Received: 21 September 2021 | Accepted: 20 December 2021

DOI: 10.1111/2041-210X.13807

Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

RESEARCH ARTICLE

Miniaturization eliminates detectable impacts of drones on bat activity

Kayla Kuhlmann | **Amélie Fontaine** | **Émile Brisson-Curadeau** | **David M. Bird** | **Kyle H. Elliott**

Department of Natural Resource Sciences, McGill University, Montréal, QC, Canada

Correspondence
Kayla Kuhlmann
Email: kayla.kuhlmann@mail.mcgill.ca

Funding information
Canadian Network for Research and Innovation in Machining Technology, Natural Sciences and Engineering Research Council of Canada, Grant/Award Number: 241061; Kenneth Molson Foundation; Natural Sciences and Engineering Research Council of Canada; Molson Foundation

Handling Editor: Veronica Zamora-Gutierrez

Abstract

1. Advances in operational simplicity and cost efficiency have promoted the rapid integration of unoccupied aerial vehicles (UAVs) into ecological research, yet UAVs often disturb wildlife, potentially biasing measurements. Studies of UAV effects on wildlife to date have focused on UAV trajectory or distance; however, UAV size and noise could be critical variables influencing wildlife responses.
2. Bats are cryptic aerial species that are difficult to survey using conventional means, and so we tested the effectiveness of drone-based acoustic surveys for bats. We recorded the number of acoustic bat detections with and without a UAV present. We used three small, commercial rotary UAVs varying in size and noise intensity (249, 907, 1,380 g).
3. Larger and louder UAVs deterred significantly more bats, with no effect of take-off distance on bat activity. The smallest and quietest UAV model had a similar change in bat activity compared with control measurements. Drone noise increased with drone size, but all drones emitted in a similar range of frequencies that overlapped with the larger bat species that were also those most impacted by the UAV. During the 5-minute surveys, there was no evidence of bat habituation to UAVs although bats returned quickly once the UAV survey ended.
4. We urge wildlife researchers to consider drone size during wildlife surveys. Smaller and quieter models have negligible impacts on wildlife, eliminating the impact of drones on wildlife in some cases.

KEYWORDS
acoustic survey, bat detection, disturbance, drone size, drone type, UAV, wildlife survey

1 | INTRODUCTION

Unoccupied aerial vehicles (UAVs or drones) are becoming valuable tools in ecological research, as they offer a safer, cheaper and quieter alternative to large aircraft and may be more accurate than conventional methods (Hodgson et al., 2018; Scholten et al., 2019). Additionally, the increasing clarity of airspace regulations on UAV activity in many regions has lifted restrictions and simplified UAV use for wildlife science (Chabot & Bird, 2015; Gonzalez et al., 2016). However, wildlife has had adverse reactions to UAV presence (Broset, 2018; Chabot & Bird, 2015; Mulero-Pázmány et al., 2017). Although several studies observed little to no obvious behavioural response to UAV flight (Broset, 2018; Christie et al., 2016; Mulero-Pázmány et al., 2014), others have documented strong behavioural responses (Brisson-Curadeau et al., 2017; Weimerskirch et al., 2018) or physiological stress responses (Ditmer et al., 2015), and the response of many animal groups remains inadequately tested. Thus, although UAVs provide the potential to survey elusive wildlife (e.g. bats), guidelines for reducing impacts on wildlife are needed.

Many studies have shown that how a UAV is flown (i.e. distance to wildlife, flight direction, take-off distance, flight pattern) can impact wildlife reactions (Brisson-Curadeau et al., 2017; Chabot & Bird, 2015; Duporge et al., 2021; Hodgson & Koh, 2016; Mulero-Pázmány et al., 2017; Vas et al., 2015). Fewer have described how wildlife responses can vary with UAV type, including one review demonstrating that larger UAVs cause animals to react from greater distances than smaller UAVs (Mulero-Pázmány et al., 2017). The choice of UAV type for wildlife research is a critical decision considering that the UAV rotary models available differ widely in power source, dimension, cost, flight parameters and battery life. UAVs also emit variable ultrasonic frequencies, ranging from 4 to 45 kHz (Broset, 2018; August & Moore, 2019; Jokisch & Fischer, 2019). UAVs emit higher frequency signals when climbing and lower frequencies when shifting positions relative to hovering (Jokisch & Fischer, 2019). Finally, UAVs increase environmental noise by about 15 dB with larger and heavier UAVs being louder than small UAVs (Broset, 2018; Christie et al., 2016; Farlik et al., 2019; Miljković, 2018). If UAV noise and size impacts wildlife behaviour, then the use of smaller UAVs could be an important best practice for drone-based wildlife surveys.

Due to bats' ability to echolocate, acoustic detectors are popular tools for bat detection, leading to important advancements in monitoring bat activity and estimating their abundance (August & Moore, 2019; Kloepper et al., 2016; Kunz et al., 2009). Bat acoustic detectors record the ultrasound calls emitted by bats, which can be used in combination with bat identification software to depict frequency range and call shape on a spectrogram. These detectors are non-invasive, with some capable of continuously recording and saving large volumes of data in nearly every environment and condition (Adams et al., 2012; Broset, 2018; Skalak et al., 2012). The range of acoustic detection varies with the model of detector, parameters of the detector, bat species and weather (Adams et al., 2012; Goerlitz, 2018). To decrease bias in detection, detectors have been elevated to altitudes, such as over the forest canopy, with masts, balloons, kites, pulleys and towers (August & Moore, 2019; Froidevaux et al., 2014; Plank et al., 2012). Even with these methods, acoustic detection is still restricted by altitude, direction and control in the air.

To facilitate mobile aerial data collection, some studies have demonstrated success with acoustically recording bats from rotary UAVs that can be flown to high altitudes and to hard-to-access locations (Broset, 2018; Fu et al., 2018; Kloepper & Kinniry, 2018). Despite these advantages, UAVs may not be suitable for recording bat echolocation calls because their noise overlaps with the frequencies of bat calls, specifically low-frequency bat calls (Broset, 2018; Fu et al., 2018; Kloepper & Kinniry, 2018). For example, attempts to use UAVs to record bird song has led to variable detection rates (Wilson et al., 2017). While some bat species may be under-represented based on the frequency range of their calls, the duration of the survey also affects results, as surveys that are too short miss some rare bat species (Skalak et al., 2012). Thus, the limited battery life of some drones (especially larger drones) should be considered, to prevent bias against rare species in drone-based acoustic bat monitoring—although the ability of a drone to survey the entire air column and inaccessible sites may also increase detection rates of rare species. Additionally, since noisy environments decrease bat foraging efficiency (Allen et al., 2021), the noise from drones may disturb bats. Ednie et al. (2021) tested a small, commercial quadcopter and found that bat activity was much lower and variable in the presence of a drone. As ultrasound generated by bat frequencies was easily detected by the bat recorder even in the presence of a drone, the lower detection of bat activity likely represented avoidance by bats of the area when the drone was present (Ednie et al., 2021). If drone presence alters detection rates variably, then this technology cannot be used to reliably survey bats (Ednie et al., 2021).

