Remote Sensing in Ecology and Conservation
Open Access
ZSL

RESEARCH ARTICLE

Robotics-assisted acoustic surveys could deliver reliable, landscape-level biodiversity insights

Peggy A. Bevan[1,2], Cristina Banks-Leite[1], Mirko Kovac[3,4,5], Jenna Lawson[6], Lorenzo Picinali[7] & Sarab S. Sethi[1]

[1]Department of Life Sciences, Imperial College London, London, UK
[2]Centre for Biodiversity and Environment Research (CBER), Department of Genetics, Evolution and Environment, University College London, London, UK
[3]Aerial Robotics Laboratory, Imperial College London, London, UK
[4]Laboratory of Sustainability Robotics, Swiss Federal Institute for Material Science and Technology (Empa), Dübendorf, Switzerland
[5]Laboratory of Sustainability Robotics, Swiss Federal Institute of Technology in Lausanne (EPFL), Lausanne, Switzerland
[6]UK Centre for Ecology and Hydrology, Wallingford, UK
[7]Dyson School of Design Engineering, Imperial College London, London, UK

Keywords
Automation, machine learning, passive acoustic monitoring (PAM), species monitoring, unmanned aerial vehicles (UAVs)

Correspondence
Peggy A. Bevan, Centre for Biodiversity and Environment Research, Department of Genetics, Evolution and Environment, University College London, Gower Street, London, WC1E 6BT UK. Tel.: +44 (0)20 3108 7691; E-mail: peggy.bevan.17@ucl.ac.uk.

Editor: Dr. Vincent Lecours

Received: 14 May 2025; Revised: 14 September 2025; Accepted: 23 September 2025

doi: 10.1002/rse2.70037

Remote Sensing in Ecology and Conservation 2026;**12** (2):260–274

Abstract

Terrestrial remote sensing approaches, such as acoustic monitoring, deliver finely resolved and reliable biodiversity data. However, the scalability of surveys is often limited by the effort, time and cost needed to deploy, maintain and retrieve sensors. Autonomous unmanned aerial vehicles (UAVs, or drones) are emerging as a promising tool for fully autonomous data collection, but there is considerable scope for their further use in ecology. In this study, we explored whether a novel approach to UAV-based acoustic monitoring could detect biodiversity patterns across a varied tropical landscape in Costa Rica. We simulated surveys of UAVs employing intermittent locomotion-based sampling strategies on an existing dataset of 26,411 h of audio recorded from 341 static sites, with automated detections of 19 bird species ($n = 1819$) and spider monkey ($n = 2977$) vocalizations. We varied the number of UAVs deployed in a single survey (sampling intensity) and whether the UAVs move between sites randomly, in a pre-determined route to minimize travel time, or by adaptively responding to real-time detections (sampling strategy), and measured the impact on downstream ecological analyses. We found that avian species detections and spider monkey occupancy were not impacted by sampling strategy, but that sampling intensity had a strong influence on downstream metrics. Whilst our simulated UAV surveys were effective in capturing broad biodiversity trends, such as spider monkey occupancy and avian habitat associations, they were less suited for exhaustive species inventories, with rare species often missed at low sampling intensities. As autonomous UAV systems and acoustic AI analyses become more reliable and accessible, our study shows that combining these technologies could deliver valuable biodiversity data at scale.

Introduction

Terrestrial remote sensing approaches provide numerous advantages for biodiversity monitoring over traditional surveys, offering a non-invasive and scalable way to study ecosystems (Allan et al., 2018; Berger-Tal & Lahoz-Monfort, 2018; Lahoz-Monfort & Magrath, 2021; Stephenson, 2020). Among these, acoustic monitoring has proven particularly effective for surveying vocal species (Gibb et al., 2018; Ross et al., 2023) and has demonstrated great potential to contribute to biodiversity monitoring and policy compliance efforts (Stowell & Sueur, 2020; Sugai et al., 2019). Acoustic data can also be analysed rapidly using machine learning, either post hoc (Lawson et al., 2023; Sethi et al., 2024) or in real-time (Sethi et al., 2018; Wägele et al., 2022). However, deploying acoustic sensors is a time-consuming and costly process, and survey locations can be limited by accessibility or safety concerns (Sethi et al., 2022).

Unmanned aerial vehicles (UAVs), or drones, are emerging as a transformative technology for ecological research (Christie et al., 2016; Millner et al., 2023; Robinson et al., 2022). By using sensors attached to UAVs, these devices can improve scalability and reduce the logistical constraints associated with manually deploying sensors. Using aerial imagery from on-board cameras is an established method for ecological studies (Duporge et al., 2025; Rahman et al., 2025; Schofield et al., 2017), but UAV-based acoustic surveys are less common due to noise interference. Early studies have explored suspending acoustic recording devices from UAVs that record during flight (Fischer et al., 2023; Michez et al., 2021; Wang et al., 2023; Wilson et al., 2017), using custom classification algorithms to detect animal vocalizations against the backdrop of engine noise (Fu et al., 2018; Wang et al., 2023). However, the noise generated by drone motors can impact detection by disturbing wildlife (Kuhlmann et al., 2022; McEvoy et al., 2016; Wilson et al., 2017), and training novel detection algorithms demands more data, effort and expertise than using established vocalization detection models (e.g. BirdNET; Kahl et al., 2021). An alternative sampling approach is to deploy a swarm of robotic UAVs with on-board sensors and processors that land during recording periods and move between sampling sites on a defined schedule. This intermittent mobile sampling approach could mitigate noise-related disturbance and more closely reflects survey designs of passive acoustic monitoring surveys (PAM), where static sensors are preferred over transect surveys for estimating animal activity or density (Browning et al., 2017; Lucas et al., 2015; Marques et al., 2013; Newson et al., 2017).

Previous UAV-based acoustic surveys have used UAVs that are manually piloted. However, autonomous UAVs, which can be deployed in coordinated 'swarms' and navigate themselves to avoid obstacles, could reduce barriers to access, enabling finer resolution and larger scale biodiversity data collection (Pringle et al., 2025). UAV prototypes have been developed to overcome challenges to automated acoustic surveys, such as perching in trees (Lan et al., 2024) and navigating UAV swarms through dense forest environments (Romanello et al., 2024; Zhou et al., 2022). These advances could reduce disturbance of wildlife and the environment by avoiding the need for any people to enter the survey area. An autonomous aquatic vehicle has been designed for ecological sensing and performed well (Lawson et al., 2024), but it remains to be tested if an autonomous swarm of UAVs can deliver reliable ecological data when compared with data from manually deployed sensors.

The deployment of autonomous UAVs for ecological surveys represents an opportunity to test novel survey designs that would not be possible with manual sensor deployment. UAV systems can be programmed with vehicle routing algorithms which optimize for a specific parameter, for example reducing the number of recharges required (Guerber et al., 2021; Gunal, 2019; Macrina et al., 2020; Phalapanyakoon & Siripongwutikorn, 2021). Additionally, adaptive systems can respond to real-time input from sensors (Dwivedi et al., 2023; Hwang et al., 2019), a method successfully employed by underwater autonomous vehicles in tasks such as mapping the extent of underwater oil spills or locating phytoplankton blooms (Das et al., 2015; Jakuba et al., 2011). In biodiversity monitoring, adaptive sampling strategies have been used to detect environmental gradients or improve occupancy model accuracy (Flint et al., 2024; Henrys et al., 2024; Pacifici et al., 2016), but these occur over several survey periods and do not respond to real-time animal detections. There is little understanding of how real-time adaptive sampling might impact the structure of ecological data, and if this could produce robust measures of biodiversity compared with more established survey techniques.

Designing a UAV-based acoustic survey presents unique limitations, particularly regarding sampling completeness. Standard PAM surveys typically deploy one recording device at each sampling site, and all devices record simultaneously over extended periods. In contrast, intermittent sampling by a swarm of UAVs means that the recording duration at any given site is restricted. As some animal vocalizations are temporally dependent, sampling at the same time of day across independent sites is important for robust comparisons of species detections across sites. It remains unclear whether the impact of incomplete sampling on key ecological indicators can be offset by sampling strategy. Addressing these gaps is critical to understanding the trade-offs associated with UAV-based acoustic monitoring and to help practitioners choose the optimal sampling strategy to meet their survey aims.

