Journal of Environmental Management 416 (2026) 130829

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Optimising bat-friendly curtailment algorithms for wind turbines

Kévin Barré [a,b,c,*,1], Kseniia Kravchenko [a,1], Thierry Chambert [d], Anne-Constance Comau [b,c], Anaïs Pessato [b,c], Andréas Ravache [b,e,c], Elise Sivault [b,c], Cassandre Treyvaud [b,c], Fabien Verniest [b,c], Christian Kerbiriou [b,c,2], Christian E. Vincenot [a,f,2]

[a] Complex Systems Group (NEXUS::CSR), Faculty of Science, Technology, and Medicine (FSTM), University of Luxembourg, 2, avenue de l'Université, Esch-sur-Alzette, L-4365, Luxembourg
[b] Centre d'Ecologie et des Sciences de la Conservation (CESCO), Muséum national d'Histoire naturelle, Centre National de la Recherche Scientifique, Sorbonne Université, Paris, France
[c] Centre d'Ecologie et des Sciences de la Conservation (CESCO), Muséum national d'Histoire naturelle, Station de Biologie Marine, Concarneau, France
[d] Departement of Anthropization and functioning of terrestrial ecosystems, DRAS, French biodiversity agency, Pérols, France
[e] UMR ENTROPIE, IRD, IFREMER, CNRS, University of Reunion, University of New Caledonia, BP A5, New Caledonia, Nouméa Cedex, 98848, France
[f] Island Bat Research Group (IBRG), Kyoto, Japan

ARTICLE INFO

Keywords:
Acoustic monitoring
Chiroptera
Collision risk
Curtailment
Mitigation
Predictive modelling
Wind energy
Wind turbines

ABSTRACT

Wind turbines worldwide cause high mortality in long-lived bats through collisions. To mitigate these impacts, operators commonly apply blanket curtailment by stopping turbine blades under low wind speed and mild temperature, when bat activity is often high and energy production is low. Nevertheless, this approach shows highly variable effectiveness. More advanced curtailment tools exist, but evidence for their efficiency and practical implementation remains limited. Using acoustic monitoring data collected over 25,588 nights at 123 wind turbine nacelles in France, we trained algorithms to predict bat presence probability from weather conditions, the time of year and time of night. We evaluated algorithm performance in simulated curtailment scenarios by estimating the proportion of bat acoustic activity protected and energy loss when turbines were stopped above a given predicted-probability threshold. We compared several implementation scenarios of algorithms, including whether site-specific data were included in model training and whether curtailment thresholds were defined at national, seasonal, or site levels. Simulations indicated high efficiency across year-round applications. The simplest scenario, which uses no site-specific training data and a national curtailment threshold, produced results similar to more restrictive approaches. For example, to protect 90% of bat activity through algorithm-based wind turbine shutdowns, mean estimated annual energy losses ranged from 5.2% to 7.6%. Furthermore, restricting curtailment to mid-April to mid-November reduced these losses to 3.5-4.9% while maintaining the same level of bat protection. Algorithms could provide an effective tool for reducing bat exposure to wind turbines, although field validation is needed to confirm real-world performance.

1. Introduction

The rapid expansion of wind energy is strongly supported by international and European policies, that set ambitious development targets for the coming decades, including Paris Agreement, the European Green Deal, REPowerEU plan. At the same time, wind power projects are often driven by financial or political interests, and do not always adequately integrate ecological evidence into planning decisions (Burke and Stephens, 2018). Because project developers must first avoid a range of technical and regulatory exclusion zones (e.g., roads, high power lines, aviation, military zones, urban areas, and wind farms; Staid and Guikema, 2013), wind turbines may still be placed near habitats that are favourable to airborne biodiversity and therefore prone to interacting with wind turbines (Barré et al., 2022).

* Corresponding author. Complex Systems Group (NEXUS::CSR), Faculty of Science, Technology, and Medicine (FSTM), University of Luxembourg, 2, avenue de l'Université, L-4365 Esch-sur-Alzette, Luxembourg
E-mail address: kevin.barre@uni.lu (K. Barré).

[1] Kévin Barré and Kseniia Kravchenko contributed equally as first authors.
[2] Christian Kerbiriou and Christian Vincenot contributed equally as last authors.

https://doi.org/10.1016/j.jenvman.2026.130829
Received 10 June 2026; Received in revised form 21 July 2026; Accepted 26 August 2026
Available online 29 August 2026
0301-4797/

This expansion intensifies the conflict between wind energy development and biodiversity conservation, with two main consequences for airborne fauna: (i) mortality caused by collision, which may be exacerbated by attraction behaviours; and (ii) reduced habitat use caused by avoidance behaviours (Gaultier et al., 2020; Guest et al., 2022; Marques et al., 2014). Although the demographic consequences of habitat loss due to avoidance of wind turbines have not yet been studied, the effects of collisions mortality are increasingly documented, with studies showing that wind turbine-induced mortality can threaten several species. This is particularly true for long-lived species with low fecundity and high survival rates, such as birds of prey and bats, which are especially sensitive to the losses of individuals (Carrete et al., 2009; Duriez et al., 2023; Frick et al., 2017; Friedenberg and Frick, 2021).

To reduce these impacts, a range of mitigation measures has been proposed in the literature and incorporated into guidelines, especially for the consideration of bats in wind farm projects in Europe (Rodrigues et al., 2015). Among them, careful wind turbine siting is an important preventive measure, as bat fatality risk tends to be higher in more attractive landscapes (Santos et al., 2013; Thompson et al., 2017). However, where impacts cannot be fully avoided at the siting stage, operational mitigation measures such as curtailment remain essential to reduce residual collision risk Indeed, siting wind turbines as far as possible from attractive habitats such as wooded edges can reduce both avoidance and attraction behaviour in bats (Leroux et al., 2022). However, current wind energy planning largely fails in Europe to avoid high-impact landscapes despite concrete guidelines (e.g. siting wind turbine at least 200m away from wooded habitats) (Barré et al., 2022; Froidevaux et al., 2025). In this context, post-construction strategies are implemented to mitigate residual impacts which could not be avoided at the wind turbine siting stage. The most common strategy consists of stopping wind turbines at low wind speeds and, in some cases, above a temperature threshold – when bat activity is often high and energy production remains low, hereafter referred to as "blanket curtailment" (Voigt et al., 2015). Most often, blades are feathered below a wind speed of 3.5 to 8 m/s and above a temperature around 10 °C, during non-winter periods (Beucher et al., 2022). This approach can significantly reduce the fatality risk but shows variable and incomplete effectiveness depending on site and wind speed curtailment thresholds (Adams et al., 2021; Whitby et al., 2021). To minimize fatality-risk, these methods often involve high wind thresholds, resulting in significant energy production losses (see e.g. Arnett et al., 2011; Martin et al., 2017; Whitby et al., 2021).