Here, we investigate whether UAV size impacts bat activity. We hypothesized that if UAV flight deters bats due to the sound and disturbance, then activity will decrease when flying louder and larger UAVs. Also, if launching UAVs is the loudest period of flight, then bat activity is predicted to be higher when a farther launch site is used. Next, we (a) analyse how different bat species are affected by drone, and (b) examine the effects of drone LED lights on bats. Finally, we examine if and how quickly bats habituate to the presence of a UAV, and how quickly they respond post-trial. We aim to determine UAV specifications most conducive to bat research and select a small, commercial UAV that could be used to survey bats with a basic drone licence.

2 | MATERIALS AND METHODS

2.1 | Field site

We conducted the study at The Kenauk Institute nature reserve in Montebello, Québec, Canada between 10 June and 12 August 2020. We were invited by the Kenauk Research Institute to conduct fieldwork without the need for a permit. All eight bat species native to Québec have been previously identified on Kenauk property (Ednie et al., 2021): the hoary bat *Lasiurus cinereus*, silver-haired bat *Lasionycteris noctivagans*, big brown bat *Eptesicus fuscus*, Eastern red bat *Lasiurus borealis*, tri-coloured bat *Perimyotis subflavus*, little brown myotis *Myotis lucifugus*, northern long-eared myotis *Myotis septentrionalis* and eastern small-footed myotis *Myotis leibii*. We chose eight sites that were near water where insects are prevalent or near structures that could act as roosts in open or semi-open habitats (Supporting Information 1), as these qualities provide suitable bat habitat.

2.2 | Drone model and launch method

We selected three off-the-shelf quadcopters to conduct the trials: the DJI Phantom 4, DJI Mavic 2 Pro and DJI Mavic Mini (DJI, Shenzhen, China). For the trials, we launched each drone model using two launch distances: (a) at the site of detection and (b) 50 m from the site of detection, resulting in six treatments. The selected drones varied in weight, dimension and cost, as well as noise level and frequency range (Table 1). To determine which drones were the loudest and which may overlap with bat calls, we acoustically profiled the drones by recording flight in the same environment. Acoustic profiling was done with a smartphone using the Decibel X (SkyPaw Co. Ltd, Hanoi, Vietnam) application where frequency of the drones (Hz) was measured as well as noise intensity (dBFS) over time of drone flight. The acoustic profiling revealed potential overlap the drones may have with the two lowest frequency calling bats (Figure 1).

2.3 | Data collection

We performed trials starting 30 min after dusk from 21:00 h to 0:00 h, following the procedure described by Ednie et al. (2021). Trials consisted of three phases where we acoustically recorded bat activity before, during and after drone treatment. We measured bat activity with the number of bat passes per trial, with more frequent bat passes indicating higher bat activity. Treatment (which drone was flown and with which launch method) was randomly assigned. At each site, we placed a control detector 250–400 m away from the treatment, enough distance to attenuate drone noise but remain in similar habitat. Drones were only flown in suitable weather conditions (nights with winds below 20 km/h and no precipitation or frost). All flights involved two operators: a pilot and an acoustic recorder operator.

Upon arriving to one of our eight detection sites, we began the first phase of the trial by attaching the Echo Meter Touch 2 plugin acoustic bat detector (Wildlife Acoustics) to a tablet and initiating recording with the corresponding Wildlife Acoustics app (Wildlife Acoustics). The detector automatically saves the time of recording, an audio recording, the frequencies the bat call occupies over time on a spectrogram and the species that it identifies to the smartphone app. Phase 1 consisted of audio recording from the ground with the Echo Meter Touch 2 for 5 min with no drone activity. After 5 min, we began Phase 2 by setting up one of the three drones for the randomly chosen treatment. We either launched the drone to 15 m above the site of detection where the drone remained hovering (Figure 2a), or we carried the drone to a launch site 50 m away, ascended it to 15 m above the launch site and then flew the drone above the detection site (Figure 2b). For all tests during Phase 2, recording with the Echo Meter Touch 2 acoustic bat detector began from the ground when the drone was 15 m above the detection site (Figure 2). While manoeuvring, the drone was flown at a standard 5 mph, but the drones were not manoeuvred during acoustic recording. The drone hovered in place for 5 min, and afterwards was returned to its launch site. Once we powered off the drone, we continued to Phase 3, that is another 5 min of audio bat detection with no drone disturbance. This completed the trial, then we repeated the

TABLE 1 Main characteristics of the three quadcopter models used for this study. Noise is on a relative scale and represents the loudest noise during flight, from powering on to turning off. Details on UAV acoustics can be found in Supporting Information 2. Image sourced from DJI website (DJI, n.d.)

UAV model	Mass	Dimensions	Cost (USD)	Max flight time	Max speed	Max wind speed resistance	Noise/sound level	Frequency range	Image
DJI Phantom 4	1,380 g	325*220*380 mm	$1,450	28 min	20 m/s	10 m/s	0 dBFS/55 dB	0–6 kHz	
DJI Mavic 2 Pro	907 g	322*232*84 mm	$1,599	31 min	20 m/s	8–10.5 m/s	−6 dBFS/50 dB	0–5.8 kHz	
DJI Mavic Mini	249 g	245*289*55 mm	$399	30 min	13 m/s	8 m/s	−24 dBFS/49 dB	0–6.8 kHz	