In this study, we ask how reduced effort resulting from an intermittent sampling protocol would impact downstream biodiversity metrics. We designed and ran simulated UAV surveys using an acoustic dataset from the Osa Peninsula, Costa Rica. This dataset has previously been analysed to measure avian (Sethi et al., 2024) and spider monkey (Lawson et al., 2023) diversity and occupancy, respectively. Using published data from these studies, we simulated surveys under four sampling strategies that could be carried out by a network of autonomous UAVs – random, routed and two types of adaptive sampling. We evaluated the performance of each strategy under varying levels of sampling intensity, defined by the numbers of UAVs deployed in a mission. By replicating key analyses from the original studies, we assessed the ability of intermittent sampling to detect 19 avian species and estimate spider monkey occupancy over a forest cover gradient. This work is the first to consider the full pipeline of UAV-based acoustic surveys and to investigate the impact of sampling techniques on downstream ecological metrics, informing future applications of this technology in ecological research.

Materials and Methods

Study area and sampling design

For our simulations, we used species vocalization detections from two open-source datasets from a large PAM survey in the Osa Peninsula, Costa Rica (Lawson et al., 2023; Sethi et al., 2024). The Osa Peninsula, located on the south Pacific coast of Costa Rica, contains biodiverse tropical broadleaf evergreen lowland rainforest (Gilbert et al., 2016; Sánchez-Azofeifa et al., 2003), embedded within a mosaic of pasture, plantations and urban centres (Fig. 1).

We chose this dataset for our drone simulations because of the sampling design. Due to access limitations, a uniform sampling design across the survey area (1093 km^2) was not possible. Instead, a set of sampling groups was created which appear as 'clusters' (Fig. 1). This mimics the sampling design of a robotic UAV survey, where UAVs begin from a central charging station and travel to recording locations within a set radius of the charging station. The dataset contained recordings from 341 sites grouped into 35 clusters, with an average of 8.7 sampling sites within each cluster (range [4, 28]).

Sampling sites were stratified across five land-use categories, with the number of recorders placed in each land-use category representative of its percentage cover across the region (determined from the 5 × 5 m Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI); Lawson et al., 2023; Shrestha et al., 2018). The land-use categories were old-growth forest, secondary forest, palm plantation, teak plantation and grassland. At each sampling cluster, the first recorder was placed by walking 500 m in a random direction, and remaining recorders were placed a minimum of 500 m apart to maximise independence between samples (Figueira et al., 2015). Where possible, trails were not used; however, where this was not possible, devices were placed a minimum distance of 200 m perpendicular to a trail. Recording devices were also placed at a minimum distance of 200 m from habitat boundaries to ensure sounds were solely from the classified habitat. Recordings were obtained using AudioMoth devices (Open Acoustics Devices, UK). Recorders ran for a minimum of seven consecutive days (range [7, 16 days]) to allow for variability in activity across different days and to allow for sufficient sampling effort. The devices were set to record on a schedule of 05:00–09:30, 14:00–18:30 and 21:00–03:00, a total of 15 h each day. Data were recorded constantly during these periods at a sample rate of 48 kHz (Metcalf et al., 2023). Sampling was conducted during the dry season (December–August). The final dataset included 26,411 h of uncompressed 16-bit audio files.

Data processing

Avian species detections

We used avian vocalization detections from Sethi et al. (2024) (data retrieved from Sethi (2024)), who used an open-source bird vocalization detection model, BirdNET (Kahl et al., 2021), to identify bird calls in the audio data. BirdNET is a convolutional neural network (CNN) trained on bird vocalizations from many online call libraries, which detects species occurrences in audio data, with a prediction probability. Sethi et al. (2024) had the geographic species filter enabled and set a model confidence threshold of 0.8. For this study, we kept detections for 19 species which the model was able to detect with $>90\%$ precision (i.e., low false-positive rate) based on verification of a random subset of 50 detections by an experienced local ornithologist (Sethi et al., 2024). This resulted in 1819 bird detections across 126 sites and 32 clusters. The 19 species represent a very small proportion of the ~465 bird species that can be found on the Osa Peninsula, a result of the geographical and taxonomic bias in the training datasets of BirdNET (Stowell, 2022). It is important to note that analyses of avian detections from this study are not intended to make conclusions about avian diversity or distribution in the Osa Peninsula, but to be used as an example of real species spatiotemporal patterns and dynamics.

Spider monkey occupancy

We used spider monkey detections from Lawson et al. (2023) (data retrieved from Lawson (2022)), who trained a deep learning CNN to detect the species' vocalizations. Lawson et al. (2023) manually annotated 561 examples from 13 sites of the 'whinny' vocalization made by spider monkeys. The neural network used, proposed by Rizos et al. (2021), used a deep, CNN architecture. All spider monkey detections were manually verified to ensure all false-positives were removed. The final dataset contained 2977 true-positives across 64 of 341 sites

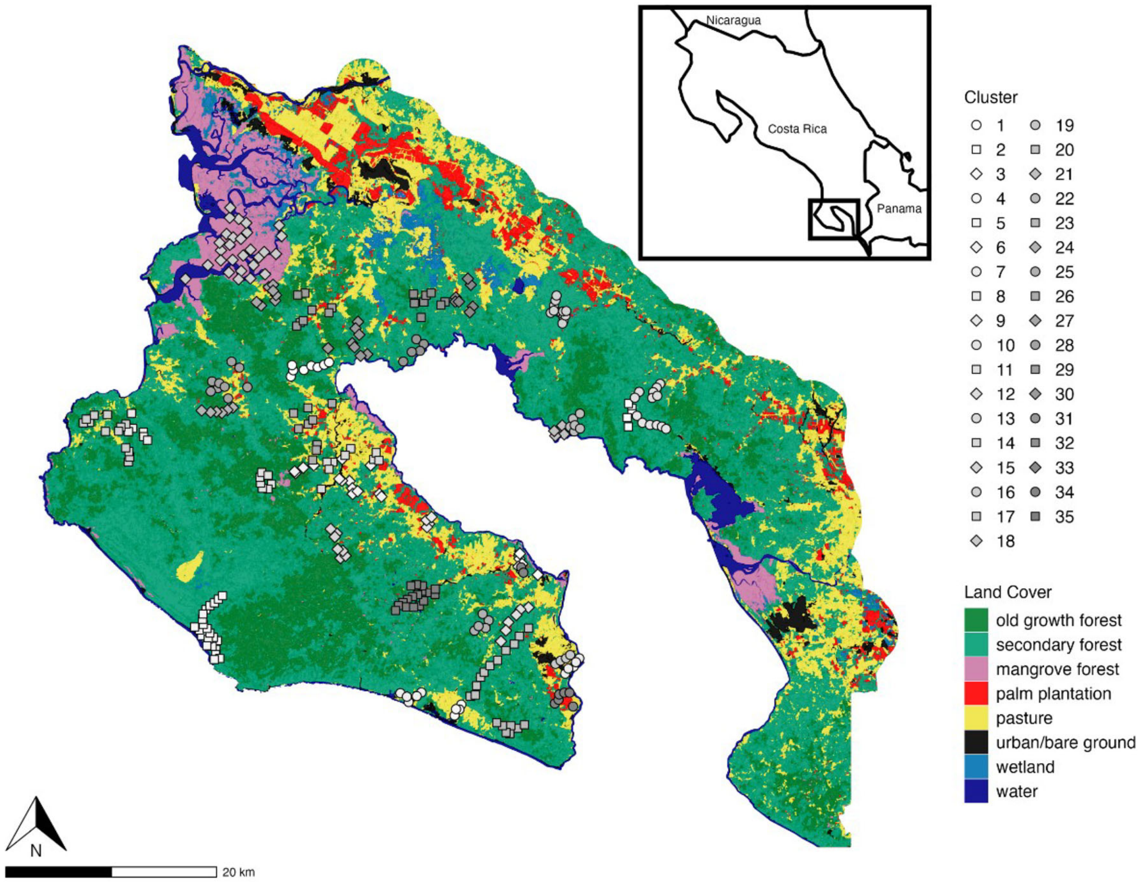

Figure 1. Map of survey area in the Osa Peninsula, Costa Rica. Each point represents a sampling location where a single acoustic recorder was placed. Acoustic recorders were deployed in 'clusters' across the landscape ($n = 35$). This is also the sampling unit used for simulated drone-based surveys. The Land Use Map shows the land-use categories in the region, created at a scale of 5×5 m using Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) (Shrestha et al., 2018).

(Lawson et al., 2023). These detections were converted into a 7-day detection history per site with each day coded as 1 or 0 to represent the presence or absence of spider monkeys. Data at a finer temporal resolution was not published, limiting the scope of our simulations for the spider monkey dataset.

UAV survey simulations

To evaluate data collectable by an autonomous UAV system, we ran simulations to collect data from the avian and spider monkey datasets. Surveys were designed as intermittent mobile sampling, meaning that data collection (i.e. sound recording) occurs when the UAV is stationary at a site to minimize the impact of flying noise on recording quality and animal disturbance. Such intermittent locomotion can be achieved by landing on the ground or perching in the canopy (e.g. Zheng et al., 2023). All simulations were run in Python 3.

