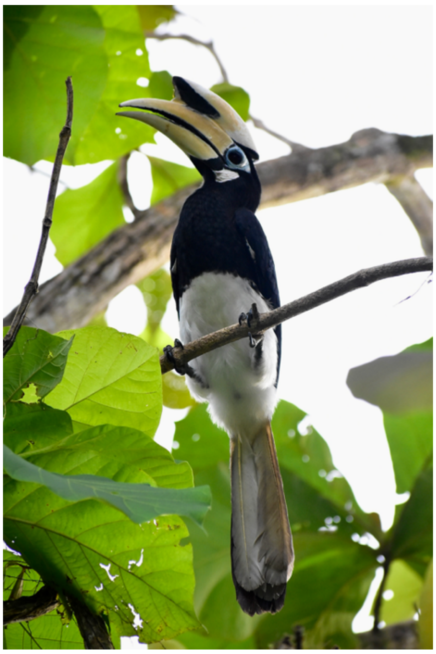

Figure 1: A male Oriental Pied Hornbill (*A. albirostris*).

METHODOLOGY

Study area

The Lower Kinabatangan Wildlife Sanctuary (LKWS) is located in eastern Sabah of Malaysian Borneo. It is a highly fragmented environment with a mix of habitat types and is surrounded by anthropogenic landscapes such as large-scale oil palm plantations (Boonratana, 2000). The LKWS consists of 10 forest lots, totaling 26,000 hectares of forest with varying connectivity, and experiences an average yearly precipitation of around 3,000 mm (Ancrenaz et al., 2004).

This study was conducted in the semi-inundated forest of Lot 6 of the LKWS (5.405240 N, 118.056123 E), which was selected primarily due to its proximity to a field station called the Danau Girang Field Centre (DGFC). DGFC has maintained a long-term research operation in Lot 6 since 2007 and provides infrastructure and logistical support for conducting intensive field-based research in the area (Jumail & Lynn, 2021). A 5 km^2 study area with 23 monitoring stations was established across the largest remaining forest block within this lot (Fig. 2).

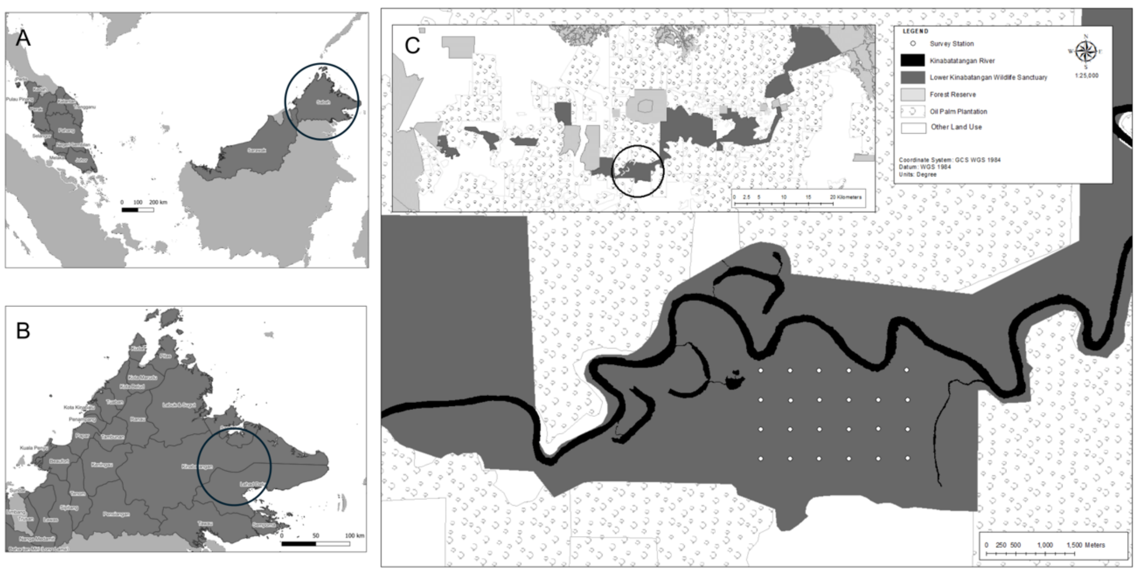

Figure 2: Study area location. A) Map of Malaysia showing the state of Sabah circled; B) Map of Sabah showing the Kinabatangan district circled; C) Location of the Lot 6 in the Lower Kinabatangan Wildlife Sanctuary where 23 monitoring stations were established for this study and the surrounding land-use types. The inset shows the highly fragmented forest lots within the Lower Kinabatangan Wildlife Sanctuary.