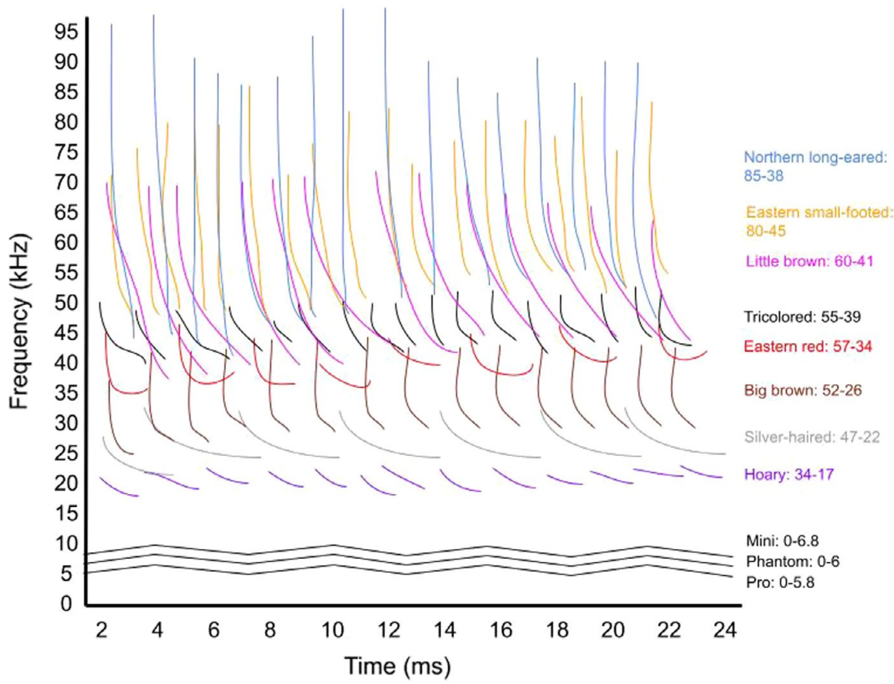

FIGURE 1 Frequency overlap between drones and bats. The echolocation calls of the eight native bat species to Québec are demonstrated, with the text representing species common name and minimum to maximum frequencies (kHz) of their calls. The drones are also represented with the maximum frequency level (kHz) that they occupy when hovering 15 m above and 5 m away from the acoustic recorder. There is potential for overlap between drone noise and the lowest frequency bat calls. Even though the frequencies depicted do not overlap, the drone is much closer to the bats compared with the recorder, and so high frequencies may be less attenuated from the bats' perspectives

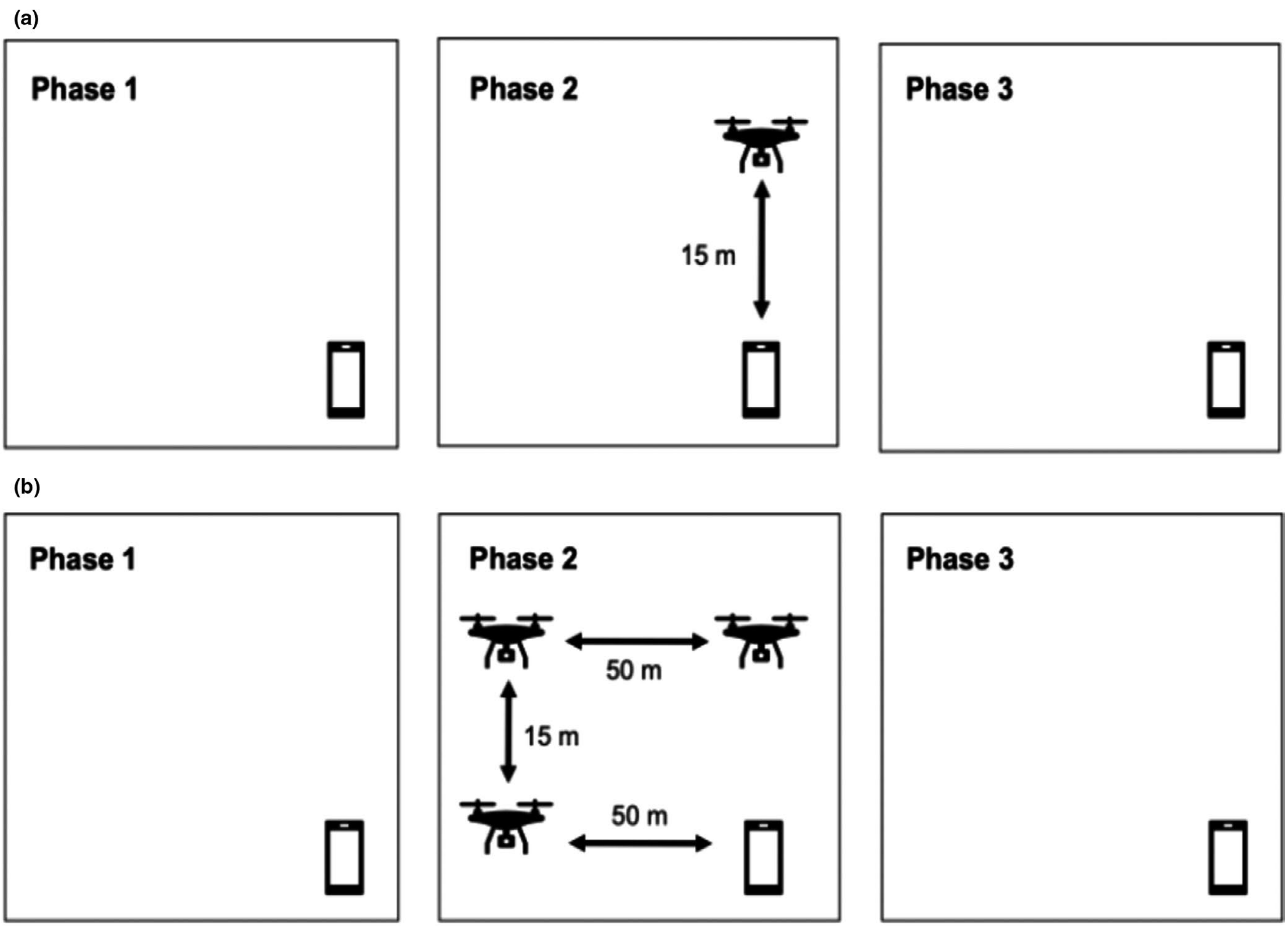

FIGURE 2 Two launch methods. (a) The drone was launched above the detection site for treatments 1 (Phantom 4), 3 (Mavic 2 Pro) and 5 (Mavic Mini). (b) The drone was launched 50 m away and was flown to the detection site for treatments 2 (Phantom 4), 4 (Mavic 2 Pro) and 6 (Mavic Mini). Treatments were randomly assigned. The device represents the site of detection with the Echo Meter Touch 2

procedure at a new site, conducting one trial at each site every night of the experiment.

To examine the effect of the drone LED lights on bat activity, we completed two sets of measurements using the DJI Phantom 4. First, we recorded bat activity during control periods with drone LED lights turned off at 15 m above the detection site (5 min; $N = 10$) and paired periods with drone LED lights turned on at 15 m above the detection site (5 min; $N = 10$). In each case, there was no drone flight or noise. Second, we recorded bat activity during Phase 2 with and without drone LED lights turned on ($N = 10$ of each). For both sets of measurements, each paired trial was run on a different night, and we randomized the paired order with LED lights on or off.

