

RESEARCH ARTICLE

Drone-mounted audio-visual deterrence of bats: implications for reducing aerial wildlife mortality by wind turbines

Yuval Werber¹ , Gadi Hareli², Omer Yinon³, Nir Sapir¹ & Yossi Yovel^{3,4}¹Department of Evolutionary and Environmental Biology and Institute of Evolution, University of Haifa, Haifa, Israel²WinGo Energy, Renewable Energy Enabling Technologies Ltd., Tel-Mond, Israel³School of Zoology, School of Neuroscience, Tel-Aviv University, Tel-Aviv, Israel⁴The Steinhardt Museum of Natural History, Tel Aviv University, Tel Aviv, Israel**Keywords**

Acoustic monitoring, bats, drone, LIDAR, RADAR, wind turbine-related mortality

CorrespondenceYuval Werber, Department of Evolutionary and Environmental Biology and Institute of Evolution, University of Haifa, 199 Aba Khoushy Avenue, 3498838 Haifa, Israel.
Tel: +972-4-8240111; Fax: +972-4-8240371;
E-mail: yuvalwerber90@gmail.com**Funding Information**

This research is sponsored by the Israeli Ministry of Energy and may lead to the development of products which may be licensed to WINGO, in which G.H. has a business and/or financial interest.

Editor: Vincent Lecours

Associate Editor: Larissa Sayuri Moreira Sugai

Received: 15 February 2022; Revised: 20 October 2022; Accepted: 1 November 2022

doi: 10.1002/rse2.316

Abstract

Wind energy is a major and rapidly expanding renewable energy source. Horizontal-axis wind turbines, the main tool in this industry, induce mortality in flying animals and consequently bring about conservation concerns and regulatory restrictions. We utilized a unique combination of RADAR, LIDAR and ultrasonic acoustic recorders to test the utility of a novel technology meant to prevent wind turbine-related mortality in bats. Our drone-mounted deterrent device produces a pulsating combination of strong auditory and visual signals while moving through the air. LIDAR was used to assess the device's impact below its flight altitude and RADAR to assess its influence above its flight altitude. Continuous acoustic recordings from ground level to ~400 m above-ground-level were used to monitor bat activity in the research site. We recorded the nightly altitudinal distributions of multiple bat species throughout the experiment. Analysis revealed a significant change in activity while the deterrent was flying compared to baseline conditions. We also recorded a significant ~40% decrease below and a significant ~50% increase above the deterrent's flight altitude during its operation compared to the post-flight control. The tested technology is independent of wind farm activities and does not require modifying wind turbine form or operation procedures. The device differs from previously proposed solutions by being dynamic – moving in the airspace and emitting constantly changing signals – thus decreasing the probability of animal habituation. Our findings suggest that the deterrent could dramatically decrease wind turbine-related mortality by deterring bats from approaching rotor-swept airspace. Focused implementation in conditions where bat activity and energy production are in conflict may provide a practical, cost-effective mortality mitigation solution compared to current alternatives. Thus, our results should be considered by the wind-turbine industry and environmental monitoring and animal conservation organizations, as well as by regulatory agencies, when pursuing alleviation of wind turbine-related mortality.

Introduction

Energy production using wind turbines is expected to substantially expand in the coming years (IEA, 2020), yet it may be lethal to flying animals and detrimental to the integrity of the aerial habitat (Alisson et al., 2019; Barrios & Rodriguez, 2004; Elizabeth & Hein, 2022; Lehnert

et al., 2014; May et al., 2019, 2020; Smallwood & Karas, 2009). Despite heavy regulation and strict guidelines (Chambert & Aurélien, 2021; Elizabeth & Hein, 2022; Rodrigues et al., 2015), wind turbines are regarded as one of the two main causes of mass bat mortality in Europe and North America, with some wind energy facilities causing thousands of fatalities annually (Agudelo

et al., 2021; Band et al., 2007; Horn et al., 2008; O'Shea et al., 2016; Rabie et al., 2022; Voigt et al., 2022). Many existing facilities are located in sensitive areas for bats, and where taller turbines (>60 m) are used, bat fatality rates can be up to 10 times higher than that of birds (Anderson et al., 2000; Barclay et al., 2007; Kunz, Arnett, et al., 2007; Kunz, Edwards, et al., 2007; Voigt et al., 2022).

Bat mortality is difficult to accurately quantify or predict prior to construction and operation of wind turbines because turbines may have cascading, unpredictable effects on the aerial habitat. Common methodologies often produce underestimations of mortality, which may cause unsuitable positioning and management of wind farms (Ferrer et al., 2012; Mathews et al., 2013; Smallwood et al., 2020; Villegas-Patracca et al., 2012). The rotation of the blades makes them invisible to aerial wildlife (Horn et al., 2008; Kunz et al., 2011) and several studies even suggest that bats are attracted to wind turbines, perhaps due to their artificial lighting, which may attract insects and subsequently insectivores (Horn et al., 2008; Kunz, Arnett, et al., 2007; Lintott et al., 2016; Roeleke et al., 2016; Solick & Newman, 2021).

The harmful impact of wind turbines on aerial organisms is a major concern for developers, governments, conservationists and the general public, which benefit from services provided by aerial wildlife and specifically bats (Kunz et al., 2011). Today, curtailment of blade rotation by "feathering" (changing blade angle to stop rotation) and raising turbines' cut-in speeds (the minimal operational wind speed), both of which cause a reduction in electricity production and profit, are the main proven methods to effectively reduce bat mortality at wind farms (Adams et al., 2021; Arnett et al., 2011; Arnett et al., 2016; Baerwald et al., 2009; Rabie et al., 2022; Voigt et al., 2022; Whitby et al., 2021). Other approaches include modifications of farms and turbines to increase their visibility and detection by aerial wildlife (Arnett & May, 2016; Cassidy, 2015) or to provide alternative habitats to attract animals away from hazardous areas (Marques et al., 2014).

Non-structural or operational attempts to actively reduce animal fatalities apply a variety of deterrence practices (Arnett et al., 2016; Arnett, Hein, et al., 2013; Cassidy, 2015; Gilmour et al., 2021; Romano et al., 2019; Smallwood, 2013; Weaver et al., 2020). These include visual (light, especially LASER) or auditory signals meant to deter approaching animals. Using deterrence measures in wind farms has shown some promising results (Arnett et al., 2016; Cassidy, 2015), but so far, none are satisfactory for a broad range of organisms. The use of unmanned aerial vehicles (UAV) for aerial wildlife research and monitoring is spreading with advances in

technology (August & Moore, 2019; Fu et al., 2018; Kloepper & Kinniry, 2018). Research regarding the potential aversive effects of these tools on the spatial distribution and activity patterns of flying animals are ongoing (Ednie et al., 2021; Kuhlmann et al., 2022).

We describe a field experiment in which we tested the effects of a novel UAV-based deterring device on bat activity from ground level to 800 m above-ground-level (AGL), covering the full range of turbine-occupied airspace and that above it. We note that at the time of the experiment, bird migration did not take place in the area (Shirihai et al., 1996), and, to the best of our knowledge, nocturnal bird activity was very rare. Therefore, aerial vertebrate activity in the monitored airspace consisted almost exclusively of bats. Most bats integrate echolocation and vision in intricate ways to facilitate navigation, foraging and obstacle avoidance (Boonman et al., 2013; Danilovich et al., 2015; Danilovich & Yovel, 2019; Eklöf et al., 2002; Gomes et al., 2016). Accordingly, the deterrent device broadcasts a pulsating, minimally repetitive combination of visual and auditory signals while moving through the airspace.

Our main objective was to quantify the deterrent's effect on bat distribution in the airspace and assess its potential as a bat mortality mitigation tool for the wind energy industry. As our experiment did not take place near a turbine, we used activity density at different altitudes and treatments as a predictor of mortality risk (Korner-Nievergelt et al., 2013). We expected an effective deterrent to reduce bat presence in the airspace during its activation or to cause changes in the altitudinal distribution of bat activity so that the activity in a specific altitude decreases.

Our results demonstrate the deterrent's impact using a combination of RADAR and LIDAR technologies. Taken together, the evidence suggests significantly reduced activity around the deterrent. The deterrent's impact and flexibility of application may provide a solution for reducing animal fatalities in the wind energy industry and thus, we suggest that the technology should undergo a thorough assessment in terms of practicality and implementation in real-life circumstances.

Materials and Methods

Study site

The experiment took place from 8 to 21 July 2020 at the Hula Research Center in the Hula Valley, Northern Israel (35°43' E, 33°03' N). The valley has ample fresh water sources and diverse habitats, creating a biodiversity hotspot (Dolev & Carmel, 2009). During summer, when migratory movements in the region are minimal, the valley is home to

a large variety of birds, bats and insects. Mean daytime and night-time temperatures during the summer of 2020 were 31 and 24°C, respectively (data from Israel Meteorological Service). Human activity in the region usually stops before dusk, and artificial lighting is scarce.