More sophisticated curtailment methods have been developed in recent years to improve bat protection. Acoustic-informed blanket curtailment was developed in North America, notably using the Turbine Integrated Mortality Reduction (TIMR) system (Normandeau Associates, Gainesville, Florida, USA) which, in addition to a wind-speed threshold, integrates a real-time bat activity criterion using a proprietary bat detection system (i.e. blades are stopped if at least one bat is detected in the last 30 min). This system appears more effective than blanket curtailment based on wind speed only (Rabie et al., 2022). Another promising method is being developed in Europe based on multicriteria algorithms that could curtail wind turbines when bat activity at nacelle height, predicted from weather and temporal variables, reaches a high-risk level. A first proof-of-concept study conducted at the scale of the whole night, despite potentially underestimating the efficiency of curtailment at finer temporal resolution, concluded that algorithm-based curtailment should protect a larger proportion of the global bat activity around the rotor compared to blanket curtailment, while losing the same amount of energy (Barré et al., 2023). A similar approach is already used in Germany with the ProBat system (OekoFor, Germany), and seems to show high effectiveness (Behr et al., 2017). Hence, to our knowledge, very little evidence about such smart and algorithm-based curtailment has so far been published in peer-reviewed journals, and even less guidance is available on how such tools should be used in practice (e.g. on which data and covariates set to train algorithms, and how to define the curtailment threshold). Importantly, the lack of scientific evidence may discourage stakeholders from opting for smart systems, given that stakeholders may perceive these systems as financially risky.

In this study, we aimed to develop a transparent and reproducible algorithm to predict bat presence around wind turbine nacelles at fine temporal resolution (i.e. from 10 to 85 min) from weather conditions and the timing of the year and night. We then evaluated through a cross-validation approach its potential use for curtailment by simulating turbine shutdown when predicted bat presence probability exceeded a defined threshold, and by quantifying the associated trade-off between protected bat detections and energy loss. We conducted these tests by comparing different implementation strategies of the algorithm, namely (1) with or without the inclusion of site-specific data in the algorithm training, and (2) by adjusting the probability of presence threshold of curtailment nationally, seasonally, or by site. We focused on two acoustic bat guilds with elevated sensitivity to wind turbine collision risk: long-range echolocators (LRE) and mid-range echolocators (MRE). LRE are especially sensitive to collision risk because they spend a large proportion of their time at blade height, followed by MRE, whereas short-range echolocators (SRE) are generally less exposed to collisions (Roemer et al., 2017). We expected bat presence around wind turbine rotor to be strongly shaped by weather and temporal variables. In particular, we predicted lower bat presence under higher wind speed and rainfall, higher presence at warmer temperatures, and peak activity during summer and the early part of the night (Barré et al., 2023; Behr et al., 2017). Finally, we expected that increasing the degree of site-specific model calibration would improve curtailment efficiency.

2. Material and methods

2.1. Bat acoustic data collection and processing

We built a large-scale acoustic monitoring dataset spanning broad spatial, temporal, and climatic gradients to develop and evaluate algorithms for predicting bat activity at wind turbine nacelle height. We collected sound files of 25,588 complete nights across 123 sites in France recorded as part of regulatory post-construction impact monitoring studies (Fig. 1). Each site consisted of a wind turbine monitored with an automated acoustic recorder whose microphone was located below the nacelle (mean ± SD microphone height: 90 ± 16 m). The monitored nights covered all months and spanned seven years between 2017 and 2023, with on average 235 nights per site (Fig. S1). Regarding years, 97 sites, 22 sites, three sites and one site were monitored one, two, three and four years, respectively. Years 2018-2022 were the most represented in terms of site and night number (Table S1). Spring and summer were the most monitored seasons, representing 33% and 37% of all monitored nights, respectively, whereas winter and autumn accounted for 9% and 22%. Information on wind turbine characteristics and on the origin, location, duration, and acoustic monitoring methods of the study sites, including data providers, is provided in Table S2.

Three types of acoustic recorders were used: Batcorder at 40 sites (versions 1, 2 and 3; ecoObs), Batmode S+ at 76 sites (bat bioacoustics technology GmbH), and Song Meters at eight sites (SM3BAT and SM4BAT; Wildlife Acoustics) (Fig. 1A; Table S1). Depending on the device, one (for Batmode and Song Meters) to three (for Batcorder) triggering thresholds per site were used, i.e. a built-in recording control system which started the recording when a sound event exceeded a given sound level (see Supporting information S1 for more details). Devices were also set to cover the frequency range of bat echolocation calls (Table S2), and to run throughout the night from 30 min before sunset to 30 min after sunrise.

To account for the effects of recorder type and trigger setting on bat detection probability, we evaluated several modelling and data selection approaches to handling acoustic material heterogeneity. The best predictive performance was obtained by retaining all material types except rare recorder/trigger combinations (i.e. 113 sites and 23,844 nights),

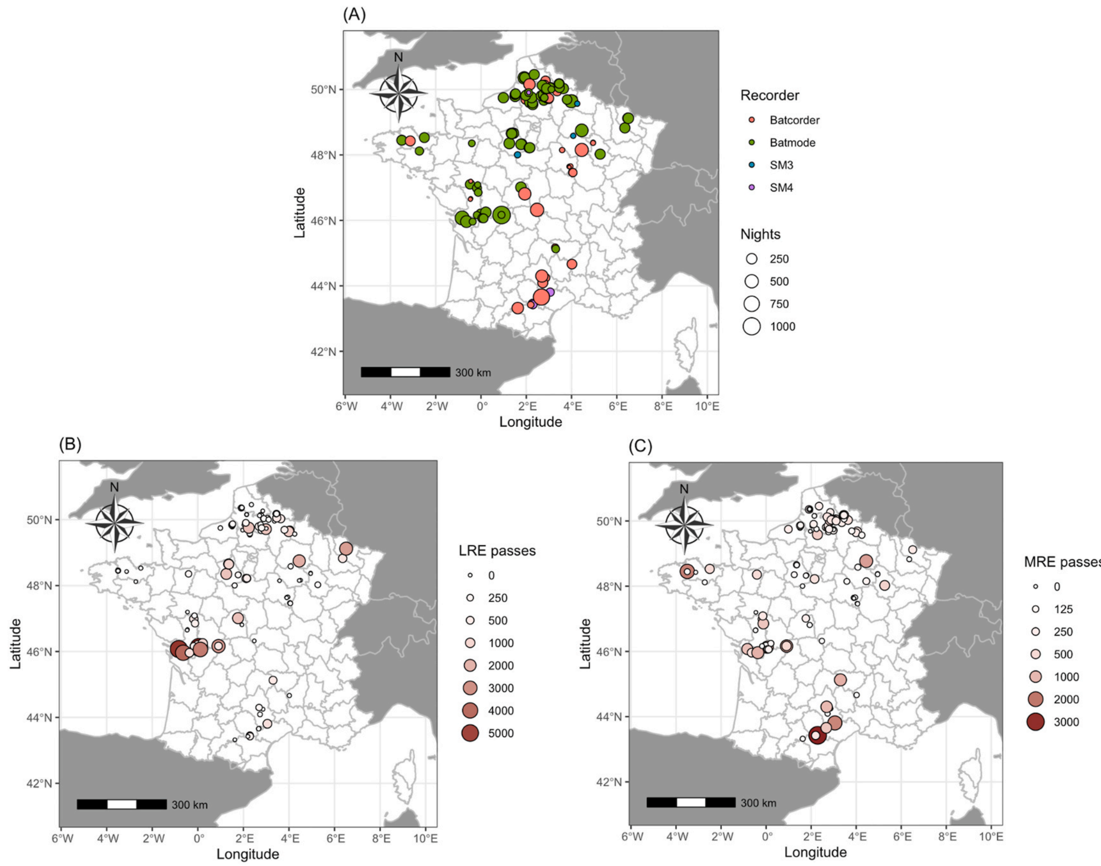

Fig. 1. Map of monitored sites in France (A), where colours indicate the type of acoustic recorder used, and circle size indicates the number of nights monitored per site. Panels B and C show the total number of bat passes recorded at each site for long-range (LRE) and mid-range (MRE) echolocators respectively.

and including recorder/trigger combination as a random effect; full details are provided in the Supplementary information S2.