Manual surveys

Manual surveys were conducted in March and April 2022 and across 23 monitoring stations. To mitigate observer bias and ensure accurate species identification, observers received training using photographic references and audio recordings obtained from Xeno-canto (www.xeno-canto.org) as well as pre-recorded calls shared among the survey team. Each survey station was visited three times on different non-rainy mornings between 6:30 and 9:00 AM. During each visit, two observers performed 20-minute point counts. Detection events were recorded in two different categories: aural detection and visual detection. Aural detection was recorded every time *A. albirostris* was heard by its calls, while visual detection was recorded when the species was seen.

PAM survey and data management

This study employed AudioMoth Dev 1.0.0 (Fig. 3) from Open Acoustic Devices for the PAM surveys. These low-cost, lightweight ARUs (58 mm × 48 mm × 8 mm) are equipped with MEMS microphones with a sensitivity of 94 dB SPL at 1.0 kHz. The ARUs were set to record at 48.0 kHz sample rate (Nyquist frequency = 24kHz), with a 16 bit-depth at medium gain. This configuration enabled the frequency information gathered to be converted for high-quality audio analysis. Audio files were saved in 1.5-hour uncompressed .wav format on SD cards, each around 520 MB in size.

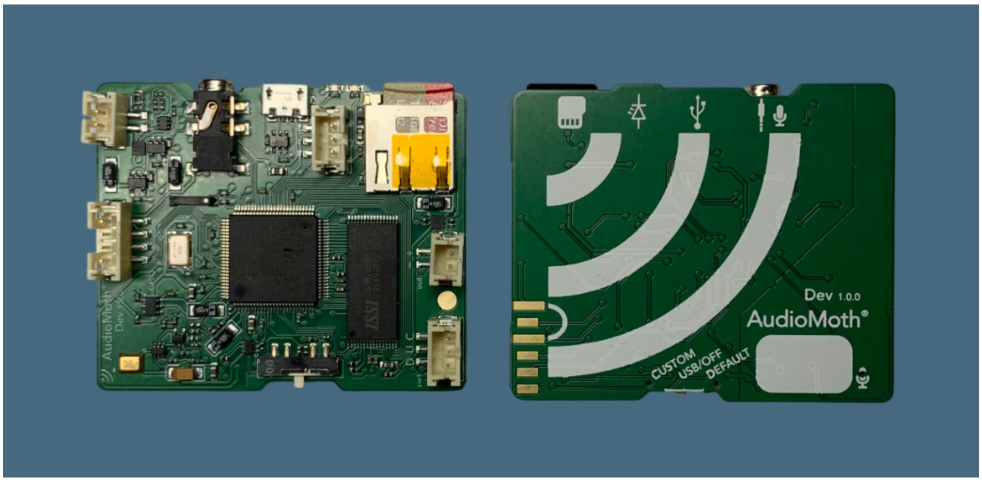

Figure 3: Acoustic recording units (ARUs) used in this study – AudioMoth Dev 1.0.0.

Acoustic recordings took place in tandem with manual surveys from March to April 2022. At each station, an ARU was mounted on a tree at an approximate height of 2 m and programmed to record from 6:30 to 9:30 AM daily. Devices remained in standby mode outside of these hours. A maximum of 12 ARUs were concurrently deployed with each unit deployed at a 500 m distance from each other.

To efficiently manage the large volume of data collected, all recordings were converted from .wav into FLAC (Free Lossless Audio Codec) format using Raven Compass (K. Lisa Yang Center for Conservation Bioacoustics, Ithaca, NY, USA). This format preserves audio quality while minimizing file size (MacPhail et al., 2023). Every file was backed up on both a primary and secondary hard drive to prevent data loss. A comprehensive quality control process was conducted to detect issues like clipping.

Cost estimation for manual and PAM survey

We conducted a comprehensive cost assessment to evaluate the financial viability of manual versus PAM methods in field-based hornbill research. Surveys were conducted in Lot 6 of the LKWS, with operations centralized at DGFC, a collaborative research facility jointly managed by the Sabah Wildlife Department and Cardiff University (Jumail & Lynn, 2021). This collaboration allowed us to directly leverage DGFC's logistical resources and staff throughout the data collection period.