Deterrence device (hereafter the deterrent) and signal

The deterrent uses movement, sound and light, which together produce an intricate, pulsating disturbance in the airspace. It consists of a modified DJI Phantom 4 Pro drone (DJI, Shenzhen, China, <https://www.dji.com/phantom-4>) stripped of its camera and gimbal to reduce weight and maximize battery-based operation duration. We connected the light and sound-producing equipment to the bottom of the drone and secured it between the drone's landing legs so that it would not interfere with rotor movement or landing. The light emitting element is made of four full spectrum square COB-LED panels (50 W each, 400–780 nm, 6200–6800 K) connected to an on-board controller which activates them intermittently, creating a bright white, flashing, dynamic stimulus visible to a human eye up to ~200 m away. The sound-emitting element is made of four piezoelectric speakers that broadcast linear chirps sweeping between 15 and 80 kHz, at ~100 dB SPL re 1 m (at all frequencies), connected to a separate controller. The speakers produced identical chirps with a short phase delay to increase randomization. Both visual and acoustic stimuli were broadcasted continuously. The light and sound-emitting components were mounted on a square frame with a COB-LED panel on each side pointed at 45° relative to the centre of the frame and a speaker on every corner; controllers, wiring and batteries were in the centre (Fig. 1). This configuration produced an approximately omnidirectional signal spreading from the device in all directions, which was most intense in the plane parallel to the ground at flight altitude and less intense above and below this altitude. The wide spectrum of both audio and visual stimuli targeted a wide perceptive range across bat taxa, aiming to stimulate as many species as possible over a roughly spherical volume of transmission up to a few 100 m away from the deterrent. The movement of the drone along with the randomization of the auditory and visual signals reduced repetitiveness to a minimum.

Radar

The BirdScan-MR1 RADAR (Swiss-birdradar, <https://swiss-birdradar.com/birdscan-mr.html>) was used to assess the deterrent's impact between 100 and 800 m AGL. The RADAR, located on the banks of the western canal of the

Jordan River, Israel and surrounded by agricultural fields, is a vertical-looking X-band pulse RADAR designed to monitor flying animals by collecting information regarding their movement speed, direction, altitude, size and wingbeat patterns. It uses a signal processing method (continuous wavelet transform) and a statistical learning method (support vector classifier) to classify echoes as insect, passerine, wader, bird flock, large single bird, bird species, aeroplane and other targets, according to the above-mentioned parameters (Zaugg et al., 2008). Because the classifier does not distinguish bats from the various bird classes, we included the signal classes bird, passerine, wader and large single bird in the analysis to study the treatment's effect on nocturnal vertebrates. The RADAR produces a standardized measure of aerial density, known as the movement traffic rate (hereafter MTR) through standardization of its range-dependent detectability. The MTR is the extrapolated number of objects crossing the sky in a cross-section of 1 km within a certain time window. Each identified object receives an MTR factor, which is calculated by accounting for its size and flight altitude (Schmaljohann et al., 2008). An MTR factor is preferable over using simple counts because it standardizes the detectability and detection volume of targets, making data from different altitudes comparable.

A pulse RADAR emits electromagnetic pulses and detects returning echoes from objects in its detection range. Short pulses produce higher-resolution data but dissipate more quickly, leading to a reduced detection range. Consequently, we used a long pulse throughout the experiment (pulse frequency was 750 ns), which allowed reliable detection at higher altitudes (up to 800 m), compromising detection resolution. When using RADAR, data from the first dozens of meters above ground level may be unreliable due to ground clutter and a small detection volume (Nilsson et al., 2018; Shi et al., 2021). The RADAR at the research site does not produce reliable results below 100 m AGL (assessed by flying a drone in the detection range and comparing the RADAR's output to the drone's flight trajectory). We thus used a LIDAR sensor (see below) to cover the bottom 100 m of the airspace during the experiment and did not analyse RADAR data from this range.

Lidar

The Livox Horizon is a high-performance LIDAR sensor designed for autonomous driving vehicles (Livox, Wanchai, Hong Kong, <https://www.livoxtech.com/horizon>). It has a potential detection range of over 200 m, but in practice, its detectability of small objects (such as bats) is lower and only reaches a range of ~100 m. The LIDAR has a wide rectangular field of view (81.7° × 25.1°),

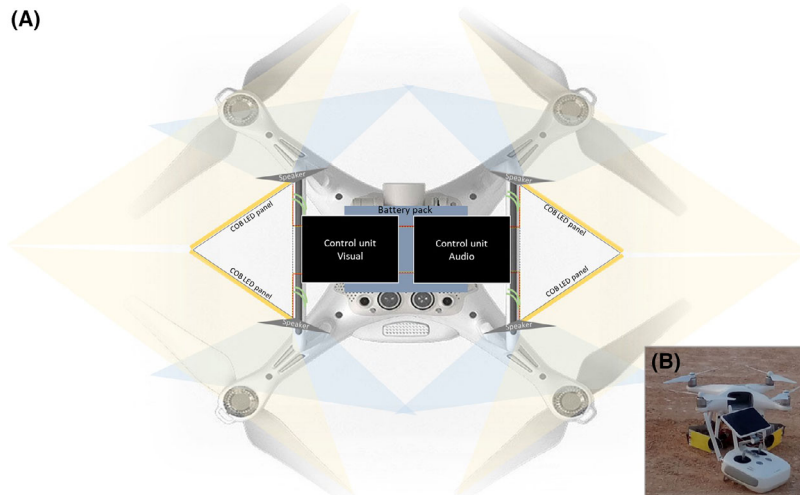


Figure 1. The deterrent. (A) Bottom view, schematic depiction: The elements are connected to plastic struts and fastened to the drone's landing gear. Light and sound beams are illustrated for demonstration and are not indicative of actual transmission range. (B) Front view of the deterrent.

corresponding to a $\sim 170 \times 90 \text{ m}^2$ detection area at a 100 m range. We used the LIDAR to quantify animal activity in the airspace below the flight altitude of the deterrent, 1.5–100 m AGL, by directing it upwards vertically. In the proposed operation scheme of the deterrent, this corresponds to activity below the tip of the turbine blades. The LIDAR outputs a two-dimensional projected recording of the scan (similar to a video recording) and a three-dimensional point cloud including any detected reflector. The LIDAR was placed on a tripod at 1 m AGL, adjacent to the RADAR.

Vertical acoustic array

An aerial acoustic array was deployed to survey bat activity in the study area and characterize it at the species level. The array was positioned using a 12 m^3 helium-filled aerostat (SKYSTAR 220, RT, Yavne, Israel, <https://www.rt.co.il/skystar-220>) tethered to a winch with 1.5 mm thick Dyneema rope (DSM Dyneema LLC, Greenville, NC, USA, https://www.dsm.com/dyneema/en_GB/home.html), anchored to a trailer. The array consisted of three Song-Meter SM4BAT ultrasonic acoustic recorders (Wildlife Acoustics, Maynard, Massachusetts, USA, <https://www.wildlifeacoustics.com/products/song-meter-sm4>) which were hung on the tether of the anchored aerostat. The aerostat was launched to 310 m AGL and recorders were placed at 300, 150 and 1 m AGL. The recorders operated continuously while the array was aloft with a sampling rate of 384 kHz, a gain of 12 dB and no high-pass filter.

The array was located 400 m away from the radar (outside its conical detection range, Fig. 2) and was launched

at 20:00 until $\sim 23:00$. The purpose of the acoustic array was to quantify bat activity in the area during the experiment, to assess its distribution in time and altitude and to identify species based on their unique acoustic signatures. The array was not deployed if wind conditions were such that it swayed considerably during takeoff and was retracted if considerable sway was evident after deployment.

Since nocturnal avian activity is negligible during non-migratory periods in the Hula Valley (Shirihai et al., 1996), we assume that objects detected by the radar with wing flapping frequencies lower than 20 Hz (which can be considered a lower limit of nocturnal insect wing flapping frequency; Wang et al., 2017) are bats of the same species distribution detected by the acoustic array. Acoustic recordings were manually processed and analysed by an experienced expert to recognize which species were active and at which altitudes and times.