To identify bat detections, we first split recordings into 5-s files to standardize their duration to the average duration of a bat pass (Kerbiriou et al., 2018). Then, all files were automatically classified to the closest taxonomic level using the Tadarida software (Bas et al., 2017). Since acoustic monitoring in wind turbine nacelles generates very noisy data due to electromagnetic interferences and blade-generated noise, we retained only bat detections with a probability (estimated by the software) to be a true positive ≥ 0.9 instead of commonly used threshold of ≥ 0.5. Whereas the 0.5 threshold retains more data but yields higher false positive rates, the 0.9 threshold strongly reduces false positives at the cost of a smaller dataset. In our case, selecting acoustic data with a ≥ 0.9 threshold prevented an inflation of false positives under adverse weather conditions, when blade-generated interference noise is strongest and may bias bat responses to environmental factors (Barré et al., 2019, 2023). Finally, since most bat species had very low occurrence (Table S3), we pooled together species into guilds based on similarity of their echolocation call structures and therefore foraging strategies: long-range echolocators (LRE), mid-range echolocators (MRE) and short-range echolocators (SRE) (Frey-Ehrenbold et al., 2013), see Table S3 for species composition. SRE were not considered further in this study due to insufficient number of detections (124 passes representing 0.1% of total passes; Table S3).

2.2. Weather and turbine operation data collection

To develop a fine-scale predictive algorithm of bat activity around wind turbine nacelles under varying weather conditions, wind speed (m/s) and air temperature (°C) were recorded at 10-min intervals, as these variables are among the strongest predictors of bat activity at nacelle height (Barré et al., 2023; Behr et al., 2017). Turbine operation data, including blade rotational speed (rpm) and energy production (W), were also obtained from wind farm operators at the same temporal resolution, although energy production data were only available for 13 sites out of 113.

Since the weather stations at the studied wind turbines did not include rain gauge, we extracted precipitations data (mm) from the Météo France observation database at 6-min intervals (https://portail-api.meteofrance.fr/web/fr/api/DonneesPubliquesClimatologie), by selecting the nearest station to each study sites (mean 9.5 ± 7.1 km). These covariates were computed for each time slot of the night (see section 2.3 for details about time slot duration). The large monitoring effort captured a broad gradient of weather conditions, allowing the algorithms to be trained on a wide range of climatic combinations (Fig. S2).

To account for large-scale biogeographic variation in bat activity among sites, we also extracted geographical variables for each site from the WorldClim 2.1 database at 30 arc-second resolution: annual mean temperature, annual precipitation, and elevation ($\sim$1 km^2; Fick and Hijmans, 2017).

Finally, we also collected from wind farm operators the rotor diameter (mean: 101 m; range: 58-132 m) and nacelle height (mean: 92; range: 57-139 m) of studied wind turbines, as these variables can influence bat activity at nacelle height (Barré et al., 2023).

2.3. Algorithms building

To train algorithms to predict bat presence on fine time slots throughout the year and in any weather condition, we modelled the presence/absence of bats in relation to weather, date, intra-night time slot, and wind turbine operation as fixed effects, using Generalized Linear Mixed Models (GLMM, R package *glmmTMB*). As night length varies substantially throughout the year, intra-night time slot was expressed as a fixed percentage of night elapsed, ensuring a constant number of time slots per night regardless of date. Thus, we performed GLMMs on three time-slot durations separately, to identify the most predictive temporal resolution (see Supporting information S2): 10%, 5%, and 2.5% of night elapsed, corresponding to 42-85 min (i.e. 10 slots per night), 21-42 min (i.e. 20 slots per night), and 10-20 min (i.e. 40 slots per night), respectively.

We excluded wind turbine size and geographical variables from the final models because preliminary comparison showed no improvement in predictive performance and curtailment efficiency: their inclusion increased estimated energy loss without a corresponding gain in bat protection (see Supporting information S3 for more details). Given the limited number of sites, these variables could also increase the risk of overfitting and reduce transferability to new sites outside the gradients represented in the training data. Final models therefore retained weather and temporal predictors, including statistically relevant interactions among them: four for mid-range echolocators and six for long-range echolocators (i.e. four for MRE and six for LRE; see Supporting information S3). All numerical fixed effects were scaled using the *scale* function from the *base* R package (i.e. subtracting each value by the mean and dividing by the standard deviation). To account for non-linear responses to Julian day, time of night, temperature, precipitations, wind speed, and blade rotation speed, we visually inspected plots from Generalized Additive Models (GAM, R package *mgcv*) to determine the polynomial degree required to apply on each covariate in GLMMs. Most of these variables required a second-degree polynomial. Real-time weather and wind turbine operation variables were calculated for the preceding time slot (e.g. between 10.40 p.m. and 10.50 p.m. for a bat presence between 10.50 p.m. and 11 p.m.), allowing bat presence in the following time slot to be predicted from current conditions and enabling realistic curtailment simulations. Given the binary response variable (presence/absence), we fitted the model with a binomial error distribution and selected a complementary *cloglog* (log-log) link, which yielded the lowest Akaike Information Criteria (AIC) among the candidate link functions. We also included random intercepts for year and site identifier to account for interannual variation in bat activity and repeated sampling within sites (i.e. many monitoring dates per site), and for material (i.e. combination of recorder type and trigger setting, as both strongly drive detection probability of bats) to account for differences in bat detection probability. We confirmed the appropriateness of this random-effect structure using likelihood-ratio test comparing models with alternative random-effect combinations.

The final models for both guilds included Julian day, time of night, blade rotation speed, wind speed, temperature and precipitation, all entered as quadratic terms, together with selected two-way interactions among temporal (i.e. Julian day and time of night) and weather variables, and random intercepts for year, site and material. Full model formulas are provided in Supporting information S3.

2.4. Evaluating algorithms efficiency under different use scenarios

We assessed whether near real-time turbines shutdown based on algorithm predictions could efficiently reduce bat exposure to rotating blades while minimizing operation losses. To mimic field implementation as closely as possible, we used a cross-validation framework in which algorithms were trained on independent training data (i.e. no date sharing with prediction data) and then used on actual weather data from the weather station of a new wind turbine (i.e. prediction data), to predict bat presence probability for the upcoming time slot. This prediction was then used to simulate the curtailment decision. When the predicted probability exceeded a given threshold and turbine rotation was greater than one rpm, we simulated turbine shutdown. We based the cross-validation analyses on the final dataset (i.e. 113 sites and 23,844 nights; see Section 2.1 and Supporting information S2 for more details).

In practice, we trained models presented in Section 2.3 on 112 sites (i.e. all sites except one; Fig. 2A–B) and generated predictions for each upcoming date and time slot at the remaining site (i.e. the site on which algorithms will be used to curtail the turbine; Fig. 2C–D). To assess whether site-specific calibration improved algorithm efficiency, we compared two training approaches: one using only data from sites other than the prediction site (i.e. without site-specific data), and one including, in addition, a random selection of 50% of prediction site data that could realistically have been collected beforehand (i.e. with site-specific data) (Fig. 2A–B). In both cases, predictions were evaluated on the remaining 50% of data from the prediction site, allowing direct comparisons on the same dataset (*stricto sensu*) (Fig. 2C–D). To ensure temporal independence, all dates included in the prediction dataset were removed from the training dataset. This procedure was repeated for each site with more than ten presences of each guild throughout prediction data (i.e. 93 sites in total).