2.4 | Echolocation call identification

Bat calls detected were automatically saved and identified to species using Kaleidoscope Pro Analysis Software (Wildlife Acoustics) integrated in the Wildlife Acoustics app. Apart from setting the region to Québec, the default settings were used for all software. Due to the difficulty differentiating between frequency spectrograms accurately, some species were combined: *Myotis* species: the eastern small-footed bat *Myotis leibii*, the little brown bat *M. lucifugus* and the northern long-eared bat *M. septentrionalis*; and *Eptesicus* complex: the big brown bat *Eptesicus fuscus* and the silver-haired bat *Lasionycteris noctivagans*.

Automatic identifications were then followed with blind manual classification to determine if all bat recordings were valid. We completed the manual classification using the spectrogram viewer in Kaleidoscope 5.4.1a (Wildlife Acoustics) and the guide to acoustics for Québec bats (Fabianek, 2015); bats were identified by the shape and frequency range of their calls. For this study, detections were defined by a sequence of three or more bat calls separated by the previous detection by at least 1 s (Fenton, 1970; Barlow et al., 2015). False detections were excluded from and incorrect detections corrected for the new set of manually identified data. Results of analysing the accuracy of automatic identification by Kaleidoscope are reported in Supporting Information 3.

Using drones requires a much smaller bat detector than has been traditionally used, which is why we used the lightweight Echo Meter Touch 2. Even so, the capabilities of bat detectors vary widely (Adams et al., 2012). To compare the sensitivity and reliability of the Echo Meter Touch 2 with a larger, more conventional bat detector, we simultaneously recorded bat detections using an Anabat SD2 (Titley Scientific) at ground level. The Anabat is an older, free-standing acoustic bat detector whose accuracy is better studied than the Echo Meter Touch 2 (Adams et al., 2012). Methods and results of comparing the Anabat SD2 with the Echo Meter Touch 2 are reported in Supporting Information 4.

2.5 | Statistical analysis

We used R version 4.0.2 (R Core Team, 2020). To test whether drone size or take-off distance affected the bat activity, we used mixed models (lme4; Bates et al., 2015) incorporating drone type and take-off method as the two fixed-effect explanatory variables against bat response, as well as their interaction, with site as a random effect. Overall bat activity compared between Phase 2 and Phase 3 and separately between Phase 1 and Phase 2 is the response variable for each mixed model test, respectively. To follow-up the lme4 analysis, we used a Tukey HSD post hoc test to investigate differences in mean bat response among drone types using the function 'TukeyHSD' as part of the STATS R package (R Core Team, 2020).

Paired *t* tests, using the '*t*-test' function as part of the 'stats' R package (R Core Team, 2020), compared the activity of each bat species as a response to the treatments. Specifically, we focused on the difference in species-specific bat activity between the three phases of the experiment (drone flight, no flight and then another drone flight). To examine species-specific effects, we repeated the same analyses for each bat species and for the two larger drones (Mavic Pro and Phantom) and the small drone (Mavic Mini) separately.

To examine habituation and determine whether bat passes per minute changed over time, we used a linear mixed model during Phases 2 and 3 with time as a fixed effect and trial as a random effect. To examine the effect of lighting on bat activity, we used pairwise *t* tests for periods with and without lights. For each analysis, we confirmed the normality (Shapiro–Wilk test) and homoscedasticity (Breusch–Pagan test) of residuals.

3 | RESULTS

3.1 | Drone model and launch method

The acoustic profiles of each drone reveal potential for overlap between the frequencies drones emit when flying and those bats emit when communicating (Supporting Information 3). They also demonstrate that take-off and landing are the loudest part of flight, followed by directional flight, regardless of direction. Finally, these profiles confirm that drone noise increases with drone size.

When considered together using a GLMM with site as a random effect, drone model ($F_{3,127} = 6.04$, $p < 0.001$), but not take-off distance ($F_{1,127} = 0.36$, $p = 0.55$) or interaction between model and distance ($F_{1,127} = 0.34$, $p = 0.58$), affected the number of bat passes detected between Phase 2 and Phase 3 (Figure 3). Similarly, drone model ($F_{3,127} = 7.58$, $p < 0.001$), but not take-off distance ($F_{1,12} = 1.59$, $p = 0.21$) or their interaction ($F_{1,12} = 2.25$, $p = 0.14$), affected the number of bat passes detected between Phase 1 and Phase 2. Given the similarity in results (but significant differences between Phases 1 and 3 [diff = 0.74, *p* adj = 0.01]; possibly because Phase 3 only occurred when Phase 1 recorded at least one bat), we use comparisons between Phases 2 and 3 for subsequent analyses. Among the drone models, the greatest and most significant difference in means (as determined with post hoc Tukey tests) was found between the Phantom drone and the control (diff = −2.51, *p* adj < 0.01), followed

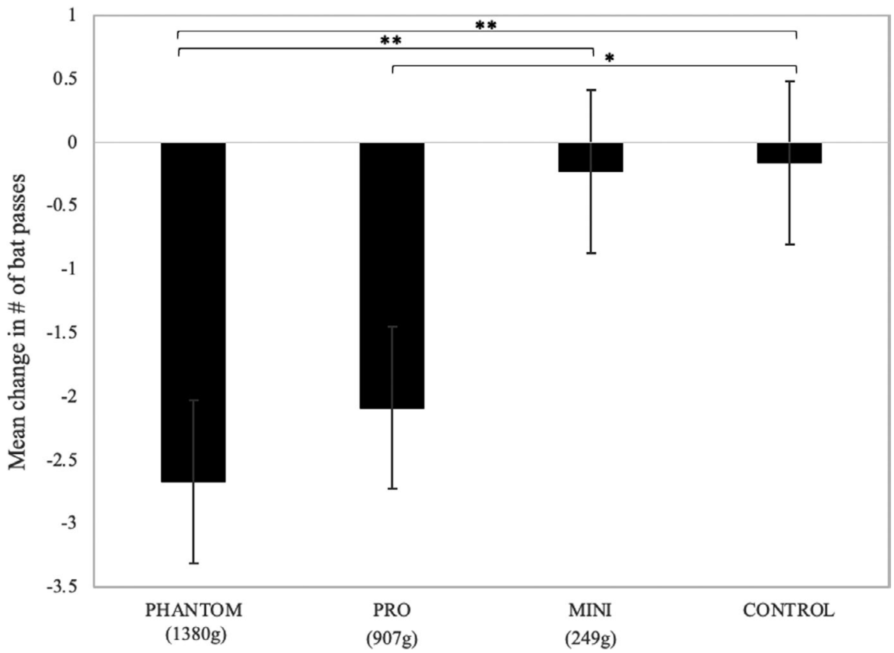

FIGURE 3 Larger drone models correlate with a larger decrease in bat activity. Change in bat passes (# of bat passes during flight minus # of bat passes after flight) among three drone models and the control. Statistical significance is marked by '**' ($p < 0.01$) and '*' ($p < 0.05$). The brackets indicate any statistical significance between the two treatments at the ends of the bracket. The response was calculated from the detections during and after flight, and then averaged

by the Phantom and the Mavic Mini (diff = −2.44, p adj < 0.01), the Mavic Pro and control (diff = −1.92, p adj < 0.05) and finally the Mavic Pro and the Mavic Mini (diff = −1.85, p adj < 0.1). The difference between the Mavic Mini and the control was not significant (diff = −0.07, p adj = 1). There was no difference in number of bat passes detected with and without the drone LED light configuration, either without a flying drone ($t_9 = 0.31$, $p = 0.76$) or when the drone was flying ($t_9 = 0.65$, $p = 0.53$).