The cost analysis includes expenses such as daily fees for field assistants, boat rental and boatman services, fuel consumption measured in litres per day, and trail-making fees. The costs of acquiring ARUs are excluded as existing devices from DGFC were employed during this study. These figures represent the actual operational expenses associated with fieldwork that was conducted in partnership with DGFC. Our findings provide a practical reference for researchers who are planning to conduct monitoring work across Borneo and other tropical regions by grounding this cost comparison in the real-world context of a functioning field station.

Data analysis

Multi-method occupancy analysis using a Bayesian hierarchical model.

We employed a Bayesian hierarchical multi-method occupancy model utilizing the jagsUI package in R (Kellner, 2024) to estimate the occupancy and detection probabilities of hornbill species. Detection histories were structured into a three-dimensional array [site (n = 23) × method × visit (n = 3)], where each element indicated presence (*1*) or absence (*0*) of detection by a specific method during each visit. Two different methods were calculated: manual survey (a combination of visual and aural surveys) and PAM. Posterior distributions were calculated for occupancy probability (ψ), presence during visits (θ), and method-specific detection probabilities (p) corresponding to manual and PAM-based surveys. Summary statistics for each parameter, including posterior means, standard deviations, and 95% credible intervals were obtained from the jagsUI output in R. The model outcomes establish a species-specific baseline for assessing detection efficiency across survey methodologies within a constant model framework.

The model followed this hierarchical framework: 1) Occupancy model: each site $\boldsymbol{s}$ was designated a latent occupancy state $\boldsymbol{z_s \sim Bernoulli(\psi)}$ where ($\boldsymbol{\psi}$) represents the likelihood of species presence at the site; 2) Availability model: for each visit $\boldsymbol{j}$, species availability given occupancy was modeled as $\boldsymbol{w_{sj} \sim \mathrm{Bernoulli}(\theta \cdot z_s)}$**,** where $\boldsymbol{\theta}$ represents the probability of species detection during that visit; and 3) Detection model: observed detections were modelled as $\boldsymbol{y_{smj} \sim Bernoulli(p_m \cdot w_{sj})}$, where $\boldsymbol{p_m}$ represents the detection probability for method $\boldsymbol{m}$, subject to the species being both present and available.

We employed non-informative priors for all parameters. The model was executed in JAGS with three Markov Chain Monte Carlo (MCMC) chains, comprising a total of 1,000,000 iterations, a burn-in period of 1,000 iterations, and no thinning (n.thin = 1). Convergence was evaluated visually by trace plots and quantitatively via the Gelman–Rubin diagnostic ($\hat{R}$), with all parameters achieving $\hat{R}$=1.0, indicating satisfactory convergence. Posterior distributions for each parameter were summarized using the posterior mean, standard deviation, and 95% credible intervals. Estimates for method-specific detection probabilities ($\boldsymbol{p}$) were generated for each species individually, allowing comparison of detection efficiency across survey methods under a consistent model structure.

Manual annotations for *A. albirostris.*

Manual annotations were conducted using Raven Pro 1.6.5 (K. Lisa Yang Center for Conservation Bioacoustics, Cornell Lab of Ornithology, Cornell University, USA). In all instances, the same parameters were employed for annotation: window size = 2400 samples, contrast = 55, and brightness = 55. This configuration helps with creating an excellent visualization to better detect *A. albirostris* call in the dataset (Fig. 4). Annotation for *A. albirostris* vocalizations was conducted throughout the entire dataset gathered from this study.