Experimental procedure

The experiment consisted of launching the deterrent at the outer bottom edge of the detection range of the RADAR with the LIDAR monitoring the airspace close to the ground (Fig. 2). We tested the deterrent at 100 AGL, well within the altitude range of typical turbine towers (Lantz et al., 2019; Wisner et al., 2021) and within the lethal altitude range for bats (Barclay et al., 2007). The treatment consisted of flying the deterrent back and forth along a 200 m long straight line on an east-west axis, 100 m north of the RADAR and LIDAR devices. The result was a continuous mobile disturbance flying along

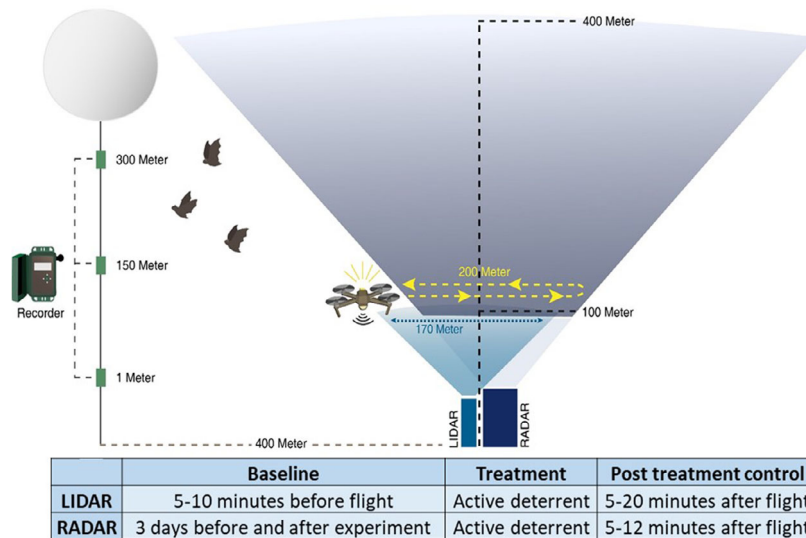


Figure 2. Experiment setup: The active deterrent was flown at 100 m above-ground-level in 200-m horizontal transects near and outside of RADAR and LIDAR detection volumes. LIDAR documented activity below the deterrent's flight altitude and the RADAR documented it above the flight altitude. An aerostat was launched outside and near the edge of the RADAR's detection volume with the vertical acoustic array deployed on its tether, recording bat activity.

the northern periphery of the RADAR's detection volume (Fig. 2). The light- and sound-producing systems were remotely activated at flight altitude. Overall, this resulted in a loud (~ 110 dB over the entire frequency range), luminous object moving through the airspace at a speed of ~ 5 m s⁻¹, which looked and sounded different at each point along its course and from any given point. We made sure that the deterrent did not enter the RADAR's detection beam by observing the RADAR prompt during flight and by keeping its flight trajectory within the pre-defined area.

We analysed the effects of the deterrent on the MTR and altitude distributions of animals as documented by both RADAR and LIDAR from the ground and up to 800 m AGL. Each experimental session lasted 20 min and consisted of a flight time (treatment) of 10–14 min and a post-flight control period of ~ 6 –10 min, depending on the treatment duration. Each deterrence session started on the hour and was followed by a 40-min break, repeated between 19:00 and 24:00, every night between 8 July and 21 July 2020. Baseline data were compiled for RADAR data based on the activity during the same hours in the 3 days before and after the experiment, and for LIDAR data based on activity in recordings before deterrent takeoff (see bottom table in Fig. 1).

Data analysis

Processing and analysis of data were conducted in R (R Development Core Team, 2021, version 4.1.2). For

LIDAR data, all detected events were observed manually (as videos) and only events in which a clear object was moving across the field of view in a non-random trajectory were kept for further analysis. This allowed filtering out false positives and erratically flying insects while retaining the tracks of passing vertebrates. To validate our procedure, we examined the speed of the retained events and found that they were distributed within a unimodal distribution with a median of 7.0 m s⁻¹ (4.6–13.7 m s⁻¹; first and third quartiles), suggesting that the great majority of detected events were indeed flying vertebrates, as insect flight speed is typically < 5 m s⁻¹ (Hu et al., 2018). Moreover, the LIDAR detection range is highly limited for insects (< 10 m for large insects). The filtering procedure described above was blind regarding the deterrent's activity. The average number of detections per minute was calculated for each session and the difference between treatment and control sessions was estimated. Differences in detections per minute between the time-periods before (LIDAR baseline), during and after the treatment (mean duration 6, 14, 8 min respectively) were compared using the Wilcoxon signed rank non-parametric test (`wilcox.test` function in the stats package) because the data were not normally distributed according to a Shapiro–Wilk test (`shapiro.test` from the same package; $W = 0.88$, $P < 0.0001$).

We checked for overdispersion of the data using the dispersion-glm function of the R package `blmeco` (Korner-Nievergelt et al., 2015), which produced a value of 2, meaning the data were overdispersed. We thus fitted

a negative binomial generalized linear mixed model with a log link function to quantify the effect of the treatment. The model was fitted using `glmer.nb` from the R package `lme4` version 1.1-26 (Douglas Bates et al., 2015). Detections per minute were set as the response variable; treatment (before, during or after flight) was the fixed effect, hour and date were factorial random effects to account for variability in activity over time, and log-transformed session duration was used as an offset variable to account for different treatment times between sessions. This was done in order to keep using count data while still considering variation in duration; the log transformation was in accordance with the log link of the model (Coelho et al., 2020). The three possible models in terms of error structure (hour as random effect, date as random effect and both factors as random effects) were averaged due to low AIC variability ($\Delta\text{AICc} < 2$). The data met all model assumptions for a generalized linear mixed effect model and model validation indicated no model fit problems (normal distribution of residuals based on linear trend in a QQ plot, appropriateness of link function based on linear trend in observed versus predicted values, and homogeneity of variance based on random dispersal in residuals over fitted values plot). A separate model of the same structure was applied on the acoustic data to check if the deterrent affected activity 400 m away. To account for the possibility that animals became habituated to the signal as the experiment progressed, we used a separate, negative binomial generalized linear model with date as a fixed factor (assuming a reduction of effect over time would be related to habituation), detection counts as the response and log-transformed session duration as the offset.

To analyse the RADAR data, we used the RADAR's raw measurements of object altitude and classification and the standardized measurement of the density of moving animals (MTR). We analysed RADAR data between 100 and 800 m AGL, a range that we consider reliable for the identification of objects the size of the common pipistrelle *Pipistrellus pipistrellus*, the smallest bat species identified in the acoustic survey. The data were grouped into three height ranges (100–400, 400–600 and 600–800). The first was used to analyse the effect of the deterrent immediately above the deterrent's altitude, and the latter two were used to assess the possible effects of the deterrent at higher altitudes.

In RADAR analysis, differences in detections per minute between treatment and post-flight control sessions were assessed using the Wilcoxon test, as described above, as the data were not normally distributed (zero-inflated). The same analysis was used to compare treatment and control to baseline. The baseline dataset was compiled in the same manner as the experimental data (long pulse

detection intervals from 20:00 to 23:00) during the 3 days before and after the experiment. We found that activity levels between the periods before and after the experiment were similar (Wilcoxon signed rank test, $W = 2306$, $P = 0.874$).

To assess the effect of the active deterrent compared to post-flight control, we modelled RADAR data only from the experiment period. RADAR data consisted of a large proportion of zero observations, which required specific analytic tools. The data were analysed using a hurdle negative binomial generalized mixed model with a log link function and a truncated negative binomial distribution. We chose to use a hurdle model over a zero-inflation model because the former models zeros separately from positive observations (Feng, 2021), which enables accurate detection of trends with zero data. This was important because the effect of the deterrent was strongly expressed by differences in the number of zero observations in the treatment compared to the post-flight control. A hurdle model estimates the log odds of a zero observation relative to the intercept, and exponentiation of model estimates produces the likelihood ratio of a zero observation. The purpose of the model was to check if the deterrent had an effect on the abundance and altitudinal distribution of animals in the airspace. Both conditional and zero-inflation parts of the model were fitted with detections per session as the dependent variable, session type (active deterrent and post-activation control) and altitude band as fixed factors, an interaction term between treatment and altitude band, session ID as a random factor to account for variability in the aerial activity over time and log-transformed session length as an offset (see LIDAR methods). Models were fitted using the `glmmTMB` function in the `glmmTMB` R package version 1.0.2.1 (Brooks et al., 2017). Confidence intervals were calculated using the `confint` function from the `stats` package in R. Model validation was done with the `DHARMA` package version 0.4.1 (Hartig, 2021). Residual zero-inflation was negated using `testzeroInflation`, proper residual dispersion assessed with `testDispersion`, heteroscedasticity negated using `testCategorical` and normal distribution of residuals was confirmed with `testUniformity`.

According to the regulations of the Israel Nature and Parks Authority, this work did not require ethical approval as all data collection was done outside of a nature reserve and was done remotely without capture or contact (see letter in Supplementary information).

Results

A total of 39 h of bat activity were recorded by the three SM4 detectors at three altitudes over nine nights (9–12, 14, 16, 18, 19, 21.07.2020), between 20:00 and 23:00 local

time. A total of 1775 passing bat events were documented by the acoustic array, belonging to nine different species from six genera. Seven of these species are known to be susceptible to wind turbine collision mortality (*Rhinopoma microphylum*, Kumar et al., 2013, *Eptesicus serotinus*, Rydell et al., 2010, *Hypsugo savii*, *Pipistrellus kuhlii*, *P. pipistrellus*, *Tadarida teniotis*, Camina, 2012). Detection times were different in each device, negating double detections. The most prevalent species at ground level, where most activity was recorded, was Kuhl's pipistrelle *P. kuhlii*, a resident species that usually roosts in agricultural warehouses in the area. At 150 and 300 m AGL, most vocalizations were recognized as Greater mouse-tailed bats *R. microphylum*, a migratory insectivorous species present in the Hula Valley during summer (see Table 1 for a summary). A clear nightly temporal pattern was evident, with activity increasing from sunset to ~21:30 and steadily decreasing throughout the rest of the monitoring period. This pattern was consistent across all measuring techniques, height ranges and for all species detected in the acoustic survey (Fig. 3).