UAV functionality was based on the DJI Mini 2, a commercially available multirotor drone. This device can achieve ~ 30 min of flight time when unweighted. As UAVs would be weighted with a microphone and related hardware (*c.* 80 g including separate batteries) (Hill et al., 2019), we estimated a maximum flight time of 20 min. Battery consumption was calculated as a function of flight time. Average flying speed was set at 15 m/s, and an extra penalty of 16 s was added per take-off to account for the increased battery consumption of increasing the UAV's altitude. We assumed that whilst stationary and landed, the UAV consumed no battery. We did not account for the impact of wind, temperature and other factors that may reduce overall battery life in a real-life scenario, as we did not have this data at appropriate resolutions.

Simulations were run at the level of a sampling cluster (Fig. 1). The sampling site closest to the mean latitude and mean longitude of all sampling sites in the cluster was selected to be a 'charging station'. Each simulation began with all UAVs (an autonomous UAV equipped with a microphone) at the charging site in the first time step. At each sequential time step, UAVs would be moved to other sampling locations within the cluster and 'collect' any detections from the real audio dataset at that time step and location. A time step was 1 h for the avian dataset simulations (15 time steps per day, ranging 7–16 days) and 1 day for the spider monkey dataset simulations (7 time steps in total). If a UAV did not have enough battery to both visit the next selected site and then return to the charging station, the UAV was sent directly back to the charging station. All simulations were repeated 50 times to account for stochasticity in site selection.

Our simulations experimented with two parameters: *sampling intensity* and *sampling strategy*. *Sampling intensity* represents the number of UAVs deployed simultaneously. We used five values of sampling intensity (0.2, 0.4, 0.6, 0.8, 1), where each value represents the number of UAVs as a proportion of the total sites in the cluster. A sampling intensity value of 1, representing complete sampling (i.e., one UAV per sampling site), is equivalent to the full static PAM survey and was used for baseline comparisons.

Sampling strategy defined how the UAV's route between sites was determined. We created four strategies: *Random, Routed, Adaptive explorative and Adaptive exploitative*.

In the random sampling strategy, the choice of the next site was determined by random selection with replacement, allowing the same site to be chosen in consecutive time steps. Sites already selected by another UAV were removed from the list of available sites to avoid multiple visits to the same site at the same time.

For the routed sampling strategy, sampling sites at each cluster were grouped into geographically distinct sub-groups using k-means clustering based on their GPS coordinates, where $k = N_{UAVs}$. Each UAV would only travel to sites within a specific sub-group. At each time step, the choice of next site was based on the number of previous visits, prioritizing sites that had been sampled the least. Among these sites, the nearest available site was selected. This strategy meant that over the course of the survey, all sites in a cluster were visited equally, and the order of site visits remained relatively consistent because the nearest-neighbour algorithm repeatedly identified the same shortest route between sites.

The third and fourth sampling strategies, adaptive explorative and adaptive exploitative, considered a scenario where UAVs had on-board processing capability such that animal vocalizations could be detected in real-time, and adapt the choice of next site. This strategy was run for the avian community dataset only, due to the higher temporal resolution of this dataset. Adaptive sampling can be configured in many ways, depending on the metric being optimized for example, finding a gradient (Hwang et al., 2019) or increasing occupancy confidence (Pacifici et al., 2016). Here, we chose to optimize sampling effort to increase confidence that all species present in each cluster were detected. To achieve this, we programmed the routing system to prioritize sites where more frequent avian vocalization rates were detected, as these were expected to represent areas of high avian activity. For the first 2 days of the simulation (30 time steps), sites were sampled using the routed sampling strategy explained above, to ensure baseline coverage of all sites. After 30 time steps, the choice of next site was decided through random selection with replacement, where the probability of choosing each site was biased by the number of vocalizations previously detected and total number of visits to that site. The probability weighting of site i ($P(i)$) was determined as:

$$P(i) = \frac{1}{N_{\text{sites}}} + (b_i \cdot w)$$

where the bias, b_i is calculated as total number of vocalizations previously detected at site i, divided by the total number of visits to site i, normalized by the sum of these values for all available sites. w represents a weighting factor that determines the disparity between high and low probabilities.

We tested two values of w to explore the difference between an 'explorative' adaptive system ($w = 0.3$), where real-time detections give a low bias to site choices, and an 'exploitative' adaptive system ($w = 100$), where real-time detections give a high bias to choice of next site.

Evaluating simulation performance

Simulation evaluation was conducted in R (V4.4.1). For simulations using the dataset of BirdNET detections, we measured the total number of species detected across the survey area and in each land-use type (Old-Growth Forest, Secondary Forest, Mangrove Forest, Grassland, Palm Plantation, Teak Plantation) and compared these values to those collected through complete sampling (sampling intensity = 1). We used a generalized linear mixed-effects model (GLMM) with a Poisson distribution to determine the effect of sampling strategy (random, routed, adaptive explorative and adaptive exploitative) and sampling intensity on avian species detections. Iteration number was included as a random effect.

For the spider monkey dataset, we used the 7-day detection history to run a logistic GLM that predicted the probability of spider monkey presence in response to forest cover, replicating the analysis from Lawson et al. (2023). To define a minimum threshold of forest cover for spider monkey occupancy, we used the receiver operating characteristic (ROC) curve to determine a cut-off point that maximized specificity and sensitivity for predicting positive occupancy. We then predicted occupancy probability over the range of forest cover and found the value of forest cover that intersected with the cut-off probability to get the minimum forest cover threshold. This threshold is not the minimum value at which spider monkeys were detected, but more closely represents the value of forest cover above which spider monkeys are consistently detected; therefore, it accounts for anomalous detections in areas of lower forest cover. We calculated the minimum forest cover threshold for each simulation and compared it to values from complete sampling (sampling intensity = 1).

Survey logistics

To show how changing the sampling strategy and intensity would impact other aspects of a UAV-based survey design, we measured sampling evenness, total UAV travel time and the number of recharges for all simulations on the avian vocalization dataset.

To measure sampling evenness across space and time, we calculated the frequency of visits to each site at each hour in the day the survey was active (05:00–09:30, 14:00–18:30 and 21:00–03:00, $n = 15$ h) and calculated the Shannon evenness index (SEI) for each cluster. The SEI value is bound between 0 and 1, where a higher value indicates more equal visits to a site across hours in the day. We calculated SEI for each cluster and averaged this across all 35 clusters for each value of sampling strategy and sampling intensity.

Average total travel time was calculated by summing the total distance travelled by all UAVs in a cluster during a single simulation, then normalized by the number of sites so that travel time was comparable across clusters with different numbers of sites. The same method was used to record the average number of visits to the charging station.

Results

Simulation results: Routed and random sampling strategies

All simulations were able to recover the patterns of BirdNET species detections across land-use types, although species richness reduced with sampling intensity (Fig. 2). Across all values of sampling intensity, the measured species richness was always highest in grassland, followed by secondary forest, old-growth forest, palm plantation, mangroves and teak plantation (Fig. 2A). Sampling strategy (random or routed) had no impact on measured species richness.

When examining the full list of BirdNET species detections across all sites, no simulations with a sampling intensity <1 were able to consistently detect the maximum species richness ($n = 19$ species), although some iterations at 0.6 and 0.8 sampling intensity did detect the maximum species richness (Fig. 2B). Results of the GLM showed no impact from sampling strategy on measured species richness ($p = 0.58$), but sampling intensity had a strong positive effect ($p < 0.001$).

For the spider monkey simulations, we found that the minimum forest cover threshold for predicting spider monkey occupancy tended to be overestimated with high uncertainty, although this improved with sampling intensity. The results from complete sampling (sampling intensity = 1) predicted a minimum threshold of 0.909, equivalent to 91% forest cover. This value was not consistently achieved by any of the simulations, regardless of sampling strategy. For simulations with the lowest sampling intensity (0.2) and random sampling strategy, the average forest cover threshold was 95%, ranging between 91% and 100% (Fig. 3). Interestingly, the raw minimum level of forest cover that a spider monkey was detected at (79%) was detected by both sampling strategies at all sampling intensities except for 0.2.

Simulation results: Adaptive Sampling

Including knowledge of real-time detections into the routing algorithm did not show an improvement on random sampling when looking at total number of species detected per survey. We investigated two adaptive routing strategies in our simulations by adapting the weighting parameter, w, in the routing algorithm: explorative ($w = 0.3$) and exploitative ($w = 100$). At very low sampling intensity (0.2), the adaptive exploitative strategy detected a higher species richness than the adaptive explorative strategy on average, but estimates of species richness were no higher than the random sampling strategy (Fig. 4). Results of the GLM showed that sampling intensity resulted in higher species richness ($p < 0.001$) but none of the tested sampling strategies had any effect (explorative: $p = 0.58$; exploitative, $p = 0.85$).