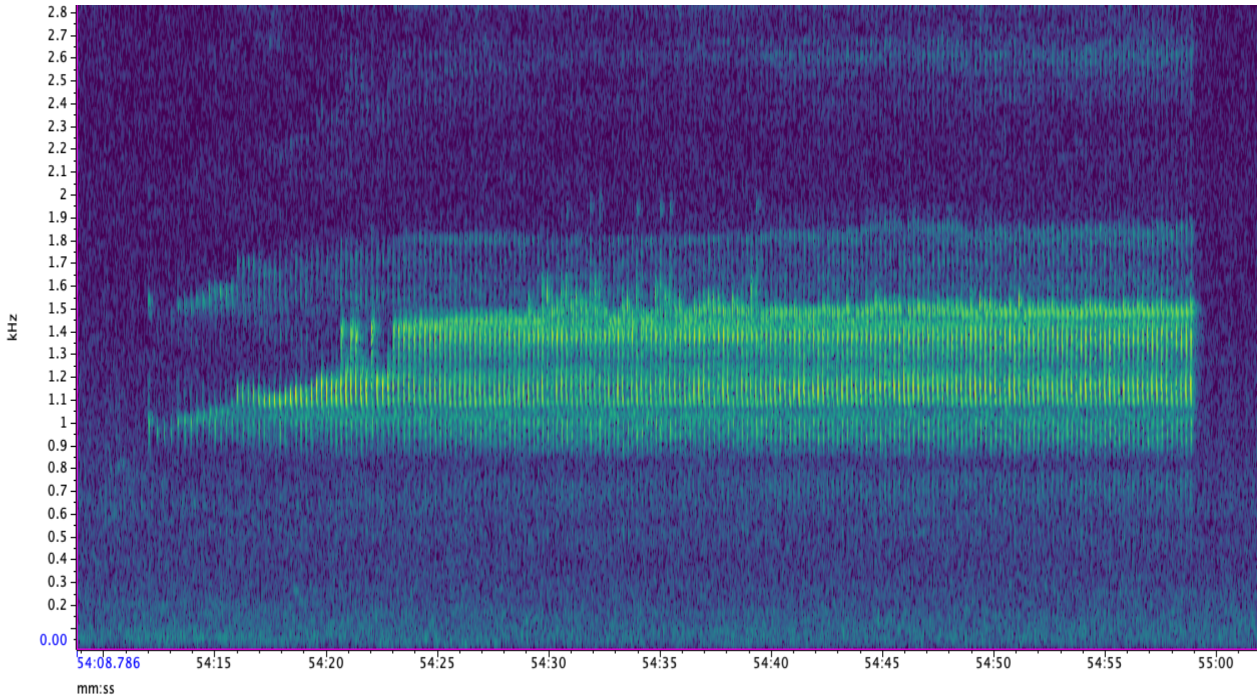

Figure 4: Spectrographic view of *A. albirostris* long call generated with Raven Pro software. X axis represents time (formatted in mm:ss); Y axis represents frequency (kHz).

Automated approach using BirdNET.

We analyzed the acoustic recordings for the presence of *A. albirostris* using BirdNET (Kahl et al., 2021). BirdNET processes recordings by splitting them into 3-second segments and assigning each a confidence score between 0 and 1. These scores are unitless and represent BirdNET's internal certainty about the species classification. Higher scores indicate greater confidence in the correctness of the classification and is not interpreted as probabilities or threshold levels (Wood & Kahl, 2024). BirdNET was deployed utilizing the "Batch Analysis" feature, concentrating on *A. albirostris* as the custom species list. The parameters were set as follows: minimum confidence = 0.1, sensitivity = 1, overlaps = 0, minimum bandpass frequency = 0 Hz, maximum bandpass frequency = 15,000 Hz, batch size = 1, and threads = 4.

Model performance evaluation.

To evaluate BirdNET's efficacy in detecting *A. albirostris* vocalizations, we computed three metrics: precision, recall, and F1-score. These were obtained by comparisons of BirdNET outputs and manual annotations utilizing a confusion matrix framework defined by the following.

- True Positive: BirdNET correctly identified an *A. albirostris* call confirmed by manual annotation.
- False Positive: BirdNET identified an *A. albirostris* call where none was present or misidentified another species.
- False Negative: BirdNET failed to detect an *A. albirostris* call present in the manual annotation.

We then computed these calculations:

- ***Precision***:

$$Precision = \frac{True\ positive}{True\ positive + False\ positive}$$

- ***Recall***:

$$Recall = \frac{True\ positive}{True\ positive + False\ negative}$$

- ***F1-Score***:

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Logistic regression analysis of BirdNET prediction.

We used logistic regression to model the relationship between BirdNET's confidence scores and the probability of a correct prediction (Wood & Kahl, 2024). To do this, we randomly segmented 100 three-second audio clips from the dataset and manually evaluated each as either a true positive or a false positive prediction. A logistic regression model was then fitted with this binary classification as the response variable and BirdNET's confidence score as the sole predictor. To assess model fit, we compared this model to a null model containing only the intercept using the corrected Akaike Information Criterion for smaller sample size (AICc).
The model is expressed as:

$$logit\ (p) = \ ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x$$

Whereby:

- p is the probability that a BirdNET prediction is correct
- x is the BirdNET confidence score
- β_0 is the intercept
- $\beta_1$is the slope (effect of confidence score)

This analysis was computed using the BBMLE package (Bolker & R Development Core Team, 2023) in R (R Core Team, 2022).