The Livox Horizon LIDAR was used to quantify animal presence from 1.5 to 100 m AGL in order to explore

Table 1. Summary of bat detections in the research area from the acoustic array by species and altitude.

Species	Total no. at 1 m AGL	Total no. at 150 m AGL	Total no. at 300 m AGL	Grand total
Greater mouse-tailed bat <i>Rhinopoma microphylum</i>	143	444	118	705
Kuhl's pipistrelle <i>Pipistrellus kuhlii</i>	671	25	6	702
Common pipistrelle <i>Pipistrellus pipistrellus</i>	128	2	1	131
Egyptian mouse-tailed bat <i>Rhinopoma cystops</i>	20	73	7	100
Naked-rumped tomb bat <i>Taphozous nudiventris</i>	45	43	2	90
Savi's pipistrelle <i>Hypsugo savii</i>	9	15	6	30
Serotine bat <i>Eptesicus serotinus</i>	13	0	0	13
European free-tailed bat <i>Tadarida teniotis</i>	0	1	2	3
Long-fingered bat <i>Myotis capaccinii</i>	1	0	0	1
Total	1030	603	142	1775

AGL, above ground level.

treatment effects in the airspace below the deterrent's altitude. A total of 894 vertebrate detections were recorded (mean altitude: 29.0 m, $SD = 15.2$). This was similar to the number of bats detected with the ground microphone ($N = 1030$ bats) suggesting that indeed we were detecting bats by the LIDAR. The number of detections per minute was significantly lower during treatment in comparison to the control periods before (baseline) and after flight [treatment: 0.76 detections/min, $SD = 0.58$, 95% CI = (0.96, 0.57), $N = 32$; controls: 1.22 detections/minute, $SD = 0.103$; 95% CI = (1.46, 0.94), $N = 59$, $W = 1153$, $P = 0.04$, see Fig. 4]. The number of detections per minute was also significantly lower during treatment in comparison to the post-treatment periods [1.29, $SD = 1.14$, 95% CI = (1.7, 0.88), $N = 30$, $W = 600$, $P = 0.04$], but the difference was not significant compared to pre-treatment periods [1.11, $SD = 0.9$, 95% CI = (0.96, 0.56), $N = 32$, $W = 553$, $P < 0.09$]. The number of detections did not differ between pre- and post-treatment periods, negating the possibility of animal attraction to the deterrent ($W = 412$, $P = 0.63$).

Hence, the deterrence treatment reduced bat activity below the deterrent's altitude by ~32% compared to the immediately before the treatment and by 42% compared to that immediately following the treatment. Accordingly, the final averaged model determined a significant main effect of treatment on vertebrate detections (Table 3). The same analysis on the acoustic data indicate that the deterrent had no effect on activity 400 m away (estimate = 0.05, $SE < 0.32$, $z = 0.16$, $P = 0.87$). A separate model that aimed at assessing nightly variability over the experiment period showed that the effect of the experimental day on detection counts was not significant, negating habituation to the deterrent (estimate < 0.0001, $SE < 0.0001$, $z = 0.92$, $P = 0.35$).

The BirdScan MR1 vertical looking RADAR was used to document animal activity above the deterrent's flight altitude (100–800 m AGL). Table 2 and Figure 5 summarize RADAR-documented activity patterns according to treatment and altitude bands. RADAR data analysis revealed that activity during and immediately after deterrent activation was significantly lower in the entire altitude range compared to the baseline activity recorded in the days before and after the experiment taken together (baseline: $n = 29$ sessions, mean = 2.75 MTR/min, $SD = 1.8$, CI = 3.4–2.1; active deterrent: $n = 62$ sessions, mean = 2 MTR/min, $SD = 2$, CI = 2.6–1.5; $W = 1136$, $P = 0.02$; after activation: $n = 54$ sessions, mean = 1.7 MTR/min, $SD = 1.8$, CI = 2.2–1.2; $W = 1063$, $P = 0.003$; Fig. 5). When comparing active deterrent flight periods to post-flight controls (recorded right after the flights), the hurdle model indicated a highly significant effect of the deterrent, resulting in greater activity above the

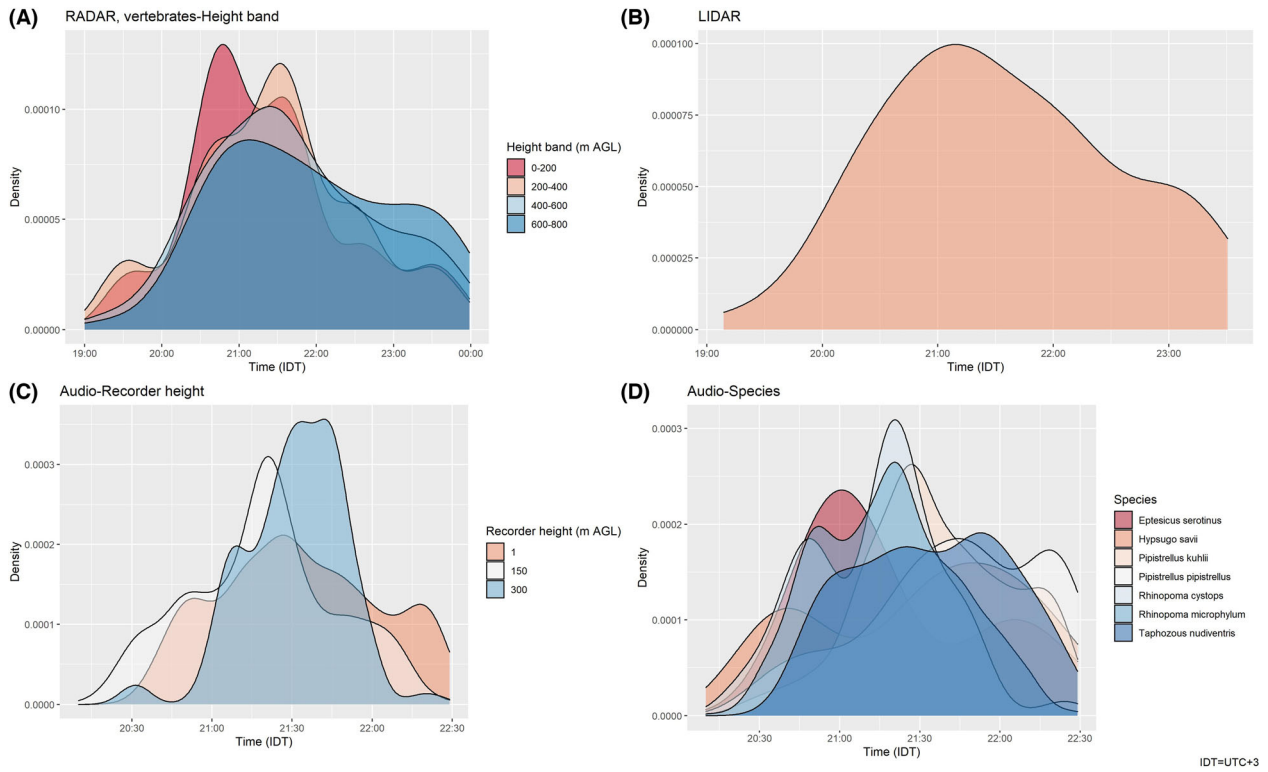


Figure 3. Temporal distribution of detections by different sensors. (A) RADAR, (B) LIDAR, (C, D) Acoustic array. *Tadarida teniotis* and *Myotis capaccinii* were excluded due to rare occurrence. A consistent peak at ~21:30 is evident throughout.

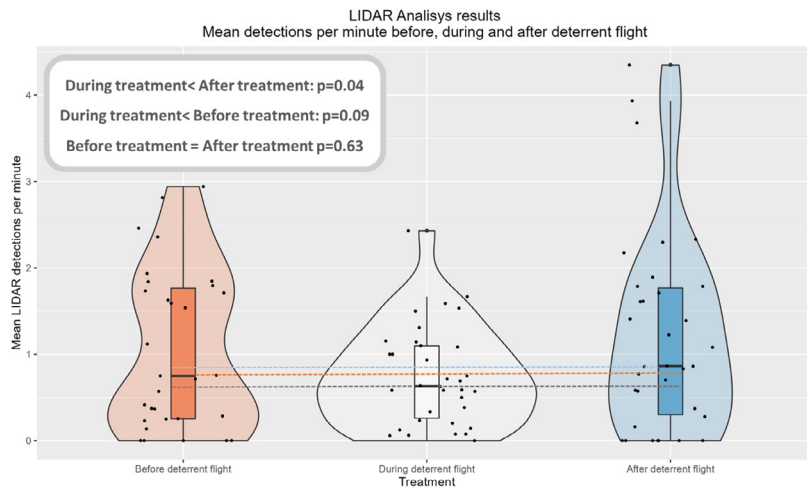


Figure 4. The effect of the presence of the deterrent on the number of targets detected by LIDAR before, during and after flight. Middle lines represent median values, edges represent upper and lower quartiles, whiskers extend to lowest or highest value, no farther than $1.5 \times$ interquartile range. Dashed lines across the plot represent median values of each treatment for visual comparison.

deterrent's altitude during the treatment (Table 3). This is evident in the zero-inflation part of the model, which indicated a likelihood ratio of 0.06 (see Methods), meaning that zero observations are over 10 times less likely

during treatment compared to after treatment control periods. These results are also supported by an overall significant decrease in activity after flight compared to during flight from all altitude bands (active deterrent:

Table 2. Means of RADAR movement traffic rates by altitude band and treatment.