Survey logistics

We found that the sampling strategy had little impact on the sampling evenness of a survey (how evenly samples were spread across hours in the day and sites per cluster over the full sampling period). We found no difference in sampling evenness between random, routed, or adaptive sampling strategies (Fig. 5A). However, the variation in

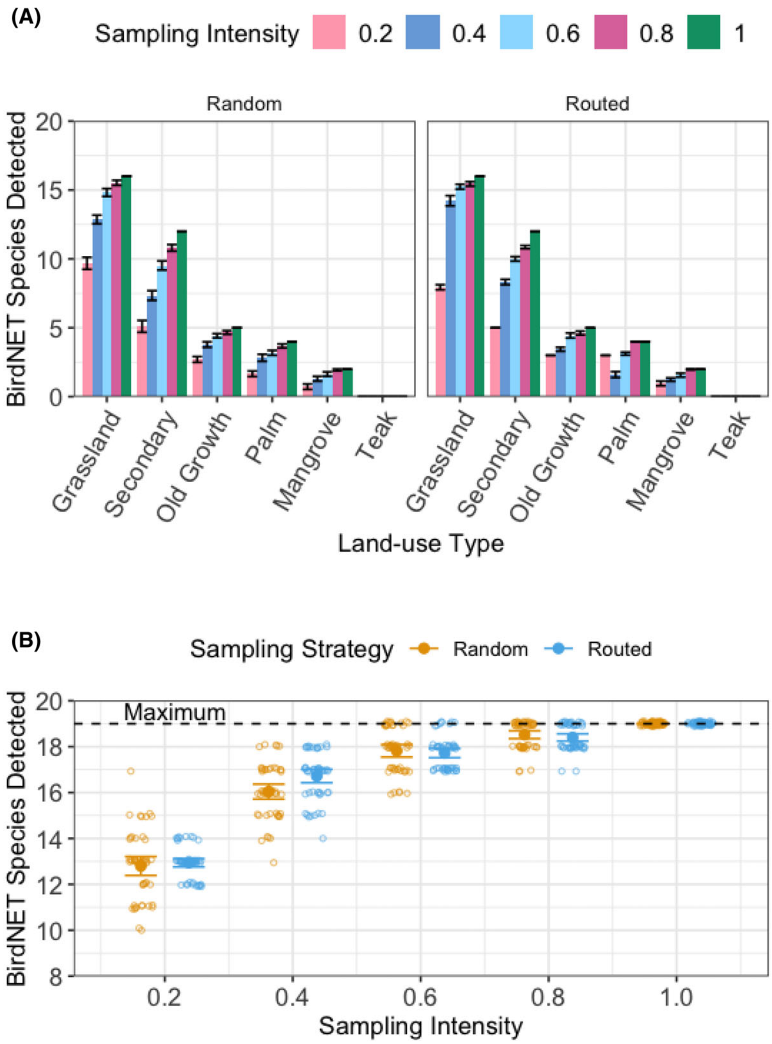

Figure 2. Patterns of biodiversity across land-use types detected with low number of UAV samplers, but full species list is hard to detect. Total BirdNET detections from UAV survey simulations that varied the number of UAVs deployed simulataneously (sampling intensity) and the sampling strategy (random movement between sites, or Routed, optimizing for the shortest travel distance). A sampling intensity of 1 represents the full dataset, a static PAM survey. (A) the number of species detected by BirdNET across five land-use types. (B) the total number of species detected by BirdNET across the entire survey (maximum 19). Note that species numbers and habitat use patterns are not indicative of real biodiversity patterns in the study area.

sampling evenness across the 50 simulation iterations was larger in the routed simulations than in random or adaptive. Although increasing sampling intensity improved the average sampling evenness score, the lowest value of sampling evenness was 0.95. This means that even high manipulations to the sampling regime had a low impact on overall sampling evenness and would have little impact on the ability to straightforwardly compare sampled data across sites without adding complexity to downstream analyses.

When looking at total energy consumption of a drone survey, using the routed sampling strategy reduced the average travel time per UAV (Fig. 5B) and total number of charger visits per UAV (Fig. 5C). This was in high contrast to the distances travelled by drones in both the random and adaptive sampling strategies. The difference in travel time and charger visits between routed strategies and the other strategies was higher at higher sampling intensities, likely due to the creation of sub-groups that forced UAVs to stay in one geographical area.

Discussion

This study demonstrates that the intermittent sampling design of a UAV-based acoustic monitoring survey can

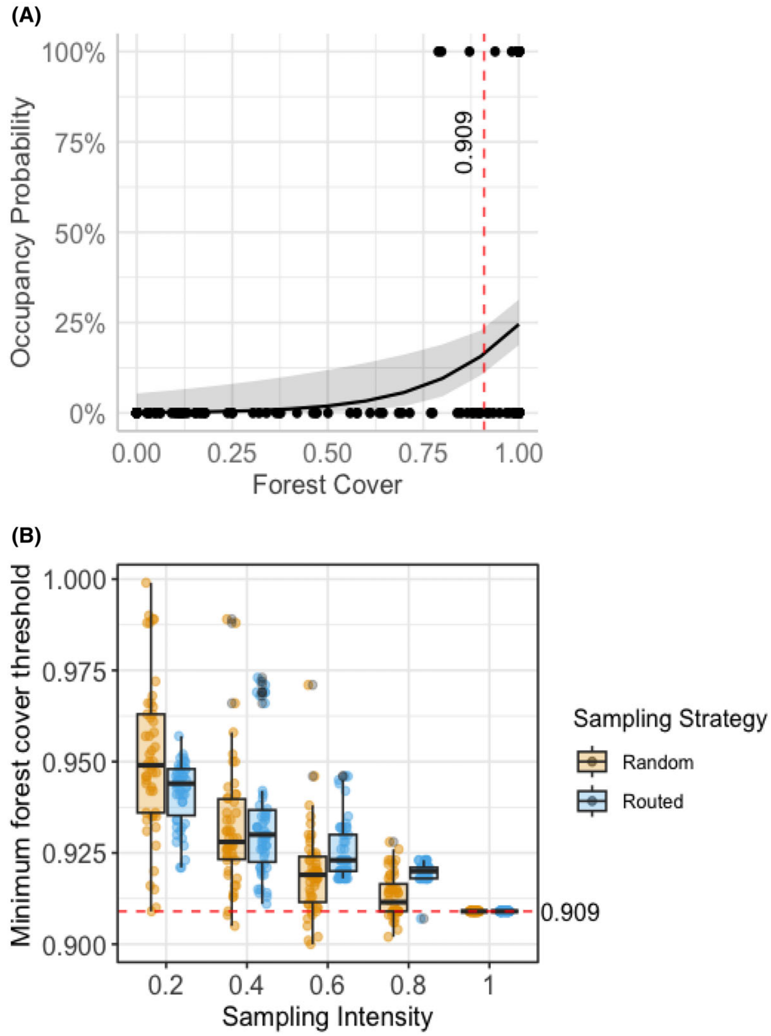

Figure 3. UAV-based acoustic surveys overestimate the minimum forest cover requirements for spider monkeys. (A) The predicted spider monkey occupancy over a gradient of forest cover within 100 m of the sensor when the entire dataset from a static PAM survey was included (Sampling Intensity = 1), as presented in Lawson et al. (2024). The minimum forest cover threshold, calculated by finding the cut-off point that maximized the probability of a positive spider monkey detection, was 0.909 (red dashed line). (B) shows a repetition of this analysis using data collected from simulated UAV surveys, where sampling intensity (the number of drones deployed simultaneously, as a proportion of total sites) and sampling strategy (Random movement between sites or Routed movement that prioritizes nearest neighbours) were varied. Boxplots summarize the minimum forest cover threshold estimated from 50 iterations of each simulation, where the box represents the lower quartile, median and upper quartile and the whiskers are 1.5 × the Interquartile Range. Points show the raw results from each simulation.

effectively detect broad biodiversity patterns such as associations with land-use types, but is limited in its ability to capture complete species lists at low sampling intensities. This suggests that a UAV-based acoustic survey could be used as a rapid, preliminary survey tool for identifying sites of high conservation value, reducing the need for manual deployments of acoustic sensors. Whilst previous studies on drone routing have largely focused on optimizing for efficiency in logistical applications (Macrina et al., 2020), this is the first study to investigate the impact of intermittent sampling strategies on the quality of downstream biodiversity data.