For predictions made without site-specific data, we used average random-effects intercepts because training and prediction data were spatially and temporally independent. For predictions made with site-specific data, we set site identifier and material random intercepts to those of the prediction site, allowing site-specific predictions. In both cases, the year random effect was set to its average intercept to avoid overestimating algorithm performance when prediction data came from the same year as much of the other training data. This choice reflects likely future use, in which algorithms would generally be trained on data from preceding years only (Fig. 2C–D).

After prediction, we simulated turbine shutdown for each predicted bat-presence probability threshold, ranging from zero to one in increments of 0.001 (Fig. 2E). For each probability threshold, we calculated the percentage of total bat passes and blade rotations included falling within shutdown periods, corresponding to protected bat detections and lost blade rotation, respectively, for each of the 93 sites included as iterations in the cross-validation (Fig. 2F). These values and associated 95% confidence intervals were then averaged across sites by bootstrapping with 1000 runs (*Hmisc* package in R) (Fig. 2G).

Averaged values of bat protection (i.e. the percentage of total bat passes protected) and wind turbine operation loss (i.e. the percentage of lost blade rotations) allowed us to identify the predicted bat-presence probability threshold required to achieve a given level of protection. However, such threshold can be defined in several ways (i.e. at national, seasonal, or site levels), leading to a different form of field implementations by stakeholders. Under a national threshold approach, bat protection and operation losses were averaged at each fixed predicted-probability threshold, yielding a single threshold applicable across all sites. Under a national season-specific threshold approach, the same procedure was applied separately by season, yielding one threshold per season applicable across all sites. Under a site-specific threshold approach, bat protection was averaged at each fixed level of operation loss, allowing the predicted probability threshold required to achieve a given bat protection level to vary among sites (Fig. 2G)

We then compared these three threshold definition methods by plotting efficiency curves describing the relationship between the mean protected bat detections and mean operation loss at each curtailment threshold (Fig. 2H). Since dataset was heterogeneous with respect to the presence of blanket curtailment during acoustic monitoring (47 of 113 sites were not curtailed, 39 operated under blanket curtailment, and information was unavailable for 27, according to information provided by wind farm operators), we repeated the analysis only on non-curtailed sites for comparison.

Blade rotation loss, used to estimate the operation loss, is not a direct measure of energy loss, so we repeated the analysis for the 13 sites for which energy production data were available. For these sites, we reported both energy loss over the monitored period, and extrapolated annual energy loss (i.e. the percentage of lost Watt produced). To estimate annual energy loss, we first calculated the average monitoring

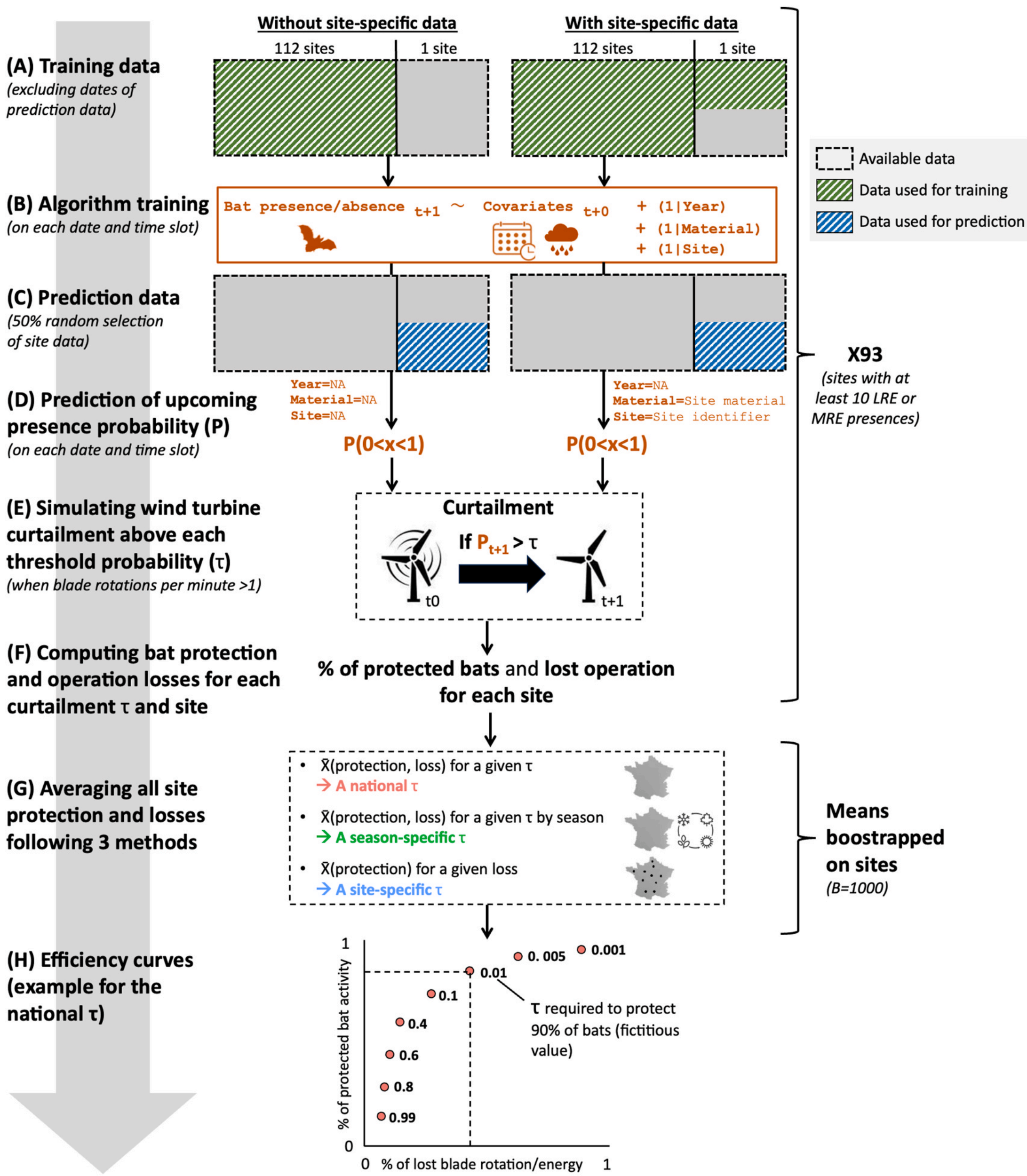

Fig. 2. Schematic representation of the iterative framework used to assess efficiency of three curtailment implementation methods. Green hatched areas indicate the subset of the full dataset used for model training and prediction. All training iteration are made on 112 sites, and prediction and wind turbine shutdown simulations are made for 93 sites in total (i.e. those with at least 10 LRE or MRE passes in prediction data).

duration in days per site (240 days for MRE and 267 days for LRE, excluding all or a part of winter) and the corresponding percentage of the average annual production represented by these periods (i.e. 53.5% and 59.5% for MRE and LRE guilds, respectively). We then estimated annual energy loss by scaling energy losses observed over the monitored period according to the proportion of annual production represented by that period. Finally, to assess whether these estimates could be generalized to all sites, we compared the range of rotational speed losses due to curtailment between sites with energy data (n = 13) and those with rotational data only (n = 93). Rotational-speed losses were similar in both subsets, supporting extrapolation of energy losses to the full dataset. For a given proportion of lost rotations, the corresponding true proportion of energy loss was much lower (Fig. S3).