Altitude band	Treatment	<i>N</i>	Mean MTR per minute	SD	95% CI	Ratio during/after flight	Ratio Baseline/experiment
100–400	Baseline	58	0.98	1.30	0.64–1.30	2.04	1.11
	Full experiment	61	0.88	1.45	0.51–1.20		
	During deterrence	62	1.00	1.54	0.56–1.42		
	After deterrence	52	0.49	1.20	0.20–0.90		
400–600	Baseline	58	1.14	1.08	0.86–1.42	1.43	1.54
	Full experiment	62	0.74	0.61	0.59–0.90		
	During deterrence	62	0.73	0.60	0.58–0.88		
	After deterrence	54	0.51	1.30	0.43–1.13		
600–800	Baseline	58	0.49	0.56	0.35–0.64	1.09	0.96
	Full experiment	62	0.51	0.61	0.36–0.66		
	During deterrence	62	0.51	0.64	0.36–0.67		
	After deterrence	54	0.47	0.60	0.30–0.63		

CI, confidence interval; MTR, movement traffic rate; SD, standard deviation.

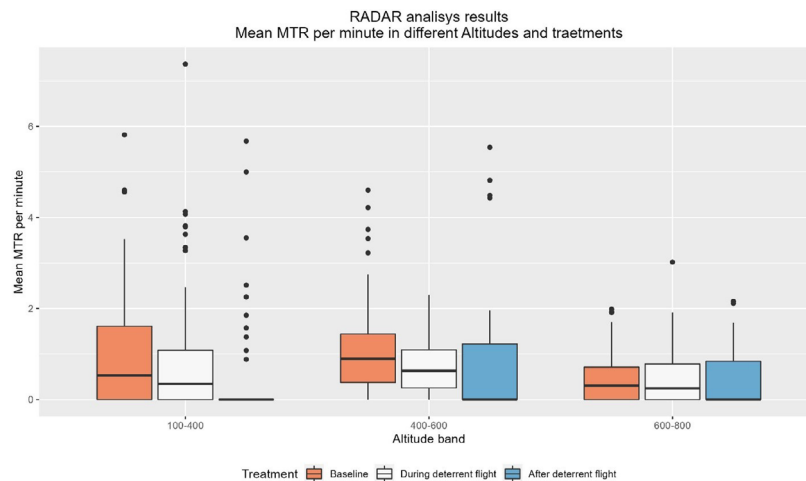


Figure 5. RADAR analysis results: Average movement traffic rate per minute for the different treatments in each altitude band. See Figure 4 for details regarding graphic depiction of statistics.

$n = 176$ sessions, mean per height band = 0.74 MTR/min, $SD = 1$, $CI = 0.88–0.585$; after activation: $n = 160$ sessions, mean = 0.59 MTR/min, $SD = 1.1$, $CI = 0.77–0.42$, $W = 17116$, $P = 0.0002$). The treatment \times altitude interaction in the hurdle model was not significant, suggesting a similar reduction of bat MTR across all altitude bins.

Summarizing RADAR results, experimental treatment sessions had significantly lower activity rates (MTR/min) compared to external baseline (27% less activity during flight and ~38% less immediately after flight), and within experimental treatments, activity during deterrent flight was significantly higher (by 25%) compared to immediately after flight above the deterrent flight altitude. The hurdle model focusing only on the experimental period (excluding the external baseline) indicates a significant negative effect of active deterrent flight on the number of zero observations, corresponding to an

increase in activity, and this is consistent through the three height bins.

Discussion

We describe an experiment in which the potential of a novel deterrence technique to mitigate bat mortality at wind farms was assessed. The area was acoustically surveyed for bat activity up to 500 m AGL, and nine species (including seven that were previously reported to suffer wind turbine mortality) were recorded in the airspace during the experiment at relevant heights (Table 1). Nocturnal flying vertebrate (mostly bats) activity summed over all RADAR altitude bins was significantly reduced when the deterrent was active compared to baseline conditions and compared to controls. The same was found for bats that flew below the deterrent flight altitude. The

Table 3. Model summary for RADAR and LIDAR data analysis.

Sensor	Airspace	Model	Model parts	Estimate meaning	Term meaning	Term	Estimate (SE)	Z	P	95% CI
LIDAR	Below deterrent 0–100 m AGL	Negative binomial GLMM		Detections per minute	Intercept	Before deterrence (intercept)	0.9 (1.27)	0.41	0.67	0.56–1.45
					Treatment effect	During deterrence	0.61 (1.24)	2.116	0.03	0.39–0.96
					Intercept	After deterrence After deterrence, 100–400 (intercept)	1.22 (1.23) 2.1 (1.27)	1.14 3.42	0.25 0.0006	0.86–1.73 1.4–3.3
RADAR	Above deterrent 100–800 m AGL	Hurdle negative binomial GLMM	Conditional part of non-zero observations	MTR per minutes	Treatment effect	During deterrence	0.67 (1.27)	–1.6	0.1	0.4–1.1
					Altitude effect	Height band 400–600	0.81 (1.29)	–0.8	0.42	0.48–1.3
						Height band 600– 800	0.42 (1.3)	–3.5	0.001	0.24–0.72
			Treatment × altitude interaction	During deterrence × 400 –600	During deterrence × 600 –800	0.8 (1.3)	–0.8	0.42	0.44–1.4	
				Log [P(0 obs)/P(0 obs intercept)]	Intercept	After deterrence, 100–400 (intercept)	9.7 (1.6)	4.4	<0.000001	3.5–25
			Zero inflation part for zero observations	Treatment effect Altitude effect	During deterrence Height band 400– 600	0.06 (1.6) 0.22 (1.6)	–4.65 –2.8	<0.000001 0.005	0.02–0.2 0.08–0.63	
				Treatment × altitude interaction	Height band 600– 800	0.2 (1.6)	–3	0.002	0.07–0.56	
					During deterrence × 400 –600	1 (2–1)	0.04	0.96	0.23–4.5	
					During deterrence × 600 –800	3.28 (0.72)	1.64	0.1	0.8–13.5	

Summary of RADAR analysis consists of the conditional part summarizing the analysis of non-zero observations and the zero-inflation part summarizing zero observation analysis. Significant effects in bold. Estimates, standard errors and confidence intervals are back transformed and indicate detections per minute in LIDAR, MTR per minute in conditional RADAR and likelihood of zero observation relative to intercept in zero inflation RADAR model.

AGL, above ground level; CI, confidence interval; GLMM, generalized linear mixed model; MTR, movement traffic rate; SE, standard error.

deterrent also altered the altitudinal distribution of bat activity reducing animal movement through the area of its operation in heights that are typical of wind turbine blade movement.

Similar to operational curtailment, our method will probably not completely eliminate mortality (Adams et al., 2021), but it has the potential to outperform many of the existing non-operational solutions (Arnett, Johnson, et al., 2013; Cassidy, 2015; Gilmour et al., 2021; Romano et al., 2019; Weaver et al., 2020), which utilize immobile, single disturbance (visual or auditory) stimuli. The observed change in activity, including a decrease in activity below the deterrent and an increase in activity above the deterrent immediately after operation, suggests that the operation of the deterrent at turbine height could substantially reduce animal mortality caused by turbine blade rotation by promoting the same pattern of upward shift in flight altitude.

Although we had insufficient data to assess activity changes around 100–150 m as a separate band, it is likely that animals were deterred from such close contact with the device. These positive results justify an in-depth assessment of the applicability of the deterrent in a wider framework, examining cost–benefit considerations and practical implementation challenges on a large scale.

The unique use of three complementary sensing systems enabled us to construct a detailed description of the local aerial fauna and its altitudinal profile while testing the impact of the deterrent on flying vertebrates consisting almost entirely of bats. We note that the aerial acoustic monitoring revealed the presence of multiple species of bats at the times and altitudes corresponding to those of the experiment. We did our best to avoid inclusion of other aerial taxa (insects and birds) in the analysed data. An educated choice of timing along the yearly cycle, based on decades of cumulative monitoring and avian research in the area (e.g., Shirihai et al., 1996), ensured that nocturnal bird activity was negligible during the experiment period. The strong similarity in activity times in the acoustic, RADAR and LIDAR datasets provides further indication of the predominance of bats in the data, as the acoustic data contained only confirmed bat vocalizations. Careful manual analysis of the LIDAR data and reliance on the well-established Birdscan RADAR classifier ensured the removal of the vast majority of insect signals from our dataset. Our strict approach towards avoiding avian contamination in the data meant that the experiment had to take place over a limited period of time in this specific locality where nocturnal bird activity is thoroughly understood. The effectiveness of the deterrent in any other scenario must be assessed prior to future operation, including over large scales and with a focus on other aerial species.