RESULTS

Multi-method occupancy analysis

We utilized multi-method occupancy analysis to predict site occupancy (ψ) and detection probability (θ) for *A. albirostris*, integrating data from manual and PAM surveys (Table 2). *A. albirostris* demonstrated posterior probability of occupancy estimate of ψ = 0.743 (95% CI: 0.407 – 0.987), with robust posterior probability of detection of using manual surveys (θ = 0.893) and satisfactory performance from passive acoustic monitoring (PAM) (θ = 0.670).

Table 2: Posterior estimates of occupancy (Ψ) and detection probability (θ) based on Bayesian models, including 95% credible intervals. Detection probabilities from two survey methods: visual + aural and PAM are also presented.

Species	Parameters	Mean	SD	2.5% CI	97.5% CI
	Ψ	0.743	0.162	0.407	0.987
Oriental Pied Hornbill	θ	0.350	0.110	0.174	0.603
(A. albirostris)	Visual+Aural	0.893	0.096	0.644	0.997
	PAM	0.670	0.130	0.396	0.892

BirdNET model performance and prediction for *A. albirostris*

The performance assessment of the BirdNET model for identifying *A. albirostris* vocalizations demonstrated high overall accuracy and precision, with moderate recall. The model attained a precision of 0.96, demonstrating a robust capacity to accurately detect true positive events while reducing false positives. The model also reported a recall value of 0.46 with an F1 score of 0.62.

The resulting plot (Fig. 5) shows a clear positive trend: as the confidence score increases, the probability that a detection is correct also increases. This trend is captured by the fitted logistic curve, which rises steeply between scores of 0.1 and 0.6 before levelling off near a predicted probability of 1. The visualized curve illustrates the model's estimate of prediction reliability at various confidence levels, with individual detection points overlaid. These points show how actual correct (1), and incorrect (0) predictions are distributed across the confidence range. The plot highlights that higher BirdNET confidence scores are generally associated with correct predictions, supporting the conclusion that confidence score is a useful predictor of detection accuracy. Based on the model, a confidence score of 0.30 corresponds to a 95% probability that a detection is correct, while a confidence score of 0.51 corresponds to a 99% probability that a detection is correct.

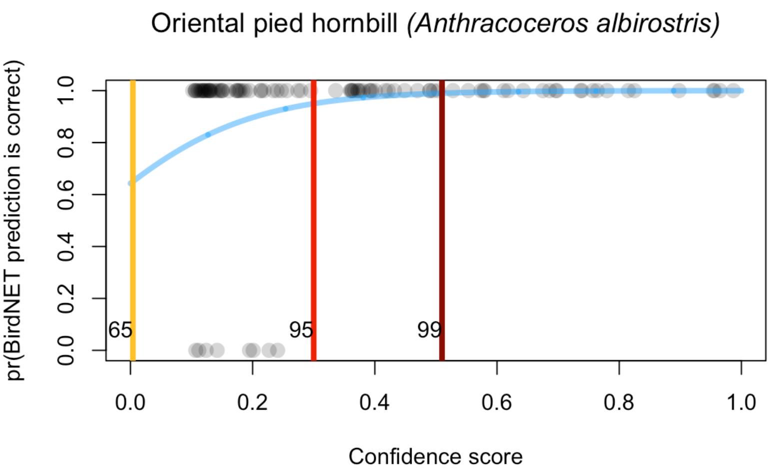

Figure 5: The probability of a true BirdNET prediction for *A. albirostris* in this study increased with the prediction score. The grey circles represent BirdNET predictions that have been validated, the blue line indicates the logistic regression line, while the yellow, red and brown lines represent confidence scores with a 65%, 95% and 99% probability of being correct.

Cost comparison of survey methods

A cost comparison between manual and PAM surveys revealed substantial differences in resource expenditure. The total cost for conducting manual surveys was MYR8,784 (USD 1.00 ≈ MYR 4.40 at the time of data collection), while the PAM-based survey incurred a significantly lower cost of MYR2,544, indicating a reduction of roughly 71% (Table 3). Manual surveys required an increased number of field days, multiple field assistants, which resulted in higher transportation and logistical costs, including trail-making fees and fuel consumption. In contrast, PAM surveys were less labour-intensive and logistically demanding, resulting in lower operational costs. These findings highlight the economic advantage of adopting PAM technologies, especially for long-term or large-scale biodiversity monitoring in remote areas.