Impact of UAV sampling strategy and sampling intensity

One key consideration of survey design is the evenness of sampling across space and time to ensure both between- and within-site variability can be straightforwardly detected (Rhodes & Jonzén, 2011). Incomplete sampling

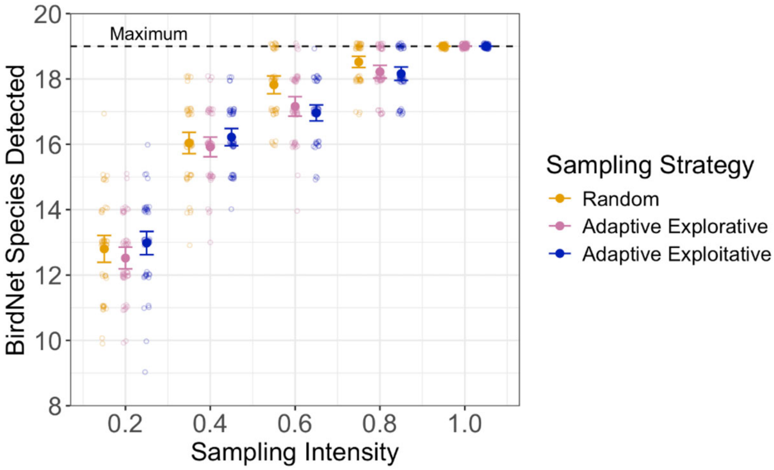

Figure 4. Incorporating very simple real-time detections into route planning does not detect more species than a random sampling strategy. Unique BirdNET species detections from three simulations of an existing acoustic dataset. In each simulation, we varied sampling intensity (number of UAVs deployed simultaneously, as a proportion of total sites) and sampling strategy, defined as random movement between sites or two types of adaptive sampling, where UAVs change routes depending on real-time detections. A sampling intensity of 1 represents the full dataset of a static PAM survey. Adaptive explorative indicates that previous vocalization frequency at a site gives a low bias towards visiting that site again over others, whereas adaptive exploitative indicates vocalization frequency at a site will give a high bias towards visiting that site again over others. Each solid point represents the average number of species detected over 50 simulation iterations, with error bars representing 95% confidence intervals. The faded points show the actual species richness from each iteration.

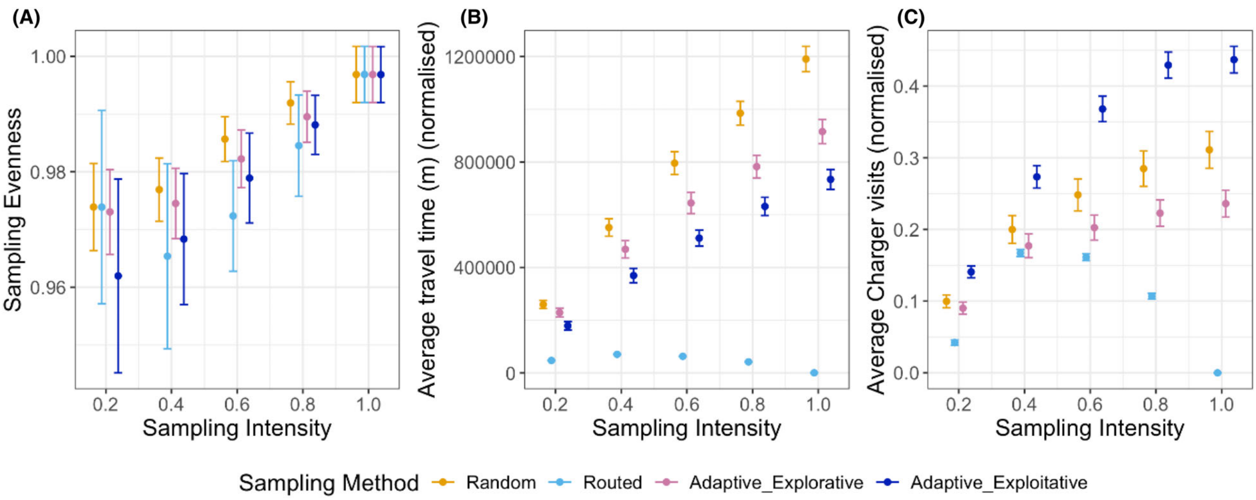

Figure 5. Distance-based, routed sampling improves energy consumption but not sampling evenness. Comparison of survey logistics for different drone survey simulations where sampling intensity (number of UAVs deployed simultaneously, as a proportion of total sites) and sampling strategy, defined as random movement between sites, routed (optimizing for the shortest travel distance) or two types of adaptive sampling, where UAVs change routes depending on real-time detections. A sampling intensity of 1 represents the full dataset of a static PAM survey. Adaptive explorative indicates that previous vocalization frequency at a site gives a low bias towards visiting that site again over others, whereas adaptive exploitative indicates previous vocalization frequency at a site will give a high bias towards visiting that site again over others. We calculated (A) sampling evenness using Shannon's evenness index (SEI), where a high value represents even sampling across sites and hours in the day. (B) Average total travel time, normalized by total number of sites in a cluster and (C) average number of charger visits, normalized by total number of sites in a cluster. For all plots, each point represents the average of 50 simulation iterations, with error bars representing 95% confidence intervals.

across either of these axes can lead to bias in biodiversity metrics like species richness (Banks-Leite et al., 2012; Chave, 2013; Field et al., 2002; Lahoz-Monfort et al., 2014). We hypothesized that the routed sampling strategy, designed to distribute visits evenly across sites, would enhance sampling evenness. However, we found that the sampling strategy had no influence on sampling evenness or downstream biodiversity metrics. This suggests that even simple, non-optimized sampling strategies can achieve sufficient site coverage, provided sampling intensity is high enough. Thus, the results of our experiments suggest the ability of UAV-based surveys to provide representative biodiversity metrics is largely dependent on the number of UAVs deployed or the length of the total survey period, rather than the routing systems tested here.

The feasibility of employing some of the sampling intensities given by our results depends on project aims, budget and scale. For a survey of 100 sites, an intensity of 0.4 could mean either deploying a swarm of 40 UAVs simultaneously or 4 UAVs visiting clusters of 10 sites sequentially. Our results suggest that lower intensities (0.2) can detect broad patterns such as land-use associations, but higher intensities (0.4–0.8) are needed to accurately detect specific signals like species' habitat thresholds or complete species lists. These findings suggest that practitioners could tailor sampling intensity to their monitoring goals, and further research could investigate how studies with a higher number of species might alter these interpretations.

Adaptive sampling is not yet widely used in biodiversity surveys, but advances in autonomous robotics present new opportunities to explore the potential of this approach (Henrys et al., 2024; Stache et al., 2023). The adaptive sampling strategy employed here showed no improvement over random sampling, possibly because sampling clusters were mostly within a single land-use type (Fig. 1), meaning that the adaptive algorithm struggled to identify a difference between sites. This strategy may perform better in fragmented landscapes, where adaptive sampling could reveal biodiversity gradients. Additionally, the adaptive strategy employed was relatively simple, relying on one variable: vocalization rate history. Although vocal activity has previously been used as an acoustic index (Towsey et al., 2014), there is no ecological theory linking it to the number of species. Vocal activity was a useful proxy in our dataset, as many sites had no detections at all, so prioritizing 'vocal' sites increased the chance of encountering species. A more advanced adaptive system could incorporate real-time abiotic or biotic (e.g. land classification) factors, similar to methods used in UAV-based pollution mapping (Boubrima & Knightly, 2021).

Study limitations and challenges for robotics-assisted acoustic surveys

Real-world deployments of UAV surveys may be influenced by additional factors such as the behavioural responses to UAVs or weather conditions, which we could not control for. Previous studies on UAV disturbance have mainly focused on optimal flight heights to minimize disturbance (Corcoran et al., 2021; Duporge et al., 2021; McEvoy et al., 2016); however, the intermittent sampling method used here would be more affected by recovery time after UAV landing. UAV take-off or landing can elicit escape responses in birds within 40 m (Weston et al., 2020), although others have found bird vocalization rates can recover in less than 4 min after noise disturbances from a snowmobile (Cretois et al., 2023). A species' tolerance to UAV noise depends on the focal taxa (Mesquita et al., 2022), UAV flight path (Afridi et al., 2024; Schad & Fischer, 2023), and the noise level of the UAV model (Kuhlmann et al., 2022). We recommend that UAV-based acoustic surveys account for disturbance effects by incorporating a latency period after landing and using quieter drone models where possible, with preliminary tests on disturbance of their study taxa before monitoring (Duporge et al., 2021; Schad & Fischer, 2023).