The findings of this work indicate that overall, the deterrent significantly reduces bat activity in the relevant airspace of up to 700 m above its flight altitude. Moreover, based on the lack of effect found in the acoustic data, we deduce the signal is undetectable, or at least not aversive 400 m from the operation site. The LIDAR results demonstrate the deterrent's immediate effect below flight altitude during flight, while RADAR results show a lasting effect, with activity levels significantly lower both during the deterrent's flight and ~10 min after landing, compared to the baseline period before and after the experiment. Furthermore, the results suggest that when encountering the deterrent, bats avoid it by increasing flight altitude (Fig. 5). This avoidance behaviour is in line with previous studies of vertebrate responses to human activity in the airspace (de Lucas et al., 2007; Johnston et al., 2014). Therefore, our work points to the potential of the proposed technology to reduce bat mortality caused by blade rotation by decreasing bat activity in the airspace around wind turbines. We hypothesized that bats will not adapt to the dynamic stimulus produced by the moving device, and indeed we did not observe any evidence of short-term habituation patterns throughout the 3-week duration of the experiment.

During the experiment, bat activity in control sessions was recorded immediately after treatment sessions without any buffer or recovery time. The consistent difference between control and treatment sessions in different sensing systems and across a large altitudinal range indicates that the effect of the deterrent is largely short-lived. This, together with the lack of deterrent effect seen in the acoustic survey, supports highly accurate implementation of the technology, which will achieve the goal of reducing bat mortality with minimal intervention in the aerial habitat. We note that most mitigation techniques used today (i.e., turbine operation manipulations) have slow reaction times, such that bats could be at high-risk many minutes after their activation. Notably, our suggested solution does not require shutting down or changing turbine operation and is immediately effective.

A realistic scenario of implementation would include a fleet of autonomous deterrents mounted on designated drones, flying on preset courses and maintained by minimal personnel. The size of the fleet would be determined by the dimensions of the facility, with a single deterrent operating around one to three turbines, depending on size, spacing, location in the facility and topography. The fleet would operate at hours and areas of the farm which are prone to bat collisions, usually known from surveys made prior to and following construction. Within this time frame, activation should start at turbine cut-in speed (determined by manufacturer and power grid requirements, Agbonaye et al., 2022) and stop at the maximal

wind speed of bat activity in the specific area and season. This scheme will enable economic use of the infrastructure and will set well-defined boundaries, known *a priori* in each facility, enabling practical assessment of the utility of the suggested method. Future applications could also initiate drone flight on the basis of acoustic- or LIDAR-based bat activity detectors, but initial applications can simply fly the drones without such input about bat activity, achieving substantial deterrence of bats from the turbine area.

The main practical limitation of this method is its dependence on short-lived batteries, which would limit flight duration and require frequent battery replacement. Even so, we believe that when operated in this scheme, the technology could reduce mortality at critical times in a cost-effective manner. Given a 2.75 MW average nameplate capacity and 40% capacity factor for a land-operated wind turbine in 2020 (Wiser et al., 2021), the average yearly output of a single machine should be ~9600 MWh. Assuming a bat-related curtailment production reduction of 1% (Arnett, Johnson, et al., 2013; Rabie et al., 2022), 96 MWh would be added to production if a proper substitute of curtailment is implemented. With a cost of wind turbine MWh between \$29–128 (Nalley & Angelina, 2022) in 2022, thousands of dollars of increased revenue would be expected for a single wind turbine, which would likely cover the expense of acquiring and operating the deterrent system in under 2 years. Assuming improvements in capacity and efficiency from the time of the above predictions, the deterrent's economic relevance is likely to increase over time.

The technique of drone-mounted audio-visual deterrence can be adapted to specific circumstances and species by adapting the broadcasted signal and operation mode following designated tests and practical assessment. We note that in spite of the significant decrease in the activity below and above the deterrent's flight altitude compared to baseline conditions, substantial bat activity may still persist in hazardous areas. Thus, the deterrent's operation should be incorporated into an inclusive scheme for preventing wind turbine-related wildlife mortality. The deterrent is independent of wind farm infrastructure and can be deployed and maintained when needed without prior preparation and planning. The farm can remain active during the deterrent's operation, and the device can be used to mitigate bat mortality in already existing facilities without considerable expense. Any aversive response of aerial wildlife would be considered a positive effect of the deterrent around wind turbines, but wildlife attraction is still a possibility in untested taxa. The deterrent's effect on terrestrial wildlife has not been assessed and could potentially bear negative consequences like aversion to a natural habitat or attraction to hazardous areas.

The tested deterrence device proved successful in a localized, time-limited experimental setting. It may substantially reduce harmful consequences induced by the wind energy industry on bats around wind farms while avoiding most shortcomings of existing solutions. As such, the feasibility and practicality of its deployment in the industry should be further tested to potentially provide viable mitigation of bat mortality.

Acknowledgments

We thank the Israeli Ministry of Energy for funding and support (Grant number: 218-11-032), Mor Taub for graphical and acoustic analysis assistance, David Troupin for assistance with data sources, and Yoni Vortman for logistical support in the field.

Conflict of Interest

This research is sponsored by the Israeli Ministry of Energy and may lead to the development of products which may be licensed to WINGO, in which G.H. has a business and/or financial interest.

References

- Adams, E.M., Gulka, J. & Williams, K.A. (2021) A review of the effectiveness of operational curtailment for reducing bat fatalities at terrestrial wind farms in North America. *PLoS One*, **16**(11), e0256382. Available from: <https://doi.org/10.1371/journal.pone.0256382>
- Agbonaye, O., Keatley, P., Huang, Y., Odiase, F.O. & Hewitt, N. (2022) Value of demand flexibility for managing wind energy constraint and curtailment. *Renewable Energy*, **190**, 487–500.
- Agudelo, M.S., Mabee, T.J., Palmer, R. & Anderson, R. (2021) Post-construction bird and bat fatality monitoring studies at wind energy projects in Latin America: a summary and review. *Heliyon*, **7**(6), e07251. Available from: <https://doi.org/10.1016/j.heliyon.2021.e07251>
- Alisson, T.D., Diffendorfer, J.E., Baerwald, E.F., Beston, J.A., Drake, D., Hale, A.M. et al. (2019) Impacts to wildlife of wind energy siting and operation in the United States. *Issues in Ecology*, **21**(1), 2–18.
- Anderson, R.L., Morrison, M., Sinclair, K., Strickland, D., Davis, H. & Kendall, W. (2000) Studying wind energy/bird interactions: a guidance document-executive summary. *Proceedings of National Avian-Wind Power Planning Meeting*, 3. Available at: <https://www.osti.gov/servlets/purl/776928>
- Arnett, E.B., Baerwald, E.F., Mathews, F., Rodrigues, L., Rodríguez-Durán, A., Rydell, J. et al. (2016) Impacts of wind energy development on bats: a global perspective. In: Voigt, C.C. & Kingston, T. (Eds.) *Bats in the Anthropocene: conservation of bats in a changing world*. Cham: Springer, pp.