3.2 | Species-specific effects

Drone flights impacted the detection of some, but not all, of the species identified during this study (Figure 4). Detections of the big brown/silver-haired complex ($N = 666$, diff = −1.87, $p < 0.05$) and hoary bats ($N = 125$, diff = −1.25, $p < 0.05$) significantly decreased during drone flight with the Mavic Pro and Phantom drones (Figure 4a). In contrast, *Myotis* spp., red bats and tri-coloured bats did not differ from one another, although sample sizes were also smaller (Figure 4a; all $p > 0.1$). For treatments with the Mavic Mini drones, none of the species groups varied significantly in bat passes in response to drone flight (Figure 4b; all $p > 0.1$).

3.3 | Habituation

Bat activity sharply declined between Phase 1 (pre-flight) and the beginning of Phase 2 (drone flight) for the two drone models that had the greater effects on bats (Figure 5). Passes remained at a low constant during flight, and then immediately increased after flight (Figure 5). For the two drones that impacted the bats (Phantom and Mavic), the bats did not habituate to drone flight as the detections did not increase for the total duration of drone flight ($t_{115} = 0.67$, $p = 0.50$). Bat numbers also did not vary in Phase 3 ($t_{115} = 0.63$, $p = 0.53$). Additionally, the bats did not completely return after drone disturbance, as the after-flight detections are fewer than the before-flight baseline.

4 | DISCUSSION

The fewest bat passes were detected during flights with larger UAVs (Figure 3). Indeed, there was no difference in bat activity between control recordings (no drone) and recordings with our smallest drone, the Mavic Mini, which does not require a basic drone licence by Transport Canada. Additionally, responses to the large drones were species specific, with the big brown/silver-haired complex and hoary bats strongly impacted and smaller, higher frequency bat species less impacted (Figure 4). As the drones did not have an impact on the ability of the audio detector to detect bats (Ednie et al., 2021), the reduction in bat activity is likely due to bats avoiding the area when the drone was present. Here, we show that miniaturization of drones can reduce noise and eliminate impacts on wildlife, at least in the case of bats. While sensor size (e.g. ultrasensitive bat detector, infrared camera, high-resolution camera) may limit the use of small drones in some applications, our study emphasizes the importance of using the smallest drone possible.

Although we had initially hypothesized that a more distant take-off would reduce the impact of drones on bat detection, as take-off is the loudest and highest frequency period of drone flights (Jokisch & Fischer, 2019), launching from 50 m away from the test site had no effect on bat activity compared with launching at the test site. Take-off is the loudest period of drone flight, but drones also emit the lowest frequencies when shifting positions (Jokisch & Fischer, 2019), and can be detected acoustically up to 300 m away (Farlik et al., 2019). Our results, along with the mixed effect of researcher

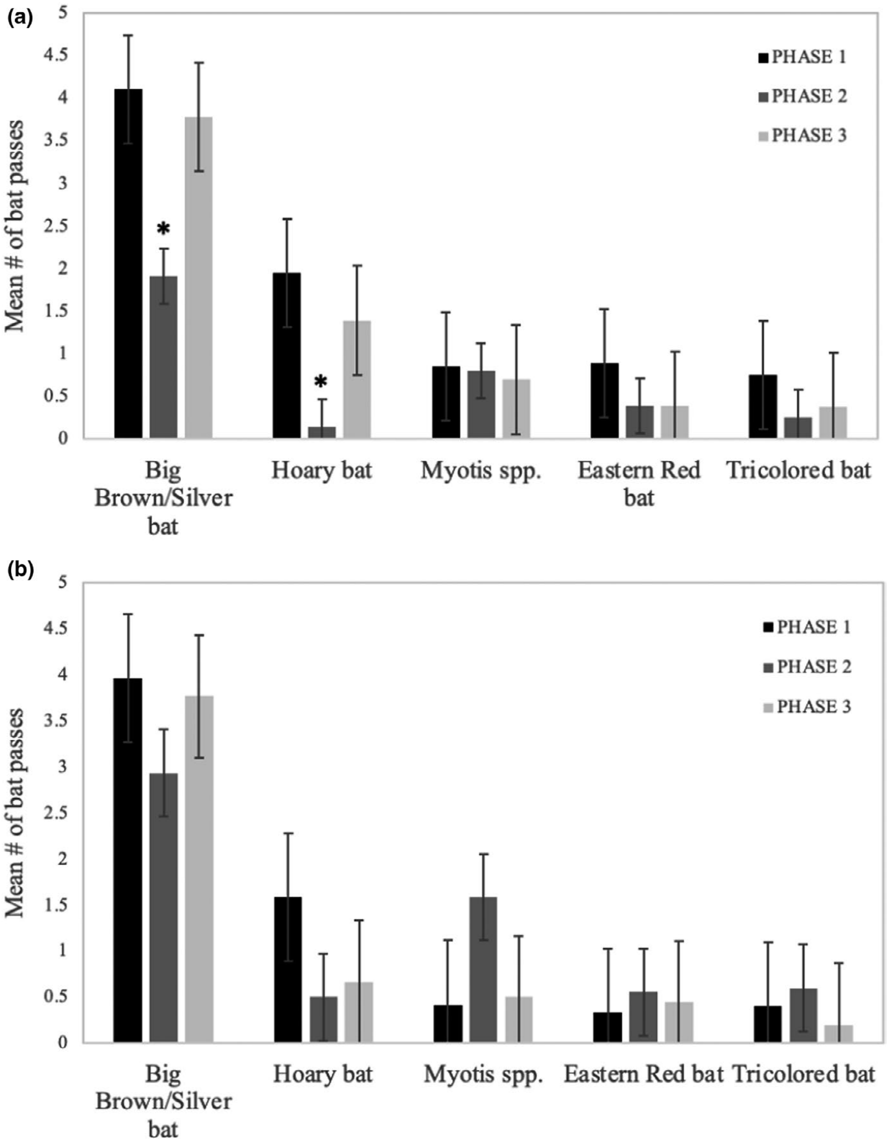

FIGURE 4 Effect of drones on bat detections by bat species group. The average number of passes from each species group is plotted and separated based on which phase of the experiment the bat was detected in for treatments with (a) Mavic Pro and Phantom drone flight and (b) Mini drone flight. Analysis was conducted using paired t tests on a 95% confidence level. Statistical significance is marked by '*' (p adj < 0.05)