3. Results

3.1. Bat survey

A total of 96,393 bat detections were recorded across the 123 sites included in the study. Detections were dominated by the LRE guild (57.5%), followed by the MRE guild (42.4%) and SRE guild (0.1%). Within the LRE guild, detections were largely dominated by *Nyctalus leislerii* (85.3%), followed by *Nyctalus noctula* (14.5%). Within the MRE guild, detections were dominated by *Pipistrellus pipistrellus* (94.4%), followed by *Pipistrellus nathusii* (2.1%) and *Pipistrellus kuhlii* (2%). Although guild activity varied strongly among sites, most sites had at least several hundred of bat detections (Fig. 1). Inter-night occurrence, defined as the proportion of nights with at least one detection, averaged 19% for LRE and 11% for MRE across the study period (mean monitoring duration: 235 nights per site). Intra-night occurrence, defined as the proportion of time slots with at least one detection, was much lower, at around 1% for the 2.5% of night time slot duration used in curtailment simulations (Table S3).

3.2. Effects of covariates

The probability of bat presence at nacelle height within intra-night time slots was driven by a similar set of fixed covariates in both guild models. In both guilds, bat presence followed a marked seasonal pattern, increasing from January to August and decreasing from September to December. Bat presence was also highest during the first half of the night and then decreased steadily thereafter. Blade rotation speed, mean wind speed and precipitations within the time slot all negatively affected bat presence probability. By contrast, the temperature increased bat presence probability up to approximately 25-30 °C, depending on the time of the year, after which the probability declined (Table S4; Figs. S4, S5 & S6).

We also identified several significant interactions among covariates. In both guilds, intra-night activity patterns and responses to temperature and wind speed varied over the course of the year. More specifically, the peak in bat presence during the first part of the night, under low wind speed and high temperature, become more pronounced as summer approached. Temperature and wind speed also interacted, such that the positive effect of temperature strengthened as wind speed decreased, and conversely, the negative effect of wind speed strengthened at low temperatures. In addition, the positive effect of temperature and negative effect of wind speed were more pronounced during the second quarter of the night. These effects occurred in both guilds, except that the interactions between temperature and wind speed and between time slot and wind speed were retained only for LRE (Table S4; Figs. S4, S5 & S6).

3.3. Algorithms efficiency

When we calculated efficiency curves from lost blade rotations, Area Under the Curve (AUC; see Supporting information S2 for more details) values were generally high (range: 0.75 to 0.92), indicating good performance of the model, and remained very similar between the two algorithm training strategies (i.e. with and without site-specific data; Table 1; Fig. 3). The only exception was the national curtailment threshold approach, which was significantly less efficient when combined with training that includes site-specific data (Table 1; Fig. 3). Apart from this case, the three threshold-definition methods performed very similarly (Table 1; Fig. 3). We observed the same pattern when we restricted analysis to non-curtailed sites, for which efficiency was often slightly higher than in analysis including all sites, regardless of curtailment status (i.e. curtailed, non-curtailed, and unknown) (Table 1; Fig. S7). Energy production data yielded the same conclusion, with AUC often even slightly higher (range: 0.76 to 0.93) (Table 1; Fig. S8).

We then compared training and algorithm implementation methods at specific bat-protection targets in terms of operation and energy losses. For 80% protection of bat detections, the season-specific national threshold with site-specific training data performed best for MRE, with an estimated annual energy loss of 1.6% (95% CI: 0.0-8.5%), and was close to those obtained with the national and site-specific threshold approaches without site-specific training data (2.6% (95% CI: 1.4-4.8%) annual energy production lost) (Table 2). For LRE, the national threshold without site-specific training data performed best at this protection level, with an estimated annual energy production loss of 4.1% (95% CI: 2.6-7.6%). For 90% protection, the national threshold without site-specific training again performed best for both bat guilds, with estimated annual energy production losses of 7.6% (95% CI: 4.6-10.3%) for LRE and 5.2% (95% CI: 3.8-9.2%) for MRE. For 95% protection, the same national threshold method without site-specific training data remained optimal for LRE, with an estimated annual energy production loss of 12.3% (95% CI: 6.6-15.0%), whereas the site-specific threshold performed best for MRE, with an estimated loss of 6.9% (95% CI: 6.4-7.4%); however, this value remained very close to that obtained with the national method without site-specific training data (7.1% (95% CI: 5.2-11.1%)) (Table 2). Overall, these comparisons showed that including site-specific data in model training did not improve efficiency when high levels of bat protection were targeted. They also confirm that the national threshold approach performed best overall, although the site-specific threshold was slightly more efficient for MRE at the highest protection level. Predicted bat-presence probability thresholds required to achieve given protection levels are provided in Table S6.

Finally, algorithm efficiency varied throughout the year (Fig. 4). Operation loss increased gradually from early January to October and then declined towards the end of December. In contrast, bat protection increased sharply from early April, peaking in August for LRE and in June and September for MRE, and then declining considerably until early November. From mid-November to mid-April, when bat protection was zero or negligible, cumulative turbine-operation loss still accounted for 35% of total annual loss for LRE and 32% for MRE under algorithm-based curtailment.

4. Discussion

Our study shows that large-scale aggregation of bat acoustic data from regulatory post-construction monitoring can be used to develop algorithms that predict bat presence probability around wind turbine rotor in near real time. Using a realistic site-by-site validation

Table 1
Area under the curve (AUC) of algorithm efficiency curves for each bat guild, curtailment threshold definition methods, and training strategy, with or without site-specific data. AUC values are reported for simulations based on blade-rotation loss across all sited and across non-curtailed sites only, and for simulations based on energy-loss data for sites with available energy-production data. The number of sites shown in the table includes only those for which simulations were possible (i.e. sites with more than ten bat passes, 93 sites out of 113).

Bat guild	Threshold definition method	Site-specific data in training	Area Under the Curve		
			All sites (N = 93)	Non-curtailed sites (N = 36)	Sites with energy data (N = 13)
LRE	national	inclusion	0.751 (0.731-0.774)	0.760 (0.716-0.804)	0.759 (0.729-0.838)
LRE	season	inclusion	0.874 (0.808-0.935)	0.855 (0.751-0.945)	0.859 (0.748-0.956)
LRE	site	inclusion	0.863 (0.850-0.873)	0.868 (0.849-0.882)	0.861 (0.841-0.877)
LRE	national	none	0.846 (0.814-0.872)	0.848 (0.787-0.888)	0.907 (0.892-0.931)
LRE	season	none	0.827 (0.761-0.891)	0.848 (0.771-0.923)	0.855 (0.756-0.948)
LRE	site	none	0.878 (0.845-0.902)	0.885 (0.854-0.910)	0.885 (0.818-0.938)
MRE	national	inclusion	0.852 (0.838-0.866)	0.862 (0.852-0.874)	0.895 (0.885-0.917)
MRE	season	inclusion	0.900 (0.851-0.949)	0.903 (0.856-0.951)	0.903 (0.787-0.990)
MRE	site	inclusion	0.917 (0.907-0.922)	0.910 (0.898-0.919)	0.929 (0.917-0.940)
MRE	national	none	0.893 (0.878-0.906)	0.902 (0.889-0.912)	0.923 (0.904-0.948)
MRE	season	none	0.878 (0.824-0.930)	0.906 (0.861-0.949)	0.865 (0.758-0.967)
MRE	site	none	0.911 (0.890-0.923)	0.904 (0.878-0.925)	0.921 (0.901-0.939)