Table 3: Comparison of costs between manual and PAM surveys across 23 monitoring stations in the Lower Kinabatangan Wildlife Sanctuary. Manual surveys required three visits per station on separate days, totaling 18 field days. PAM surveys required two visits per station (deployment and retrieval), totaling 8 field days. Costs are shown in Malaysian Ringgit (MYR). 1000 MYR = 236.41 USD.

Survey type	Cost item	Unit Cost (MYR)	Quantity	Duration (Days)	Subtotal (MYR)
Manual Survey	Field assistant fees	120 / person / day	2 persons	18	4,320.00
	Boat rental + boatman	150 / day	1 person	18	2,700.00
	Fuel	4 / liter	12 liters / day	18	864.00
	Trail-making fees	25 / person / day	2 persons	18	900.00
				Total:	8,784.00
PAM Survey	Field assistant fee	120 / person	1 person	8	960.00
	Boat rental + boatman	150 / day	1 person	8	1,200.00
	Fuel	4 / liter	12 liters / day	8	384.00
				Total:	2,544.00

DISCUSSION

We found an estimate posterior probability of occupancy ($\psi = 0.743$), with varying posterior probability of detection in manual surveys ($\theta = 0.893$) and PAM ($\theta = 0.670$) in *A. albirostris* across monitoring stations. Their occupancy estimate reflects the species' generalist ecology, adaptability to disturbed habitats, and frequent vocalizations (also observed in Kemp, 1995; Datta, 1998; Yusran et al., 2023), which facilitate detection by both by human observers and automated approaches. Detection probability by PAM was moderately lower than manual surveys which reflected missed detection events by the autonomous recorders. This may be explained by microphone detection distance and the distance of the source of the calls from the recorder together with sound propagation that may limit sound detection (Fristrup & Mennit, 2012). Another potential explanation would be the high rate of sound attenuation due to the presence of tall vegetation in an area and low signal-to-noise ratio of the signal of interest (Turgeon et al., 2017).

Our results indicate a discrepancy in PAM detections for *A. albirostris* in contrast to previous avian studies that reported comparable human and PAM performance (Darras et al., 2019; Budka et al., 2022; Jarrett & Willis 2025). The observed discrepancy may raise the need for further investigation into performance of different ARU types, particularly in relation to detecting Asian hornbills, like *A. albirostris*. However, it is worth noting that the visual-based method yielded the least number of detections (see Supplementary Materials; Yusni, 2026). This is not exclusive to our study as past studies too have reported limited detection in the visual-based method as opposed to PAM and aural surveys (Alquezar & Machado, 2015; McGrann & Furnas, 2016; Darras et al., 2019). Past studies have proven PAM to be an effective tool to monitor variety of cryptic and elusive species, including birds, bats, and elephants (Gorresen et al., 2008; Zwart et al., 2014; Wrege et al., 2017). This warrants a future study looking at other hornbill species in the area, especially the elusive ones.

In our study, BirdNET model demonstrated high precision (0.96) in detecting *A. albirostris* vocalizations, while showing strong positive relationship between high confidence scores and prediction correctness. This reflects BirdNET's potential as an effective tool for automated approach in hornbill research. Large-scale and long-term PAM studies will produce a sheer volume of acoustic data, necessitating the need for reliable automated approaches like deployment of neural network architectures (Kelly et al., 2023). One of the ongoing efforts in the bioacoustics community is focused on benchmarking different neural network architectures and evaluating their model performance for each of their study species (Ghani et al., 2023; Clink et al., 2026). Continued efforts to refine such models are of paramount importance to expand the scope of PAM and machine learning application across different hornbill species.

The application of PAM in this study led to an exceptional 71% reduction in data collection costs, highlighting its operational efficiency. PAM also required substantially fewer field days for deployment and retrieval of ARUs (n = 8 days) compared to manual surveys (n = 18 days). Moreover, manual surveys incurred an additional cost component related to the establishment of access trails within the study area. In Lot 6 of the LKWS, dense undergrowth and semi-inundated conditions limited accessibility and made foot travel between monitoring stations logistically challenging, with some stations needing up to 70 minutes of walking and river departures as early as 04:00 AM. Under these conditions, trail establishment was necessary to ensure safe travel during low-visibility periods and to commence surveys on time.