presence on wildlife activity (Larm et al., 2019; Piel et al., 2014; Rosenfield et al., 2007) and the limited evidence on the effect of flight speed on drone noise (Tinney & Sirohi, 2018), document few reasons to favour one launch method over the other. However, it may be more cost-effective to launch the drone at the site of detection due to drone's limited battery life. Drone noise has presented issues for several wildlife studies and has previously been resolved by distancing equipment or launching from distances farther away from the targets (Brisson-Curadeau et al., 2017; Broset, 2018). Alternative approaches, such as creating home-made baffles (i.e. a device to restrain or minimize sound) for the drones, have also been successful (Fu et al., 2018; Kloepper & Kinniry, 2018). In this case, using smaller drones was the most successful in diminishing the effects of drone noise on wildlife activity.

When the two largest and loudest drone models were flown in bat habitat, bat detections significantly decreased compared with the control (Figure 3). Indeed, the effect of drone presence on bat detections was proportional to drone size. The effect does not appear to be due to the presence of the LED lights on the drone, as there was no statistical difference in bat activity between periods with and without the LED lights for the largest drone (Phantom 4). Size and noise of drones are usually correlated (Christie et al., 2016; Miljković, 2018), so it is difficult to disentangle whether the bats were deterred by drone's noise or its physical presence. Fu et al. (2018) observed no collisions between bats and drones in their experiment, indicating that bats evade airspace obstacles. Since bats also tend to avoid noisy environments (Murphy et al., 2009), they could respond to both drone noise and presence. The frequency ranges of each drone did not demonstrate a clear association between drone size and noise. In fact, the quietest drone generated some of the highest frequencies while having minimal impact on bat detections. Thus, noise amplitude rather than frequency caused us to detect lower bat activity.

Some bat species were more sensitive to drone disturbance than others, with the big brown/silver-haired complex and hoary bats showing significantly fewer bat passes in the presence of the large drones (Figure 4). Even the Mavic Mini showed a tendency for lower bat activity for these species. In contrast, no such effect occurred

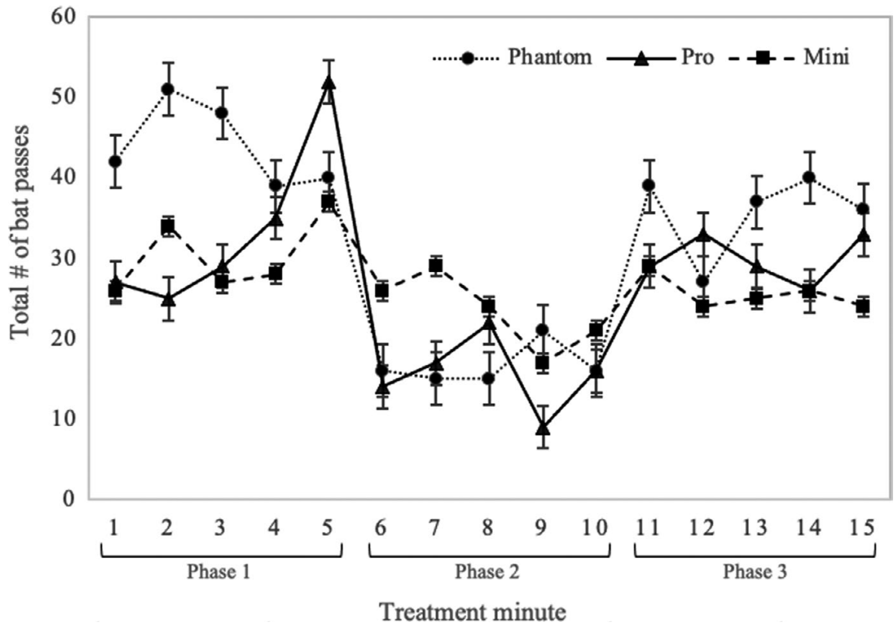

FIGURE 5 Bat activity over time for each drone treatment. Detections were separated by each minute of the trial for the three drones and the total detections of each minute are plotted. Minutes 1 through 5 represent the first phase, before drone flight; minutes 6 through 10 represent the second phase, during drone flight; and minutes 11 through 15 are the last phase, after drone flight

in the presence of drones regardless of size for *Myotis* species, the eastern red bat and the tri-coloured bat, although sample sizes were much smaller. This difference is because big brown (44–28 kHz), silver-haired (39–24 kHz) and hoary bats (28–20 kHz) have the lowest frequency calls with the most potential for overlap with drone noise; indeed, hoary bats with the lowest frequency calls were the most impacted. The two largest drones occupied noticeable frequencies below 6 kHz when hovering, compared with below 7 kHz for the Mavic Mini. As calls emitted by bats in Québec occupy frequencies from 75 to 20 kHz (Fabianek, 2015), there is potential frequency overlap between drone noises and bat calls, especially for the bats with lower frequency calls. As the Mini's frequency ranges are closer to overlapping with bat calls than the Phantom and Pro's frequency ranges, it is possible that frequency overlap was not an issue in this study and that drone size and noise level are larger bat deterrents than frequency overlap. Regardless, it appears that drones have the most impact on bats with low-frequency calls that overlap more closely with the drone frequency.

Bats did not habituate to drone flight within 5 min (Figure 5). This is surprising, as many other flying animals rapidly habituate to drones within a few minutes (Brisson-Curadeau et al., 2017; Chabot & Bird, 2015). For example, breeding tree swallows habituated to drone flights in a similar amount of time that they habituated to other foreign objects, indicating that drone flight is not a unique stressor for some species (Scholten et al., 2020). In contrast, some terrestrial mammals became more likely to react to drones with increasing number of flights (Brunton et al., 2019; Hahn et al., 2016) while others rapidly habituate (Ditmer et al., 2018). Regardless, our results demonstrate that bats do not habituate to drone flight within minutes, but they are not permanently disturbed as bat activity rebounded quickly after drone flight ended. Seeing as our drone surveys only lasted 5 min, these results cannot determine the implications of a longer drone flight on wildlife activity. Currently, drone-based wildlife surveys are limited by the short battery life of modern drones, but with technological advancements, the effects of extended drone flights on wildlife activity will become another factor wildlife surveyors must consider, especially with larger drones.