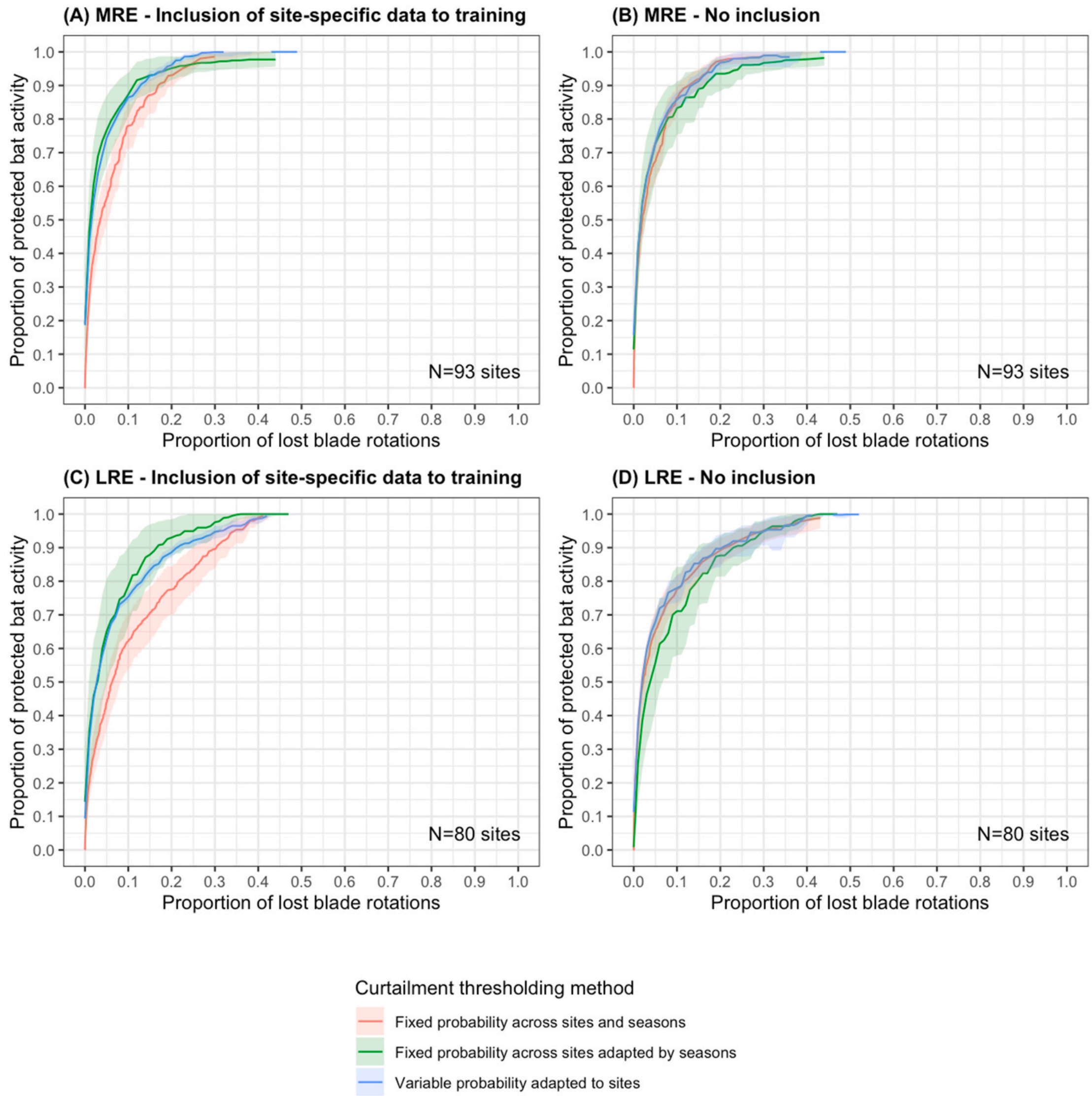

Fig. 3. Efficiency curves showing the relationship between the proportion of protected bat activity and lost blade rotations under simulated curtailment scenarios, with site-specific data included in model training (A, C) or excluded from model training (B, D). Curves are shown for the national curtailment threshold method (in red), the national season-specific threshold method (in green), and the site-adapted threshold method (in blue).

framework with independent training data, we show that algorithm-based curtailment applied at fine temporal resolution can achieve high bat protection efficiency. By optimising algorithms composition, training strategy and threshold definition, we show that for curtailment applied over most of the year, bat protection can reach at least 90% while mean annual energy losses remain 7.6% (95% CI: 4.6-10.3%) for LRE and 5.2% (95% CI: 3.8-9.2%) for MRE. Restricting curtailment to the period from mid-April to mid-November further reduces these losses by 32–35% while maintaining the same bat protection level. Our results also provide practical recommendations for the training and the implementation of such algorithms in the near future.

4.1. Training data and algorithms composition

To exploit the predictive power of algorithms, we aimed to train algorithms on the largest possible set of existing post-construction monitoring data. However, the aggregated dataset exhibited strong variations in acoustic recorder and recording trigger types, showed substantial heterogeneity in acoustic recorder types and trigger settings, both of which are known to affect bat detection probability through differences in detection distance (Adams et al., 2012; Darras et al., 2020). Rather than training separate algorithms for each recorder/trigger combination, which would have reduced the sample size and therefore predictive power across space and time, we compared alternative approaches. Cross-validation showed that predictive power was highest when algorithms were trained on all data, from all material combinations, excluding only the rarest recorder/trigger combinations, while including recorder/trigger combination as a random intercept. This approach preserved the advantage of large sample size while limiting detection bias. A likely explanation is that a larger, heterogeneous dataset captures a broader range of climatic conditions than smaller homogeneous subsets, thereby reducing the risk that predictions are made under conditions poorly represented in the training data.

A further prerequisite was to identify a predictor set that maximized predictive power while remaining sufficient parsimony for operational implementation. Although spatial covariates such as landscape composition and configuration, are known to influence bat activity (Frey-Ehrenbold et al., 2013; Heim et al., 2015; Put et al., 2019), their contribution to curtailment performance was limited in our dataset. Their inclusion did not improve bat protection and increased estimated

Table 2
Proportion of the estimated annual loss of energy production per site of a year-round curtailment for each bat guild, curtailment threshold definition methods, site-specific data inclusion in training or not, and three proportions of protected bat activity by simulated wind turbine shutdown. Numbers in parentheses show the 95% confidence intervals. Best performing option for each guild and protection level are highlighted in bold. It should be noted that best options at 80% and 95% protection levels for MRE are both very close to the national threshold method without site-specific data inclusion in model training. A more complete version of this table showing in addition the proportion of lost rotations and energy loss over the study period only is provided in Table S5.