A limitation of the avian detections dataset was that BirdNET only detected a subset of the total bird species in the study area, limiting the possibilities for ecological analyses. The accuracy of BirdNET species detections has been shown to depend on the number of vocalizations available in public repositories (Funosas et al., 2024) that the training data are drawn from (Kahl et al., 2021). As a result, species that are frequent vocalizers and commonly encountered in human-dominated habitats tend to be detected with greater accuracy (Van Merriënboer et al., 2024), which is the case for the Costa Rica dataset (Sethi et al., 2024). Further work is needed to understand how reduced sampling intensity affects the data quality when looking at more detailed metrics of species habitat use that are possible with static acoustic surveys, such as occupancy (Rhinehart et al., 2022), community composition (Kümmet et al., 2025), or behaviour (Szymański et al., 2021; Wrege et al., 2017).

For our simulations, we based battery capacity on a commercially available UAV and did not test other models with longer flight capacity or differing propeller noise, since our study area was not distance-limited and we could not account for disturbance. Implementing the survey proposed in this study would require careful integration of emerging technologies, such as integrated sensors, solar-powered docking stations (e.g. Florczak et al., 2025) and efficient data-sharing systems (e.g. Li et al., 2021).

Whilst a single UAV is more expensive than a static acoustic sensor, the overall cost could be lower depending on sampling intensity, labour savings and extended survey duration. Legal constraints also shape feasibility, as many countries require UAV flights to maintain visual line of sight (VLOS), though regulations are evolving, with the UK Civil Aviation Authority aiming to permit Beyond VLOS operations by 2027 (UKCAA, 2024). Given that much of the technology already exists in prototype form, we believe that further investment in the development of advanced UAV swarm designs is justified.

Conclusion

In conclusion, our findings highlight the feasibility of UAV-based acoustic monitoring as a scalable approach for biodiversity assessment and highlight barriers to making robotics-assisted UAV surveys a reality. We demonstrate that the number of UAVs deployed simultaneously plays a greater role in determining detection success than the choice of sampling strategy, though routing will reduce power consumption. As UAV technology continues to advance, further research is needed to explore the applications of autonomous UAV-based ecological surveys across different ecosystems, taxonomic groups and data collection methods (e.g. camera trapping, eDNA). In addition, future studies should prioritize developing novel sensor placement methods and autonomy frameworks that are validated in field conditions to maximize their potential for conservation science.

Acknowledgements

We thank the UK Acoustics Network Plus (UKAN+) for providing funding to complete this research. We would also like to thank the staff at El Ministerio de Ambiente y Energia (MINAE) and La Sistema Nacional de Áreas de Conservación (SINAC) for their support with permits and for the field support from their park rangers. This work was partially supported by funding from the Engineering and Physical Sciences Research Council, the SERI-funded ERC ProteusDrone consolidator grant (grant no: MB22.00066), and the Empa-Imperial College London research partnership. Mirko Kovac was supported by the Royal Society Wolfson fellowship (RSWF/R1/18003). Jenna Lawson was supported by the Natural Environment Research Council (grant no. NE/L002515/1).

Author Contributions

Peggy A. Bevan: Conceptualization; investigation; writing – original draft; methodology; visualization; writing – review and editing; project administration. **Cristina Banks-Leite:** Funding acquisition; writing – review and editing; supervision; data curation; conceptualization. **Mirko Kovac:** Conceptualization; funding acquisition; writing – review and editing; supervision. **Jenna Lawson:** Conceptualization; methodology; writing – review and editing; data curation. **Lorenzo Picinali:** Conceptualization; funding acquisition; writing – review and editing; supervision. **Sarab S. Sethi:** Conceptualization; investigation; funding acquisition; writing – original draft; methodology; writing – review and editing; project administration; supervision; data curation.

Data Availability Statement

All code used for analysis is available at https://github.com/PeggyBevan/PAM_drones_simulator. All data used are publicly available at https://zenodo.org/records/6511837 (From Lawson et al., 2023) and https://zenodo.org/records/10820823 (From Sethi et al., 2024).

References

Afridi, S., Hlebowicz, K., Cawthorne, D., & Lundquist, U. P. S. (2024). Unveiling the Impact of Drone Noise on Wildlife: A Crucial Research Imperative. 2024 International Conference on Unmanned Aircraft Systems (ICUAS).

Allan, B.M., Nimmo, D.G., Ierodiaconou, D., Vanderwal, J., Koh, L.P. & Ritchie, E.G. (2018) Futurecasting ecological research: the rise of technoecology. *Ecosphere*, **9**(5), e02163. https://doi.org/10.1002/ecs2.2163

Banks-Leite, C., Ewers, R.M., Pimentel, R.G. & Metzger, J.P. (2012) Decisions on temporal sampling protocol influence the detection of ecological patterns. *Biotropica*, **44**(3), 378–385. https://doi.org/10.1111/j.1744-7429.2011.00801.x

Berger-Tal, O. & Lahoz-Monfort, J.J. (2018) Conservation technology: the next generation. *Conservation Letters*, **11**(6), e12458. https://doi.org/10.1111/conl.12458

Boubrima, A. & Knightly, E.W. (2021) Robust environmental sensing using UAVs. *ACM Transactions on Internet of Things*, **2**(4), 1–20. https://doi.org/10.1145/3464943

Browning, E., Gibb, R., Glover-Kapfer, P., & Jones, K. E. (2017). *Passive acoustic monitoring in ecology and conservation* (Conservation Technology Issue).

Chave, J. (2013) The problem of pattern and scale in ecology: what have we learned in 20 years? *Ecology Letters*, **16**(s1), 4–16. https://doi.org/10.1111/ele.12048

Christie, K.S., Gilbert, S.L., Brown, C.L., Hatfield, M. & Hanson, L. (2016) Unmanned aircraft systems in wildlife research: current and future applications of a transformative technology. *Frontiers in Ecology and the Environment*, **14**(5), 241–251. https://doi.org/10.1002/fee.1281

Corcoran, E., Denman, S. & Hamilton, G. (2021) Evaluating new technology for biodiversity monitoring: are drone surveys biased? *Ecology and Evolution*, **11**(11), 6649–6656. https://doi.org/10.1002/ece3.7518

Cretois, B., Bick, I.A., Balantic, C., Gelderblom, F.B., Pávon-Jordán, D., Wiel, J. et al. (2023) Snowmobile noise alters bird vocalization patterns during winter and pre-breeding season. *Journal of Applied Ecology*, **61**(2), 340–350. https://doi.org/10.1111/1365-2664.14564

Das, J., Py, F., Harvey, J.B.J., Ryan, J.P., Gellene, A., Graham, R. et al. (2015) Data-driven robotic sampling for marine ecosystem monitoring. *The International Journal of Robotics Research*, **34**(12), 1435–1452. https://doi.org/10.1177/0278364915587723

Duporge, I., Kholiavchenko, M., Harel, R., Wolf, S., Rubenstein, D.I., Crofoot, M.C. et al. (2025) BaboonLand dataset: tracking primates in the wild and automating behaviour recognition from drone videos. *International Journal of Computer Vision*, **133**(9), 6578–6589. https://doi.org/10.1007/s11263-025-02493-5

Duporge, I., Spiegel, M.P., Thomson, E.R., Chapman, T., Lamberth, C., Pond, C. et al. (2021) Determination of optimal flight altitude to minimise acoustic drone disturbance to wildlife using species audiograms. *Methods in Ecology and Evolution*, **12**(11), 2196–2207. https://doi.org/10.1111/2041-210x.13691

Dwivedi, K., Govindarajan, P., Srinivasan, D., Keerthi Sanjana, A., Selvanambi, R. & Karuppiah, M. (2023) Intelligent autonomous drones in industry 4.0. In: *Artificial intelligence and cyber security in industry 4.0, Advanced Technologies and Societal Change*. Singapore: Springer, pp. 133–163. https://doi.org/10.1007/978-981-99-2115-7_6

Field, S.A., Tyre, A.J. & Possingham, H.P. (2002) Estimating bird species richness: how should repeat surveys be organized in time? *Austral Ecology*, **27**(6), 624–629. https://doi.org/10.1046/j.1442-9993.2002.01223.x

Figueira, L., Tella, J.L., Camargo, U.M. & Ferraz, G. (2015) Autonomous sound monitoring shows higher use of Amazon old growth than secondary forest by parrots. *Biological Conservation*, **184**, 27–35. https://doi.org/10.1016/j.biocon.2014.12.020

Fischer, S., Edwards, A.C., Garnett, S.T., Whiteside, T.G. & Weber, P. (2023) Drones and sound recorders increase the number of bird species identified: a combined surveys approach. *Ecological Informatics*, **74**, 101988. https://doi.org/10.1016/j.ecoinf.2023.101988

Flint, I., Wu, C.H., Valavi, R., Chen, W.J. & Lin, T.E. (2024) Maximising the informativeness of new records in spatial sampling design. *Methods in Ecology and Evolution*, **15**(1), 178–190. https://doi.org/10.1111/2041-210x.14260