While using smaller drones is undoubtedly the solution to minimizing the effects of drone-based acoustic surveys on wildlife, small drones have their limitations and are not the most suitable devices for other types of surveys. For instance, many wildlife surveys done with drones rely on specialized cameras—including thermal infrared, infrared and high-resolution video cameras—to detect wildlife (Fu et al., 2018; Hodgson et al., 2018). Attaching other sensors to drones, such as GPS devices and frequency receivers for radiotelemetry (Desrochers et al., 2018), would also be heavy payloads necessitating a large drone. Even some acoustic detectors, such as the Anabat SD2, weigh more than the Mavic Mini. Thus, we encourage researchers to minimize drone noise by using the smallest and quietest drone available within the needs of their study or modify their drones to produce less noise.

Some drones cause less disturbance and are better suited for acoustic wildlife surveys compared with others. Flying drones in bat habitat demonstrates how species of a nocturnal, echolocating order are deterred by aerial noises and obstacles, but response to drone flights also differed among species. Nonetheless, using the smallest drone eliminated the impact of the drone with no difference from control flights. Moreover, the Mini is classified as a toy in Canada and therefore does not require a permit to fly, further facilitating its use, although still subject to wildlife, protected area and other regulations. We argue that the use of small drones in wildlife studies should be more widely studied, as drone miniaturization improves drone-based acoustic wildlife surveys by eliminating any measurable impact of drones on wildlife.

ACKNOWLEDGEMENTS

The authors thank the Kenauk Institute for hosting their data collection, specifically Liane Nowell for her support and everyone who helped collect data, including Mailys Laprevotte. They also thank the Kenneth Molson Foundation and the Natural Sciences and Engineering Research Council of Canada for funding this research, and J. Hare for providing equipment used to conduct data collection.

CONFLICT OF INTEREST

The authors declare no competing interests.

AUTHORS' CONTRIBUTIONS

K.K., K.H.E., A.F and E.B.C. conceived the ideas and designed the methodology; K.K. collected the data; K.K., K.H.E., A.F. and E.B.C. analysed the data; K.K. led the writing of the manuscript with substantial revisions from all authors. All authors contributed critically to the drafts and gave final approval for publication.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/2041-210X.13807.

DATA AVAILABILITY STATEMENT

Data available from the Dryad Digital Repository https://doi.org/10.5061/dryad.g4f4qrfs1 (Kuhlmann et al., 2022).

ORCID

Kayla Kuhlmann https://orcid.org/0000-0002-3623-3530
Émile Brisson-Curadeau https://orcid.org/0000-0001-5795-9915
Kyle H. Elliott https://orcid.org/0000-0001-5304-3993

REFERENCES

Adams, A. M., Jantzen, M. K., Hamilton, R. M., & Fenton, M. B. (2012). Do you hear what I hear? Implications of detector selection for acoustic monitoring of bats. *Methods in Ecology and Evolution*, *3*(6), 992–998. https://doi.org/10.1111/j.2041-210X.2012.00244.x

Allen, L. C., Hristov, N. I., Rubin, J. J., Lightsey, J. T., & Barber, J. R. (2021). Noise distracts foraging bats. *Proceedings of the Royal Society B*, *288*, 2020–2689. https://doi.org/10.1098/rspb.2020.2689

August, T., & Moore, T. (2019). Autonomous drones are a viable tool for acoustic bat surveys. bioRxiv. https://doi.org/10.1101/673772

Barlow, K. E., Briggs, P. A., Haysom, K. A., Hutson, A. M., Lechiara, N. L., Racey, P. A., Walsh, A. L., & Langton, S. D. (2015). Citizen science reveals trends in bat populations: The National bat Monitoring Programme in Great Britain. *Biological Conservation*, *182*, 14–26. https://doi.org/10.1016/j.biocon.2014.11.022

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Brisson-Curadeau, É., Bird, D., Burke, C., Fifield, D. A., Pace, P., Sherley, R. B., & Elliott, K. H. (2017). Seabird species vary in Behavioural response to drone census. *Scientific Reports*, *7*(1), 1–9.

Broset, S. (2018). Assessment of UAV potential for bioacoustic monitoring of birds and bats: Tests under controlled conditions in Belgium (Thesis). Gembloux Agro-Bio Tech. Retrieved from http://hdl.handle.net/2268.2/5155

Brunton, E., Bolin, J., Leon, J., & Burnett, S. (2019). Fright or flight? Behavioural responses of kangaroos to drone-based monitoring. *Drones*, *3*(2), 41. https://doi.org/10.3390/drones3020041

Chabot, D., & Bird, D. M. (2015). Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in? *Journal of Unmanned Vehicle Systems*, *3*(4), 137–155. https://doi.org/10.1139/juvs-2015-0021

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

Desrochers, A., Tremblay, J. A., Aubry, Y., Chabot, D., Pace, P., & Bird, D. M. (2018). Estimating wildlife tag location errors from a VHF receiver mounted on a drone. *Drones*, *2*(4), 44. https://doi.org/10.3390/drones2040044

Ditmer, M. A., Vincent, J. B., Werden, L. K., Tanner, J. C., Laske, T. G., Iaizzo, P. A., Garshelis, D. L., & Fieberg, J. R. (2015). Bears show a physiological but limited behavioral response to unmanned aerial vehicles. *Current Biology*, *25*(17), 2278–2283. https://doi.org/10.1016/j.cub.2015.07.024

Ditmer, M. A., Werden, L. K., Tanner, J. C., Vincent, J. B., Callahan, P., Iaizzo, P. A., Laske, T. G., & Garshelis, D. L. (2018). Bears habituate to the repeated exposure of a novel stimulus, unmanned aircraft systems. *Conservation Physiology*, *6*(1), coy067. https://doi.org/10.1093/conphys/coy067

DJI (n.d.). DJI Official Website. Retrieved from https://www.dji.com/ca.

Duporge, I., Spiegel, M. P., Thomson, E. R., Chapman, T., Lamberth, C., Pond, C., Macdonald, D. W., Wang, T., & Klinck, H. (2021). Determination of optimal flight altitude to minimise acoustic drone disturbance to wildlife using species audiograms. *Methods in Ecology and Evolution*, *12*, 2196–2207.

Ednie, G., Bird, D. M., & Elliott, K. H. (2021). Fewer bat passes are detected during small. Commercial drone flights. *Scientific Reports*, *11*, 11529.

Fabianek, F. (2015). *Formation Acoustique sur les Chiroptères du Québec*. Groupe Chiroptères Québec.

Farlik, J., Kratky, M., Casar, J., & Stary, V. (2019). Multispectral detection of commercial unmanned aerial vehicles. *Sensors*, *19*(7), 1517. https://doi.org/10.3390/s19071517

Fenton, M. B. (1970). A technique for monitoring bat activity with results obtained from different environments in southern Ontario. *Canadian Journal of Zoology*, *48*(4), 847–851. https://doi.org/10.1139/z70-148

Froidevaux, J. S. P., Zellweger, F., Bollmann, K., & Obrist, M. K. (2014). Optimizing passive acoustic sampling of bats in forests. *Ecology and Evolution*, *4*(24), 4690–4700. https://doi.org/10.1002/ece3.1296

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.