Bat guild	Threshold definition method	Protection level	Site-specific data in training	Estimated annual energy loss
LRE	national	0.8	inclusion	0.166 (0.046-0.203)
LRE	national	0.9	inclusion	0.199 (0.076-0.212)
LRE	national	0.95	inclusion	0.204 (0.126-0.215)
LRE	season	0.8	inclusion	0.059 (0.017-0.136)
LRE	season	0.9	inclusion	0.124 (0.029-0.178)
LRE	season	0.95	inclusion	0.166 (0.047-0.208)
LRE	site	0.8	inclusion	0.083 (0.071-0.089)
LRE	site	0.9	inclusion	0.118 (0.101-0.130)
LRE	site	0.95	inclusion	0.160 (0.130-0.166)
LRE	**national**	**0.8**	**none**	**0.041 (0.026-0.076)**
LRE	**national**	**0.9**	**none**	**0.076 (0.046-0.103)**
LRE	**national**	**0.95**	**none**	**0.123 (0.066-0.150)**
LRE	season	0.8	none	0.077 (0.017-0.130)
LRE	season	0.9	none	0.130 (0.035-0.178)
LRE	season	0.95	none	0.178 (0.077-0.202)
LRE	site	0.8	none	0.065 (0.035-0.113)
LRE	site	0.9	none	0.107 (0.059-0.136)
LRE	site	0.95	none	0.160 (0.071-0.237)
MRE	national	0.8	inclusion	0.046 (0.019-0.078)
MRE	national	0.9	inclusion	0.078 (0.037-0.098)
MRE	national	0.95	inclusion	0.098 (0.072-0.117)
MRE	**season**	**0.8**	**inclusion**	**0.016 (0.000-0.085)**
MRE	season	0.9	inclusion	0.058 (0.010-0.251)
MRE	season	0.95	inclusion	0.230 (0.016-0.251)
MRE	site	0.8	inclusion	0.032 (0.026-0.042)
MRE	site	0.9	inclusion	0.058 (0.053-0.069)
MRE	site	0.95	inclusion	0.074 (0.064-0.091)
MRE	national	0.8	none	0.026 (0.014-0.048)
MRE	**national**	**0.9**	**none**	**0.052 (0.038-0.092)**
MRE	national	0.95	none	0.071 (0.052-0.111)
MRE	season	0.8	none	0.026 (0.010-0.112)
MRE	season	0.9	none	0.128 (0.010-0.251)
MRE	season	0.95	none	0.219 (0.026-0.251)
MRE	site	0.8	none	0.048 (0.032-0.058)
MRE	site	0.9	none	0.064 (0.053-0.069)
MRE	**site**	**0.95**	**none**	**0.069 (0.064-0.074)**

energy loss, indicating that they were not enhanced curtailment efficiency under the scenarios tested. Weather and temporal predictors therefore offered a more practical and transferable basis for predicting bat presence around wind-turbine rotors. This result suggests that relatively simple models may be sufficient for scalable bat-friendly curtailment, especially where site-specific spatial data are incomplete or where algorithms must be applied to new wind farms.

By contrast, temporal and meteorological predictors did not raise the same concern regarding model transferability. Monitoring was sufficiently intensive at each site to cover broad gradients of weather, season, and time of night, thereby reducing the risk of making prediction outside the range of training conditions. Nevertheless, climate change may progressively alter the relationship between training and future prediction conditions, and periodic model updates may therefore become necessary under continued climatic shifts.

The effects of predictors were consistent with previous studies. Bat presence probability increased with temperature and decreased with precipitation, wind speed, and blade rotation, all with quadratic responses (Arnett et al., 2006; Behr et al., 2017; Cryan et al., 2014; Horn et al., 2008; Wellig et al., 2018). Seasonal variation was also consistent with the literature, with peak activity in summer (Barré et al., 2023; Behr et al., 2017; Peterson et al., 2025), as was intra-night phenology, with peak detections during the first part of the night (Mariton et al., 2023). The weaker even missing late-night peak compared with ground-level observations from Mariton et al. (2023) might reflect less favourable conditions at nacelle height, where bat abundance is lower (Brabant et al., 2020; Collins and Jones, 2009).

4.2. Algorithm training and implementation methods

Our results show that including site-specific data in the training dataset is not necessary and, in most cases, does not improve performance. This is an important from an operational point of view result. Calibrating an algorithm to each site would require applying a non-site-specific curtailment strategy after turbine installation, conducting additional acoustic monitoring, processing those data in a standardized way, incorporating them into the training dataset, and retraining the model. Avoiding these steps is therefore a major practical advantage. One possible explanation is that the current monitoring duration, averaging 235 nights per site, is still insufficient for site-specific intercepts to provide a clear advantage over the broader weather information contained in the full dataset.

We also show that, in most cases, defining a single national predicted probability threshold for a given protection objective yields the lowest energy loss, or at least values very close to those obtained with more restrictive methods such as season- or site-specific thresholds. This is again advantageous from an operational perspective, because stakeholders would not need to conduct additional acoustic monitoring to derive local thresholds. Although adapting thresholds to season or site could theoretically improve prediction, such approaches may also increase the risk of overfitting when the amount of supporting data is limited. In practice, the average balance between potential gain and overfitting risk appears to favour the simplest method, namely the national threshold without site- or season-specific calibration.

A further explanation may be that the main drivers of bat presence probability at nacelle height, weather conditions, date and time of night, are both strong and relatively consistent among sites. Under this interpretation, site-specific characteristics account for only a limited fraction of variation in bat presence at nacelle height. This is consistent with previous study showing that local landscape variables have smaller effects than temporal and meteorological predictors (Barré et al., 2023).

4.3. Algorithm efficiency

The algorithm efficiency values we report in this study, defined as the energy cost required to protect a given proportion of bats from rotating blades, appear high. They are at least comparable to, and in many cases better than, those reported for other curtailment strategies in the literature, although those studies quantified effectiveness using fatality surveys rather than acoustic monitoring. Indeed, for an 80% bat protection level, energy losses in our study over the monitored period ranged from 4.9 to 7% for the national threshold method without site-specific training data. For comparison, Arnett et al. (2011) demonstrated on 12 turbines at one site that blanket curtailment at 5.0 or 6.5 m/s reduced bat fatalities by 72-82% while reducing energy production by 3-11% over the study period (i.e. July to October). Similarly, Martin et al. (2017) reported a 62% reduction in fatalities and a 3% energy loss over June to September using wind-speed and temperature thresholds of 6.0 m s^{-1} and 9.5 °C. Finally, Rabie et al. (2022) found that acoustically informed curtailment (Turbine Integrated Mortality Reduction, TIMR, based on an 8.0 m/s wind speed threshold and at least one bat detection in the previous 30 min) and blanket curtailment at 4.5 m/s wind speed, reduced fatalities by 75% and 46%, respectively, with corresponding energy losses of 14.8% and 5.3% over July to September. In addition, following the same curtailment simulation logic as explained in our study, we simulated blanket curtailment based on different wind speeds thresholds and a temperature threshold of 10 °C,