Florczak, D., Jacewicz, M., Kopyt, A. & Głębocki, R. (2025) Autonomous solar-powered docking station for quadrotor drones–design and testing. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*. https://doi.org/10.1177/09544100251331282

Fu, Y., Kinniry, M. & Kloepper, L.N. (2018) The Chirocopter: a UAV for recording sound and video of bats at altitude. *Methods in Ecology and Evolution*, **9**(6), 1531–1535. https://doi.org/10.1111/2041-210x.12992

Funosas, D., Barbaro, L., Schillé, L., Elger, A., Castagneyrol, B. & Cauchoix, M. (2024) Assessing the potential of BirdNET to infer European bird communities from large-scale ecoacoustic data. *Ecological Indicators*, **164**, 112146. https://doi.org/10.1016/j.ecolind.2024.112146

Gibb, R., Browning, E., Glover-Kapfer, P., Jones, K.E. & Börger, L. (2018) Emerging opportunities and challenges for passive acoustics in ecological assessment and monitoring. *Methods in Ecology and Evolution*, **10**(2), 169–185. https://doi.org/10.1111/2041-210x.13101

Gilbert, L.E., Christen, C.A., Altrichter, M., Longino, J.T., Sherman, P.M., Plowes, R. et al. (2016) The southern Pacific lowland evergreen moist forest of the Osa Region. In: *Costa Rican ecosystems*. Chicago, Illinois: The University of Chicago Press, pp. 360–412. https://doi.org/10.7208/chicago/9780226121642.003.0012

Guerber, C., Royer, M. & Larrieu, N. (2021) Machine learning and software defined network to secure communications in a swarm of drones. *Journal of Information Security and Applications*, **61**, 102940. https://doi.org/10.1016/j.jisa.2021.102940

Gunal, M.M. (2019) Data collection inside industrial facilities with autonomous drones. In: *Simulation for Industry 4.0, Springer Series in Advanced Manufacturing*. Cham: Springer, pp. 141–151. https://doi.org/10.1007/978-3-030-04137-3_9

Henrys, P.A., Mondain-Monval, T.O. & Jarvis, S.G. (2024) Adaptive sampling in ecology: key challenges and future opportunities. *Methods in Ecology and Evolution*, **15**(9), 1483–1496. https://doi.org/10.1111/2041-210x.14393

Hill, A.P., Prince, P., Snaddon, J.L., Doncaster, C.P. & Rogers, A. (2019) AudioMoth: a low-cost acoustic device for monitoring biodiversity and the environment. *HardwareX*, **6**, e00073. https://doi.org/10.1016/j.ohx.2019.e00073

Hwang, J., Bose, N. & Fan, S. (2019) AUV adaptive sampling methods: a review. *Applied Sciences*, **9**(15), 3145. https://doi.org/10.3390/app9153145

Jakuba, M.V., Kinsey, J.C., Yoerger, D.R., Camilli, R., Murphy, C.A., Steinberg, D. et al. (2011) Exploration of the gulf of Mexico oil spill with the sentry autonomous underwater vehicle. *Proceedings of the international conference on intelligent robots and systems (IROS)*, Workshop on Robotics for Environmental Monitoring (WREM), San Francisco, CA, USA.

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

Kuhlmann, K., Fontaine, A., Brisson-Curadeau, É., Bird,D.M. Elliott, K.H.2022) Miniaturization eliminates detectable impacts of drones on bat activity. *Methods in Ecology and Evolution*, **13**(4), 842–851. https://doi.org/10.1111/2041-210x.13807

Kümmet, S., Müller, J., Burivalova, Z., Schaefer, H.M., Gelis, R., Freile, J. et al. (2025) Acoustic indices predict recovery of tropical bird communities for taxonomic and functional composition. *Conservation Letters*, **18**(4), e13131.

Lahoz-Monfort, J.J. & Magrath, M.J.L. (2021) A comprehensive overview of technologies for species and habitat monitoring and conservation. *Bioscience*, **71**(10), 1038–1062. https://doi.org/10.1093/biosci/biab073

Lahoz-Monfort, J.J., Harris, M.P., Morgan, B.J.T., Freeman, S.N. & Wanless, S. (2014) Exploring the consequences of reducing survey effort for detecting individual and temporal variability in survival. *Journal of Applied Ecology*, **51**(2), 534–543. https://doi.org/10.1111/1365-2664.12214

Lan, T., Romanello, L., Kovac, M., Armanini, S. F., & Bahadir Kocer, B. (2024). Aerial Tensile Perching and Disentangling Mechanism for Long-Term Environmental Monitoring. 2024 IEEE International Conference on Robotics and Automation (ICRA).

Lawson, J. (2022). JennaLawson/spider-monkey: spider-monkey-acoustics (version v.1.0). *Zenodo*. https://doi.org/10.5281/zenodo.6511837.

Lawson, J., Farinha, A., Romanello, L., Pang, O., Zufferey, R. & Kovac, M. (2024) Use of an unmanned aerial-aquatic vehicle for acoustic sensing in freshwater ecosystems. *Remote Sensing in Ecology and Conservation*, **10**(3), 343–359. https://doi.org/10.1002/rse2.373

Lawson, J., Rizos, G., Jasinghe, D., Whitworth, A., Schuller, B. & Banks-Leite, C. (2023) Automated acoustic detection of Geoffroy's spider monkey highlights tipping points of human disturbance. *Proceedings of the Biological Sciences*, **290**(1995), 20222473. https://doi.org/10.1098/rspb.2022.2473

Li, C.-I., Yen, L.-H., & Cho, M.-C. (2021). Distributed mission and charging scheduling for UAV swarm to maximize service coverage. 2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall).

Lucas, T.C.D., Moorcroft, E.A., Freeman, R., Rowcliffe, J.M. & Jones, K.E. (2015) A generalised random encounter model for estimating animal density with remote sensor data. *Methods in Ecology and Evolution*, **6**(5), 500–509. https://doi.org/10.1111/2041-210x.12346

Macrina, G., Di Puglia Pugliese, L., Guerriero, F. & Laporte, G. (2020) Drone-aided routing: a literature review. *Transportation Research Part C: Emerging Technologies*, **120**, 102762. https://doi.org/10.1016/j.trc.2020.102762

Marques, T.A., Thomas, L., Martin, S.W., Mellinger, D.K., Ward, J.A., Moretti, D.J. et al. (2013) Estimating animal population density using passive acoustics. *Biological Reviews of the Cambridge Philosophical Society*, **88**(2), 287–309. https://doi.org/10.1111/brv.12001

McEvoy, J.F., Hall, G.P. & McDonald, P.G. (2016) Evaluation of unmanned aerial vehicle shape, flight path and camera type for waterfowl surveys: disturbance effects and species recognition. *PeerJ*, **4**, e1831. https://doi.org/10.7717/peerj.1831

Mesquita, G., Mulero-Pázmány, M., Wich, S. & Rodríguez-Teijeiro, J. (2022) Terrestrial megafauna response to drone noise levels in ex situ areas. *Drones*, **6**(11), 333. https://doi.org/10.3390/drones6110333

Metcalf, O., Abrahams, C., Ashington, B., Baker, E., Bradfer-Lawrence, T., Browning, E. et al. (2023). Good practice guidelines for long-term ecoacoustic monitoring in the U.K.

Michez, A., Broset, S. & Lejeune, P. (2021) Ears in the sky: potential of drones for the bioacoustic monitoring of birds and bats. *Drones*, **5**(1), 9. https://doi.org/10.3390/drones5010009

Millner, N., Cunliffe, A.M., Mulero-Pázmány, M., Newport, B., Sandbrook, C. & Wich, S. (2023) Exploring the opportunities and risks of aerial monitoring for biodiversity conservation. *Global Social Challenges Journal*, **2**, 2–23. https://doi.org/10.1332/tiok6806

Newson, S.E., Bas, Y., Murray, A., Gillings, S. & Freckleton, R. (2017) Potential for coupling the monitoring of bush-crickets with established large-scale acoustic monitoring of bats. *Methods in Ecology and Evolution*, **8**(9), 1051–1062. https://doi.org/10.1111/2041-210x.12720

Pacifici, K., Reich, B.J., Dorazio, R.M. & Conroy, M.J. (2016) Occupancy estimation for rare species using a spatially-adaptive sampling design. *Methods in Ecology and Evolution*, **7**(3), 285–293. https://doi.org/10.1111/2041-210x.12499

Phalapanyakoon, K. & Siripongwutikorn, P. (2021) Route planning of unmanned aerial vehicles under recharging and mission time constraints. *International Journal of Mathematical, Engineering and Management Sciences*, **6**(5), 1439–1459. https://doi.org/10.33889/ijmems.2021.6.5.087