Goerlitz, H. R. (2018). Weather conditions determine attenuation and speed of sound: Limitations for monitoring and analyzing bat echolocation. *Ecology and Evolution*, *8*(10), 5090–5100. https://doi.org/10.1002/ece3.4088

Gonzalez, L. F., Montes, G. A., Puig, E., Johnson, S., Mengersen, K., & Gaston, K. J. (2016). Unmanned aerial vehicles (UAVs) and artificial intelligence revolutionizing wildlife monitoring and conservation. *Sensors*, *16*(97), 1–18.

Hahn, N., Mwakatobe, A., Konuche, J., De Souza, N., Keyyu, J., Goss, M., Chang'a, A., Palminteri, S., Dinerstein, E., & Olson, D. (2016). Unmanned aerial vehicles mitigate human-elephant Conflict on the Borders of Tanzanian parks: A case study. *Oryx*, *51*(3), 513–516. https://doi.org/10.1017/S0030605316000946

Hodgson, J. C., & Koh, L. P. (2016). Best practice for Minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology*, *26*(10), R404–R405.

Hodgson, J. C., Mott, R., Baylis, S. M., Pham, T. T., Wotherspoon, S., Kilpatrick, A. D., Raja Segaran, R., Reid, I., Terauds, A., & Koh, L. P. (2018). Drones count wildlife more accurately and precisely than humans. *Methods in Ecology and Evolution*, *9*(5), 1160–1167.

Jokisch, O., & Fischer, D. (2019). Drone sounds and environmental signals – A first review. 30th ESSV Conference: TU Dresden.
Kloepper, L. N., & Kinniry, M. (2018). Recording animal vocalizations from a UAV: Bat echolocation during roost re-entry. *Scientific Reports*, *8*, 7779.
Kloepper, L. N., Linnenschmidt, M., Blowers, Z., Branstetter, B., Ralston, J., & Simmons, J. A. (2016). Estimating colony sizes of emerging bats using acoustic recordings. *Royal Society Open Science*, *3*(3), 160022.
Kuhlmann, K., Fontaine, A., Brisson-Curadeau, É., Bird, D., Elliott, K.H. (2022). Data from: Miniaturization eliminates detectable impacts of drones on bat activity. *Dryad Digital Repository*. https://doi.org/10.5061/dryad.g4f4qrfs1
Kunz, T. H., Betke, M., Hristov, N. I., & Vonhof, M. J. (2009). Methods for assessing Colony size, population size, and relative abundance of bats. In T. H. Kunz & S. Parsons (Eds.), *Ecological and behavioral methods for the study of bats* (2nd ed., pp. 133–157). Johns Hopkins University Press. Retrieved from: https://www.cs.bu.edu/fac/betke/papers/KunzBetkeHristovVonhof-2009.pdf.
Larm, M., Erlandsson, R., Norén, K., & Angerbjörn, A. (2019). Fitness effects of ecotourism on an endangered carnivore. *Animal Conservation*, *23*(4), 386–395. https://doi.org/10.1111/acv.12548
Miljković, D. (2018). Methods for attenuation of unmanned aerial vehicle noise. *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 0914-0919. 10.23919/MIPRO.2018.8400169
Mulero-Pázmány, M., Jenni-Eiermann, S., Strebel, N., Sattler, T., Negro, J. J., & Tablado, A. (2017). Unmanned aircraft systems as a new source of disturbance for wildlife: A systematic review. *PLoS ONE*, *12*(6), e0178668.
Mulero-Pázmány, M., Stolper, R., van Essen, L. D., Negro, J. J., & Sassen, T. (2014). Remotely piloted aircraft systems as a rhinoceros anti-poaching tool in Africa. *PLoS ONE*, *9*(1), e0083873.
Murphy, S., Hill, D., & Greenaway, F. (2009). Pilot study of a technique for investigating the effects of artificial light and noise on bat activity. *Monitoring Light and Noise*, 1–32.
Piel, A. K., Lenoel, A., Johnson, C., & Steward, F. A. (2014). Deterring poaching in western Tanzania: The presence of wildlife researchers. *Global Ecology and Conservation*, *3*, 188–199. https://doi.org/10.1016/j.gecco.2014.11.014
Plank, M., Fiedler, K., & Reiter, G. (2012). Use of forest strata by bats in temperate forests. *Journal of Zoology*, *286*, 154–162.
R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/
Rosenfield, R. N., Grier, J. W., & Fyfe, R. W. (2007). Reducing management and research disturbance. In D. M. Bird & K. L. Bildsteind (Eds.), *Raptor research and management techniques* (pp. 351–364). Hancock House.
Scholten, B. D., Beard, A. R., Choi, H., Baker, D. M., Caulfield, M. E., & Proppe, D. S. (2020). Short-term exposure to unmanned aerial vehicles does not Alter stress responses in breeding tree swallows. *Conservation Physiology*, *8*(1), coaa080.
Scholten, C. N., Kamphuis, A. J., Vredevoogd, K. J., Lee-Strydhorst, K. G., Atma, J. L., Shea, C. B., Lamberg, O. N., & Proppe, D. S. (2019). Real-time thermal imagery from an unmanned aerial vehicle can locate ground nests of a grassland songbird at rates similar to traditional methods. *Biological Conservation*, *233*, 241–246.
Skalak, S. L., Sherwin, R. E., & Brigham, R. M. (2012). Sampling period, size and duration influence measures of bat species richness from acoustic surveys: Effective acoustic monitoring. *Methods in Ecology and Evolution*, *3*(3), 490–502.
Tinney, C. E., & Sirohi, J. (2018). Multirotor drone noise at static thrust. *AIAAJ*, *56*(7), 2816–2826. https://doi.org/10.2514/1.J056827
Vas, E., Lescroel, A., Duriez, O., Boguszewski, G., & Grémillet, D. (2015). Approaching birds with drones: First experiments and ethical guidelines. *Biology Letters*, *11*, 20140754.
Weimerskirch, H., Prudor, A., & Schull, Q. (2018). Flights of drones over sub-Antarctic seabirds show species-and status-specific behavioural and physiological responses. *Polar Biology*, *41*(2), 259–266.
Wilson, A. M., Barr, J., & Zagorski, M. (2017). The feasibility of counting songbirds using unmanned aerial vehicles. *The Auk: Ornithological Advances*, *134*(2), 350–362.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: 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, 842–851. https://doi.org/10.1111/2041-210X.13807