In contrast, PAM surveys were more flexible and ARU deployment and retrieval can take place at any time prior to the start of the survey period. Similar cases of cost efficiencies where high-quality acoustic data were obtained at a fraction of the cost of manual surveys were also seen in other PAM studies (Williams et al., 2018; Beranek et al., 2024). Beyond cost reduction, PAM also minimized logistical challenges and safety concerns associated with field-based surveys. In our case, semi-inundated tropical forests of LKWS posed other logistical and safety concerns, especially during flooding events (Fig. 6), during which areas were becoming inaccessible and may also serve as temporary breeding ground for saltwater crocodiles, further elevating safety risks for field personnel (Sidom, 2025; Sokial, 2025).

Figure 6: Manual hornbill survey conducted in a semi-inundated forest within the Lower Kinabatangan Wildlife Sanctuary. Field personnel navigated knee-deep water for extended period of the surveys, reflecting the challenging terrain of the area.

While operational costs of data collection were notably reduced with PAM, we would like to note that the upfront cost of acquiring recording devices can be significant. For example, ARUs used in this study were purchased by DGFC at approximately MYR381 per unit, which can be a substantial upfront cost for early-career researchers. This cost may also vary depending on the brand and the supplier of the ARU. The ARUs, however, are reusable for future and long-term studies, making them an economical solution in hornbill monitoring efforts. Our study demonstrates that PAM not only reduces the operational costs of data collection but also offers a safer and more practical alternative for hornbill monitoring in challenging terrains.

While our study highlighted an array of advantages of applying PAM in hornbill research, it is not without limitations. When applying PAM at scale, initial resources needed to purchase ARUs, SD cards, and batteries are even greater. Although low-cost ARUs are increasingly available (Hill et al., 2018), we acknowledge this still poses financial constraint of acquiring equipment for researchers in the Global South and across Asia, where Asian hornbill species occur. Additionally, data management and processing become increasingly significant cost drivers in large-scale PAM studies. Petabytes of data generated require a vast computing power and processing infrastructure for analysis, which can be costly (Zwerts et al., 2021). However, tools like Raven Compass (K. Lisa Yang Center for Conservation Bioacoustics, Ithaca, NY, USA) can now compress recording files by up to 50% into a format that would not compromise data quality (MacPhail et al., 2023), helping to reduce storage demands. Furthermore, web- or cloud-based platforms like Arbimon and AcoustiCloud would also mitigate high computational demands associated with bioacoustics data processing (Aide et al., 2013; Brown et al; 2020), with Arbimon additionally offering unlimited cloud storage at no cost.

Building on the findings of this research, future studies should expand the spatial and temporal coverage of acoustic data collection across hornbill species in Malaysia. Broader-scale datasets will improve understanding of species distribution across their ranges. Further studies into species-specific vocal behaviours, diel and seasonal vocal activity patterns, and acoustic space partitioning among sympatric species would further improve our understanding of their behaviours and ecology. Furthermore, benchmarking and refining machine learning models across hornbill species will improve the efficiency and reliability of automated analyses. Collectively, these efforts will strengthen the integration of bioacoustics approaches in hornbill research and support more effective monitoring and conservation planning of these iconic birds in Malaysia.

CONCLUSIONS

This study represents the first application of passive acoustic monitoring for hornbill research in the Lower Kinabatangan Wildlife Sanctuary. By comparing PAM with manual surveys, we found method-specific differences in the detection of Oriental Pied Hornbill (*Anthracoceros albirostris convexus*) within this highly fragmented landscape. Our findings are consistent with the species' established characterization as an ecological generalist and its persistence in disturbed and fragmented habitats. We also demonstrate that deep learning models such as BirdNET are a great tool that can improve efficiency in processing and analyzing bioacoustics data. Lastly, PAM can reduce future operational costs to monitor Asian hornbill, especially at a time when their forest habitats are undergoing rapid and accelerating change.

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DECLARATIONS

Research permit(s). We extend our sincere thanks to the Sabah Biodiversity Centre, and the Sabah Wildlife Department, for granting permission for this study (License Ref. No. JKM/MBS.100–2/2 JLD. 13(22)).
Ethical approval/statement. Not applicable.
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SUPPLEMENTARY MATERIALS

Author: Yusni ASA.
Data type: R script and CSV data file.
Explanation note: R script and CSV data file for Bayesian multiple method occupancy analysis.
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