- 295–323. Available from: <https://doi.org/10.1007/978-3-319-25220-9>
- Arnett, E.B., Hein, C.D., Schirmacher, M.R., Huso, M.M.P. & Szewczak, J.M. (2013) Evaluating the effectiveness of an ultrasonic acoustic deterrent for reducing bat fatalities at wind turbines. *PLoS One*, **8**(6), e65794. Available from: <https://doi.org/10.1371/journal.pone.0065794>
- Arnett, E.B., Huso, M.M.P., Schirmacher, M.R. & Hayes, J.P. (2011) Altering turbine speed reduces bat mortality at wind-energy facilities. *Frontiers in Ecology and the Environment*, **9**(4), 209–214. Available from: <https://doi.org/10.1890/100103>
- Arnett, E.B., Johnson, G., Erickson, W. & Hein, C. (2013) *A synthesis of operational mitigation studies to reduce bat fatalities at wind energy facilities in North America*. A report submitted to the National Renewable Energy Laboratory. Bat Conservation International. Austin, Texas, USA.
- Arnett, E.B. & May, R.F. (2016) Mitigating wind energy impacts on wildlife: approaches for multiple taxa. *Human–Wildlife Interactions*, **10**(1), 5. Available from: <https://doi.org/10.26077/1jeg-7r13>
- August, T. & Moore, T. (2019) Autonomous drones are a viable tool for acoustic bat surveys. *bioRxiv*, 673772. Available from: <https://doi.org/10.1101/673772>
- Baerwald, E.F., Edworthy, J., Holder, M. & Barclay, R.M.R. (2009) A large-scale mitigation experiment to reduce bat fatalities at wind energy facilities. *The Journal of Wildlife Management*, **73**(7), 1077–1081. Available from: <https://doi.org/10.2193/2008-233>
- Band, W., Madders, M. & Whitfield, D.P. (2007) Developing field and analytical methods to assess avian collision risk at wind farms. In: *Birds and wind farms: risk assessment and mitigation*. Madrid: Quercus, pp. 259–275.
- Barclay, R.M.R., Baerwald, E.F. & Gruver, J.C. (2007) Variation in bat and bird fatalities at wind energy facilities: assessing the effects of rotor size and tower height. *Canadian Journal of Zoology*, **85**(3), 381–387. Available from: <https://doi.org/10.1139/Z07-011>
- Barrios, L. & Rodriguez, A. (2004) Behavioural and environmental correlates of soaring-bird mortality at on-shore wind turbines. *Journal of Applied Ecology*, **41**(1), 72–81. Available from: <https://doi.org/10.1111/j.1365-2664.2004.00876.x>
- Boonman, A., Bar-On, Y. & Yovel, Y. (2013) It's not black or white—On the range of vision and echolocation in echolocating bats. *Frontiers in Physiology*, **4**, 248. Available from: <https://doi.org/10.3389/fphys.2013.00248>
- Brooks, M.E., Kristensen, K., van Benthem, K.J., Magnusson, A., Berg, C.W., Nielsen, A. et al. (2017) Modeling zero-inflated count data with glmmTMB. *bioRxiv*, 132753. Available from: <https://doi.org/10.1101/132753>
- Camina, Á. (2012) Bat fatalities at wind farms in northern Spain—Lessons to be learned. *Acta Chiropterologica*, **14**(1), 205–212. Available from: <https://doi.org/10.3161/150811012X654402>
- Cassidy, F.L. (2015) *The potential of lasers as deterrents to protect birds in the Alberta oil sands and other areas of human-bird conflict* (M.Sc. thesis). Available from: <https://doi.org/10.7939/R3RV0DC06>
- Chambert, T. & Aurélien, B. (2021) *Assessing the demographic impact of bird collisions with wind turbines*.
- Coelho, R., Infante, P. & Santos, M.N. (2020) Comparing GLM, GLMM, and GEE modeling approaches for catch rates of bycatch species: a case study of blue shark fisheries in the South Atlantic. *Fisheries Oceanography*, **29**(2), 169–184. Available from: <https://doi.org/10.1111/fog.12462>
- Danilovich, S., Krishnan, A., Lee, W.J., Borrisov, I., Eitan, O., Kosa, G. et al. (2015) Bats regulate biosonar based on the availability of visual information. *Current Biology*, **25**(23), R1124–R1125. Available from: <https://doi.org/10.1016/j.cub.2015.11.003>
- Danilovich, S. & Yovel, Y. (2019) Integrating vision and echolocation for navigation and perception in bats. *Science Advances*, **5**(6), eaaw6503. Available from: <https://doi.org/10.1126/sciadv.aaw6503>
- de Lucas, M., Janss, G.F.E. & Ferrer, M. (2007) Wind farm effects on birds in the strait of Gibraltar. In: *Birds and wind farms: risk assessment and mitigation*. Madrid: Quercus, pp. 219–228.
- Dolev, A. & Carmel, Y. (2009) Distribution of threatened-protected vertebrates as a basis for conservation planning. *Israel Journal of Ecology and Evolution*, **55**(2), 117–132.
- Douglas Bates, D., Martin, M.M., Bolker, B. & Walker, S. (2015) Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, **67**(1), 1–48. Available from: <https://doi.org/10.18637/jss.v067.i01>
- Ednie, G., Bird, D.M. & Elliott, K.H. (2021) Fewer bat passes are detected during small, commercial drone flights. *Scientific Reports*, **11**(1), 1–8. Available from: <https://doi.org/10.1038/s41598-021-90905-0>
- Eklöf, J.A., Svensson, M. & Jens, R.J. (2002) Northern bats, *Eptesicus nilssonii*, use vision but not flutter-detection when searching for prey in clutter. *Oikos*, **99**(2), 347–351. Available from: <https://doi.org/10.1034/j.1600-0706.2002.990216.x>
- Elizabeth, G. & Hein, C. (2022) *IEA wind white paper: cumulative effects analysis for wind energy development: current practices, challenges, and opportunities*. Golden, CO: National Renewable Energy Lab. (NREL). Available from: <https://doi.org/10.2172/1855171>
- Feng, C.X. (2021) A comparison of zero-inflated and hurdle models for modeling zero-inflated count data. *Journal of Statistical Distributions and Applications*, **8**, 1–19. Available from: <https://doi.org/10.1186/s40488-021-00121-4>
- Ferrer, M., de Lucas, M., Janss, G.F.E., Casado, E., Muñoz, A.R., Bechard, M.J. et al. (2012) Weak relationship between risk assessment studies and recorded mortality in wind

- farms. *Journal of Applied Ecology*, **49**(1), 38–46. Available from: <https://doi.org/10.1111/j.1365-2664.2011.02054.x>
- 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. Available from: <https://doi.org/10.1111/2041-210X.12992>
- Gilmour, L., Holderied, M.W., Pickering, S.P.C. & Jones, G. (2021) Acoustic deterrents influence foraging activity, flight and echolocation behaviour of free-flying bats. *Journal of Experimental Biology*, **224**, jeb.242715. Available from: <https://doi.org/10.1242/jeb.242715>
- Gomes, D.G.E., Page, R.A., Geipel, I., Taylor, R.C., Ryan, M.J. & Halfwerk, W. (2016) Bats perceptually weight prey cues across sensory systems when hunting in noise. *Science*, **353** (6305), 1277–1280. Available from: <https://doi.org/10.1126/science.aaf7934>
- Hartig, F. (2021) *DHARMA: residual diagnostics for hierarchical (multi-level/mixed) regression models*. R Package Version 0.4.1. Available at: <https://CRAN.R-project.org/package=DHARMA>
- Horn, J.W., Arnett, E.B. & Kunz, T.H. (2008) Behavioral responses of bats to operating wind turbines. *The Journal of Wildlife Management*, **72**(1), 123–132. Available from: <https://doi.org/10.2193/2006-465>
- Hu, C., Li, W., Wang, R., Li, Y., Li, W. & Zhang, T. (2018) Insect flight speed estimation analysis based on a full-polarization radar. *Science China Information Sciences*, **61** (10), 1–3. Available from: <https://doi.org/10.1007/s11432-018-9484-2>
- International Energy Agency. (2020) *Global energy review 2020*. Paris: OECD.
- Johnston, N.N., Bradley, J.E. & Otter, K.A. (2014) Increased flight altitudes among migrating golden eagles suggest turbine avoidance at a Rocky Mountain wind installation. *PLoS One*, **9**(3), e93030. Available from: <https://doi.org/10.1371/journal.pone.0093030>
- Kloepper, L.N. & Kinniry, M. (2018) Recording animal vocalizations from a UAV: bat echolocation during roost re-entry. *Scientific Reports*, **8**(1), 1–6. Available from: <https://doi.org/10.1038/s41598-018-26122-z>
- Korner-Nievergelt, F., Brinkmann, R., Niermann, I. & Behr, O. (2013) Estimating bat and bird mortality occurring at wind energy turbines from covariates and carcass searches using mixture models. *PLoS One*, **8**(7), e67997. Available from: <https://doi.org/10.1371/journal.pone.0067997>
- Korner-Nievergelt, F., Roth, T., von Felten, S., Guélat, J., Almasi, B. & Korner-Nievergelt, P. (2015) *Bayesian data analysis in ecology using linear models with R BUGS and Stan*. Cambridge, MA: Academic press.
- 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. Available from: <https://doi.org/10.1111/2041-210X.13807>
- Kumar, S.R., Ali, A.M.S. & Arun, P.R. (2013) Bat mortality due to collision with wind turbines in Kutch District, Gujarat, India. *Journal of Threatened Taxa*, **5**(13), 4822–4824. Available from: <https://doi.org/10.11609/JoTT.o3503.4822-4>
- Kunz, T.H., Arnett, E.B., Erickson, W.P., Hoar, A.R., Johnson, G.D., Larkin, R.P. et al. (2007) Ecological impacts of wind energy development on bats: questions, research needs, and hypotheses. *Frontiers in Ecology and the Environment*, **5**(6), 315–324. Available from: [https://doi.org/10.1890/1540-9295\(2007\)5\[315:EIOWED\]2.0.CO;2](https://doi.org/10.1890/1540-9295(2007)5[315:EIOWED]2.0.CO;2)
- Kunz, T.H., Braun de Torrez, E., Bauer, D., Lobo, T. & Fleming, T.H. (2011) Ecosystem services provided by bats. *Annals of the New York Academy of Sciences*, **1223**(1), 1–38. Available from: <https://doi.org/10.1111/j.1749-6632.2011.06004.x>
- Kunz, T.H., Edward, B., Cooper, B.M., Erickson, W.P., Larkin, R.P., Mabee, T. et al. (2007) Assessing impacts of wind-energy development on nocturnally active birds and bats: a guidance document. *The Journal of Wildlife Management*, **71** (8), 2449–2486. Available from: <https://doi.org/10.2193/2007-270>
- Lantz, E.J., Roberts, O., Nunemaker, J., DeMeo, E., Dykes, K. & Scott, G. (2019) *Increasing wind turbine tower heights: opportunities and challenges*. Golden, CO: National Renewable Energy Lab. (NREL). Available from: <https://doi.org/10.2172/1515397>
- Lehnert, L.S., Kramer-Schadt, S., Schönborn, S., Lindecke, O., Niermann, I. & Voigt, C.C. (2014) Wind farm facilities in Germany kill noctule bats from near and far. *PLoS One*, **9** (8), e103106. Available from: <https://doi.org/10.1371/journal.pone.0103106>
- Lintott, P.R., Richardson, S.M., Hosken, D.J., Fensome, S.A. & Mathews, F. (2016) Ecological impact assessments fail to reduce risk of bat casualties at wind farms. *Current Biology*, **26**(21), R1135–R1136. Available from: <https://doi.org/10.1016/j.cub.2016.10.003>
- Marques, A.T., Batalha, H., Rodrigues, S., Costa, H., Pereira, M.J.R., Fonseca, C. et al. (2014) Understanding bird collisions at wind farms: an updated review on the causes and possible mitigation strategies. *Biological Conservation*, **179**, 40–52. Available from: <https://doi.org/10.1016/j.biocon.2014.08.017>
- Mathews, F., Swindells, M., Goodhead, R., August, T.A., Hardman, P., Linton, D.M. et al. (2013) Effectiveness of search dogs compared with human observers in locating bat carcasses at wind-turbine sites: a blinded randomized trial. *Wildlife Society Bulletin*, **37**(1), 34–40.
- May, R., Masden, E.A., Bennet, F. & Perron, M. (2019) Considerations for upscaling individual effects of wind energy development towards population-level impacts on wildlife. *Journal of Environmental Management*, **230**, 84–93. Available from: <https://doi.org/10.1016/j.jenvman.2018.09.062>