Pringle, S., Dallimer, M., Goddard, M.A., Le Goff, L.K., Hart, E., Langdale, S.J. et al. (2025) Opportunities and challenges for monitoring terrestrial biodiversity in the robotics age. *Nature Ecology & Evolution*, **9**(6), 1031–1042. https://doi.org/10.1038/s41559-025-02704-9

Rahman, D.A., Putro, H.R., Mufawwaz, T.A., Rinaldi, D., Yudiarti, Y., Prabowo, E.D. et al. (2025) Developing a new method using thermal drones for population surveys of the world's rarest great ape species, *Pongo tapanuliensis*. *Global Ecology and Conservation*, **58**, e03463. https://doi.org/10.1016/j.gecco.2025.e03463

Rhinehart, T.A., Turek, D. & Kitzes, J. (2022) A continuous-score occupancy model that incorporates uncertain machine learning output from autonomous biodiversity surveys. *Methods in Ecology and Evolution*, **13**(8), 1778–1789. https://doi.org/10.1111/2041-210x.13905

Rhodes, J.R. & Jonzén, N. (2011) Monitoring temporal trends in spatially structured populations: how should sampling effort be allocated between space and time? *Ecography*, **34**

(6), 1040–1048. https://doi.org/10.1111/j.1600-0587.2011.06370.x

Rizos, G., Lawson, J., Han, Z., Butler, D., Rosindell, J., Mikolajczyk, K. et al. (2021). Multi-attentive detection of the spider monkey whinny in the (actual) wild, Interspeech 2021,

Robinson, J.M., Harrison, P.A., Mavoa, S. & Breed, M.F. (2022) Existing and emerging uses of drones in restoration ecology. *Methods in Ecology and Evolution*, **13**(9), 1899–1911. https://doi.org/10.1111/2041-210x.13912

Romanello, L., Lan, T., Kovac, M., Armanini, S. F., & Kocer, B. B. (2024). *Exploring the potential of multi-modal sensing framework for forest ecology*. IEEE International Conference on Robotics and Automation, Yokohama, Japan.

Ross, S.R.P.J., O'Connell, D.P., Deichmann, J.L., Desjonquères, C., Gasc, A., Phillips, J.N. et al. (2023) Passive acoustic monitoring provides a fresh perspective on fundamental ecological questions. *Functional Ecology*, **37**(4), 959–975. https://doi.org/10.1111/1365-2435.14275

Sánchez-Azofeifa, G.A., Daily, G.C., Pfaff, A.S.P. & Busch, C. (2003) Integrity and isolation of Costa Rica's national parks and biological reserves: examining the dynamics of land-cover change. *Biological Conservation*, **109**(1), 123–135. https://doi.org/10.1016/s0006-3207(02)00145-3

Schad, L. & Fischer, J. (2023) Opportunities and risks in the use of drones for studying animal behaviour. *Methods in Ecology and Evolution*, **14**(8), 1864–1872. https://doi.org/10.1111/2041-210x.13922

Schofield, G., Katselidis, K.A., Lilley, M.K.S., Reina, R.D. & Hays, G.C. (2017) Detecting elusive aspects of wildlife ecology using drones: new insights on the mating dynamics and operational sex ratios of sea turtles. *Functional Ecology*, **31**(12), 2310–2319. https://doi.org/10.1111/1365-2435.12930

Sethi, S. (2024). *Data associated with global-bird-detection-paper [Data set]* (Zenodo). https://doi.org/10.5281/zenodo.10820823.

Sethi, S.S., Bick, A., Chen, M.-Y., Crouzeilles, R., Hillier, B.V., Lawson, J. et al. (2024) Large-scale avian vocalization detection delivers reliable global biodiversity insights. *Proceedings of the National Academy of Sciences of the United States of America*, **121**(33), e2315933121. https://doi.org/10.1073/pnas.2315933121

Sethi, S.S., Ewers, R.M., Jones, N.S., Orme, C.D.L., Picinali, L. & Parrini, F. (2018) Robust, real-time and autonomous monitoring of ecosystems with an open, low-cost, networked device. *Methods in Ecology and Evolution*, **9**(12), 2383–2387. https://doi.org/10.1111/2041-210x.13089

Sethi, S.S., Kovac, M., Wiesemüller, F., Miriyev, A. & Boutry, C.M. (2022) Biodegradable sensors are ready to transform autonomous ecological monitoring. *Nature Ecology & Evolution*, **6**(9), 1245–1247. https://doi.org/10.1038/s41559-022-01824-w

Shrestha, S., Johnson, T., Langstaff, J., Rashid, T., Bouffard, M. & Candice, L. (2018). Utilizing NASA earth observations to evaluate effects of land use change on watershed health and carbon sequestration in the Osa Peninsula, Costa Rica. NASA DEVELOP National Program. See https://develop.larc.nasa.gov/2018/summer/posters/2018Sum_GA_OsaPeninsulaWaterII_Poster.pdf.

Stache, F., Westheider, J., Magistri, F., Stachniss, C. & Popović, M. (2023) Adaptive path planning for UAVs for multi-resolution semantic segmentation. *Robotics and Autonomous Systems*, **159**, 104288. https://doi.org/10.1016/j.robot.2022.104288

Stephenson, P.J. (2020) Technological advances in biodiversity monitoring: applicability, opportunities and challenges. *Current Opinion in Environmental Sustainability*, **45**, 36–41.

Stowell, D. (2022) Computational bioacoustics with deep learning: a review and roadmap. *PeerJ*, **10**, e13152. https://doi.org/10.7717/peerj.13152

Stowell, D. & Sueur, J. (2020) Ecoacoustics: acoustic sensing for biodiversity monitoring at scale. *Remote Sensing in Ecology and Conservation*, **6**(3), 217–219. https://doi.org/10.1002/rse2.174

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

Szymański, P., Olszowiak, K., Wheeldon, A., Budka, M. & Osiejuk, T.S. (2021) Passive acoustic monitoring gives new insight into year-round duetting behaviour of a tropical songbird. *Ecological Indicators*, **122**, 107271. https://doi.org/10.1016/j.ecolind.2020.107271

Towsey, M., Wimmer, J., Williamson, I. & Roe, P. (2014) The use of acoustic indices to determine avian species richness in audio-recordings of the environment. *Ecological Informatics*, **21**, 110–119. https://doi.org/10.1016/j.ecoinf.2013.11.007

UKCAA. (2024). *Delivering scalable UAS BVLOS in the specific category*.

Van Merriënboer, B., Hamer, J., Dumoulin, V., Triantafillou, E. & Denton, T. (2024) Birds, bats and beyond: evaluating generalization in bioacoustics models. *Frontiers in Bird Science*, **3**, 1369756. https://doi.org/10.3389/fbirs.2024.1369756

Wägele, J.W., Bodesheim, P., Bourlat, S.J., Denzler, J., Diepenbroek, M., Fonseca, V. et al. (2022) Towards a multisensor station for automated biodiversity monitoring. *Basic and Applied Ecology*, **59**, 105–138. https://doi.org/10.1016/j.baae.2022.01.003

Wang, L., Clayton, M. & Rossberg, A.G. (2023) Drone audition for bioacoustic monitoring. *Methods in Ecology and Evolution*, **14**(12), 3068–3082. https://doi.org/10.1111/2041-210x.14234

Weston, M.A., O'Brien, C., Kostoglou, K.N. & Symonds, M.R.E. (2020) Escape responses of terrestrial and aquatic birds to drones: towards a code of practice to minimize disturbance. *Journal of Applied Ecology*, **57**(4), 777–785. https://doi.org/10.1111/1365-2664.13575

Wilson, A.M., Barr, J. & Zagorski, M. (2017) The feasibility of counting songbirds using unmanned aerial vehicles. *The Auk*, **134**(2), 350–362. https://doi.org/10.1642/auk-16-216.1

Wrege, P.H., Rowland, E.D., Keen, S. & Shiu, Y. (2017) Acoustic monitoring for conservation in tropical forests: examples from forest elephants. *Methods in Ecology and Evolution*, **8**(10), 1292–1301. https://doi.org/10.1111/2041-210x.12730

Zheng, P., Xiao, F., Nguyen, P.H., Farinha, A. & Kovac, M. (2023) Metamorphic aerial robot capable of mid-air shape morphing for rapid perching. *Scientific Reports*, **13**(1), 1297. https://doi.org/10.1038/s41598-022-26066-5

Zhou, X., Wen, X., Wang, Z., Gao, Y., Li, H., Wang, Q. et al. (2022) Swarm of micro flying robots in the wild. *Science Robotics*, **7**(66), eabm5954. https://doi.org/10.1126/scirobotics.abm5954