- May, R., Middel, H., Stokke, B.G., Jackson, C. & Verones, F. (2020) Global life-cycle impacts of onshore wind-power plants on bird richness. *Environmental and Sustainability Indicators*, **8**, 100080. Available from: <https://doi.org/10.1016/j.indic.2020.100080>
- Nalley, S. & Angelina, L. (2022) *Annual Energy Outlook 2022 (AEO2022)*. Available at: https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf
- Nilsson, C., Dokter, A.M., Schmid, B., Scacco, M., Verlinden, L., Bäckman, J. et al. (2018) Field validation of radar systems for monitoring bird migration. *Journal of Applied Ecology*, **55.6**(2018), 2552–2564. Available from: <https://doi.org/10.1111/1365-2664.13174>
- O'Shea, T.J., Cryan, P.M., Hayman, D.T.S., Plowright, R.K. & Streicker, D.G. (2016) Multiple mortality events in bats: a global review. *Mammal Review*, **46**(3), 175–190. Available from: <https://doi.org/10.1111/mam.12064>
- R Core Team. (2021) *R: a language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Available at: <https://www.R-project.org/>
- Rabie, P.A., Welch-Acosta, B., Nasman, K., Schumacher, S., Schueller, S. & Gruver, J. (2022) Efficacy and cost of acoustic-informed and wind speed-only turbine curtailment to reduce bat fatalities at a wind energy facility in Wisconsin. *PLoS One*, **17**(4), e0266500. Available from: <https://doi.org/10.1371/journal.pone.0266500>
- Rodrigues, L., Bach, L., Dubourg-Savage, M., Karapandža, B., Kovač, D., Kervyn, T. et al. (2015) *Guidelines for consideration of bats in wind farm projects—revision 2014*. EUROBATs publication series no. 6 (English version). Bonn, Germany: UNEP/EUROBATs Secretariat.
- Roeleke, M., Blohm, T., Kramer-Schadt, S., Yovel, Y. & Voigt, C.C. (2016) Habitat use of bats in relation to wind turbines revealed by GPS tracking. *Scientific Reports*, **6**(1), 1–9. Available from: <https://doi.org/10.1038/srep28961>
- Romano, W.B., Skalski, J.R., Townsend, R.L., Kinzie, K.W., Coppinger, K.D. & Miller, M.F. (2019) Evaluation of an acoustic deterrent to reduce bat mortalities at an Illinois wind farm. *Wildlife Society Bulletin*, **43**(4), 608–618. Available from: <https://doi.org/10.1002/wsb.1025>
- Rydell, J., Bach, L., Dubourg-Savage, M.-J., Green, M., Rodrigues, L. & Hedenström, A. (2010) Bat mortality at wind turbines in northwestern Europe. *Acta Chiropterologica*, **12**(2), 261–274. Available from: <https://doi.org/10.3161/150811010X537846>
- Schmaljohann, H., Liechti, F., Bächler, E., Steuri, T. & Bruderer, B. (2008) Quantification of bird migration by radar—a detection probability problem. *Ibis*, **150**(2), 342–355. Available from: <https://doi.org/10.1111/j.1474-919X.2007.00797.x>
- Shi, X., Schmid, B., Tschanz, P., Segelbacher, G. & Liechti, F. (2021) Seasonal trends in movement patterns of birds and insects aloft simultaneously recorded by radar. *Remote Sensing*, **13**(9), 1839. Available from: <https://doi.org/10.3390/rs13091839>
- Shirihai, H., Dovart, E., Christie, D.A. & Harris, H. (1996) *The birds of Israel*, Vol. **876**. London: Academic Press.
- Smallwood, K.S. (2013) Comparing bird and bat fatality-rate estimates among north American wind-energy projects. *Wildlife Society Bulletin*, **37**(1), 19–33. Available from: <https://doi.org/10.1002/wsb.260>
- Smallwood, K.S., Bell, D.A. & Standish, S. (2020) Dogs detect larger wind energy effects on bats and birds. *The Journal of Wildlife Management*, **84**(5), 852–864. Available from: <https://doi.org/10.1016/j.cub.2008.06.029>
- Smallwood, K.S. & Karas, B. (2009) Avian and bat fatality rates at old-generation and repowered wind turbines in California. *The Journal of Wildlife Management*, **73**(7), 1062–1071. Available from: <https://doi.org/10.2193/2008-464>
- Solick, D.I. & Newman, C.M. (2021) Oceanic records of north American bats and implications for offshore wind energy development in the United States. *Ecology and Evolution*, **11**(21), 14433–14447. Available from: <https://doi.org/10.1002/ece3.8175>
- Villegas-Patracca, R., Macías-Sánchez, S., MacGregor-Fors, I. & Muñoz-Robles, C. (2012) Scavenger removal: bird and bat carcass persistence in a tropical wind farm. *Acta Oecologica*, **43**, 121–125. Available from: <https://doi.org/10.1016/j.actao.2012.06.004>
- Voigt, C.C., Kaiser, K., Look, S., Scharnweber, K. & Scholz, C. (2022) Wind turbines without curtailment produce large numbers of bat fatalities throughout their lifetime: a call against ignorance and neglect. *Global Ecology and Conservation*, **37**, e02149. Available from: <https://doi.org/10.1016/j.gecco.2022.e02149>
- Wang, R., Hu, C., Fu, X., Long, T. & Zeng, T. (2017) Micro-Doppler measurement of insect wing-beat frequencies with W-band coherent radar. *Scientific Reports*, **7**(1), 1–8. Available from: <https://doi.org/10.1038/srep44875>
- Weaver, S.P., Hein, C.D., Simpson, T.R., Evans, J.W. & Castro-Arellano, I. (2020) Ultrasonic acoustic deterrents significantly reduce bat fatalities at wind turbines. *Global Ecology and Conservation*, **24**, e01099. Available from: <https://doi.org/10.1016/j.gecco.2020.e01099>
- Whitby, M.D., Schirmacher, M.R. & Frick, W.F. (2021) *The state of the science on operational minimization to reduce bat fatality at wind energy facilities*. A report submitted to National Renewable Energy Lab., Austin, Texas.
- Wiser, R.H., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G. et al. (2021) *Land-based wind market report: 2021 edition*. Lawrence Berkeley National Lab (LBNL), Berkeley, CA.
- Zaugg, S., Saporta, G., van Loon, E., Schmaljohann, H. & Liechti, F. (2008) Automatic identification of bird targets with radar via patterns produced by wing flapping. *Journal of the Royal Society Interface*, **5**(26), 1041–1053. Available from: <https://doi.org/10.1098/rsif.2007.1349>

Supporting Information

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

Appendix S1. Acoustic recording database: bat detection by species, altitude band, date and time.

Appendix S2. LIDAR recoring sessions database: recoding date, duration and detection amounts.

Appendix S3. RADAR database: summary of monitoring sessions by experiment session and altitude band, and MTR per session.