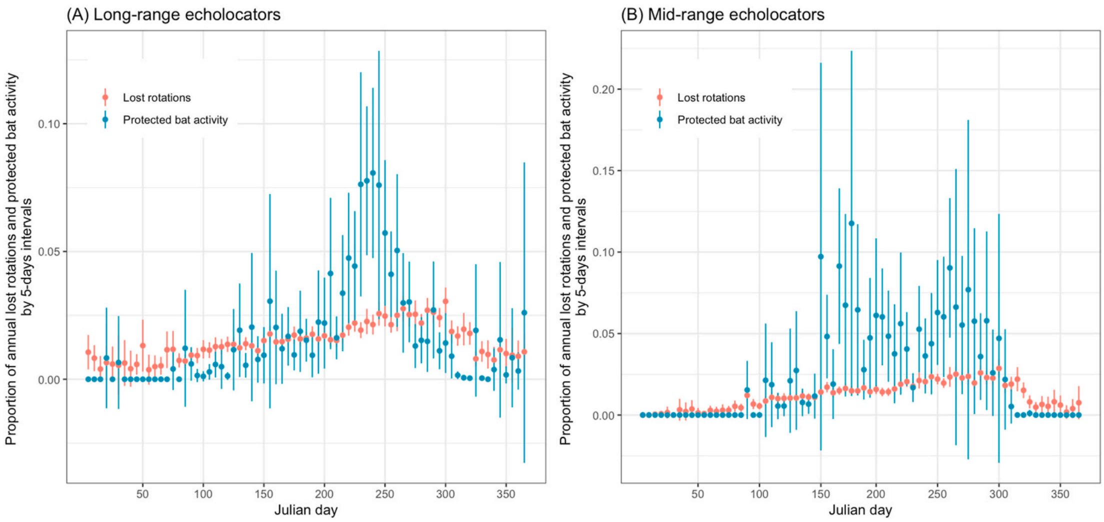

Fig. 4. Seasonal variation in algorithm-based curtailment efficiency for the LRE (A) and MRE (B) guilds, using the national threshold method without site-specific training data and targeting 90% protection of bat detections. Red and blue lines show the proportions of annual lost rotations and protected bat activity, respectively, in 5-days intervals throughout the year. Points represent mean values, and error bars show 95% confidence intervals obtained by bootstrapping across sites with 1000 iterations.

below and above which, respectively, the wind turbine is shut down. We found that, to protect 90% of bat activity, an average threshold of 7.5 m/s for MRE and 8 m/s for LRE is required (Table S7). Under these conditions, the proportion of lost blade rotations is 14% higher than under algorithm-based curtailment (based on the national curtailment threshold scenario without inclusion of site-specific data in training) (Tables S5 and S7). Finally, since fatality at ground is highly correlated with acoustic activity at nacelle height (Peterson et al., 2025), we assume our acoustic-based estimates is comparable to fatality-based efficiency estimates of these studies.

Since our study covers substantially longer curtailment periods at most sites (Fig. S1), we expect the advantage of the algorithm-based curtailment to be even greater if comparisons were restricted to identical seasonal windows, such as June to October in Northern Hemisphere. This interpretation is reinforced by the seasonal distribution of costs and benefits. We estimate that 32–35% of annual operation losses occur during the period from mid-November to mid-April, when annual bat protection is zero or negligible. Thus, restricting algorithm use outside this period should therefore reduce energy loss by 32–35% for the same protection level. For example, at a 90% protection level using the national method without site-specific training data, mean annual energy loss would decrease from 7.6% (95% CI: 4.6-10.3%) to 4.9% (95% CI: 3.0-6.7%) for LRE and from 5.2% (95% CI: 3.8-9.2%) to 3.5% (95% CI: 2.6-6.3%) for MRE.

Furthermore, our algorithms were tested across a much larger number of sites, than in most previous studies. Yet, despite this broader validation, uncertainty around average efficiency remained low, suggesting that the approach should perform reliably across sites within the range of bat communities represented in our dataset. This contrasts with the strong variability reported for blanket curtailment. A meta-analysis by Whitby et al. (2021), for instance, confirmed that blanket curtailment can produce highly variable bat protection for a given wind speed threshold, and that high thresholds, around 7 m s^{-1}, may be required to reduce fatalities by 80%, at the cost of substantial energy loss. Finally, although the algorithms performed consistently across sites at the national scale, they would likely need to be updated using country-specific data before being applied in more distinct contexts, such as northern, southern and eastern Europe, where bat communities may be dominated by different species with differing responses to weather conditions. In such different contexts, the way of using algorithms (i.e. using site-specific curtailment threshold and training data or not) should therefore be confirmed.

4.4. Perspectives and recommendations

In our simulations, we assumed that wind farm operators could implement real-time communication between algorithm and wind turbine, with updated predictions generated every 10-20 min based on the t-1 weather data transmitted by the nacelle weather station. Although such implementation is technically plausible, some turbine models or operational contexts may not support it directly and could require case-specific pipelines, complicating large-scale deployment. Under such constraints, it would be useful to evaluate a simpler implementation approach in which the algorithm predicts, for each future date and time slot and for a given bat protection level, the temperature and wind-speed thresholds above or below which the turbine should be shut down. This would allow operators to generate a predefined curtailment schedule in advance. Because nacelle weather stations rarely include rain gauges, precipitation would in many cases need to be approximated, for example from recent local weather data.

Additional operational work is also needed to determine how the two guild-specific algorithms should be combined into a single decision framework. One simple option would be to run both algorithms simultaneously and shut down the turbine whenever either guild is predicted to be at risk. We conducted a preliminary proof of concept by simulating curtailments using the same prediction datasets as those used in this study. To this end, the decision to curtail was made as soon as the probability of presence required to protect 90% of each guild's activity was exceeded, and this for the national method without including site-specific data in model training. We show that a curtailment combining the two guilds, each protected at 90% coverage, results in a 19.8% loss in blade rotations over the study period. Thus, the overall loss does not appear to exceed the maximum loss observed for each guild independently (12.5% and 20.3% for MREs and LREs, respectively).

Then, field validation with fatality monitoring is now an important step to confirm the effectiveness of algorithms. Although we expect a strong correlation between bat activity at wind turbine nacelle height and fatality at ground-level (Peterson et al., 2025), a certain degree of stochasticity is unavoidable, especially given the filtering applied to the acoustic data to remove likely artifacts caused by noise parasites or blade-generated noise (Voigt et al., 2021).

Future work could also improve predictive performance by expanding the range of weather predictors considered. For example, models could incorporate lagged weather variables over previous days or more distant atmospheric conditions, such as weather northeast of the turbine during autumn migration (Bailey and van de Pol, 2016). Such variables may explain residual variation in bat detections, including sudden peaks in bat activity that could reflect movements of migratory individuals driven by previous distant weather conditions (Hurme et al., 2025). In addition, although blade rotation is a significant predictor in the models, its inclusion may lead to unintended repeated curtailment and reduced estimated efficiency. Given the negative relationship between the probability of bat presence and the number of blade rotations, each curtailment event may, under equivalent weather conditions, slightly increase in the predicted probability of presence in the following time slot, simply because the turbine is already stopped. This may in turn increase the probability of further curtailment. Therefore, before field implementation, the benefits and drawbacks of retaining this variable in the models should be assessed. In this respect, the efficiency values reported here are likely conservative, and algorithm performance in practice may therefore be at least as good as reported.

Overall, the study shows that algorithm-based curtailment has strong potential to reduce bat exposure while maintaining relatively low energy loss. It also indicates that the variability in efficiency is lower than that reported for blanket curtailment, which may reflect the fact that blanket thresholds are often calibrated from limited data collected over only one year or a few months. Under such conditions, performance is expected to vary when future weather differs from those represented in the calibration period. Finally, although operational mitigation measures such as curtailment schemes can substantially reduce impacts on bats, avoidance remains the cornerstone of the mitigation hierarchy (Voigt et al., 2024). Therefore, avoiding high-risk areas through careful siting should remain the first step in mitigation, while algorithm-based curtailment provides an important complementary tool to reduce residual impacts once turbines are operating.

CRediT authorship contribution statement

Kévin Barré: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kseniia Kravchenko:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Thierry Chambert:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Anne-Constance Comau:** Data curation. **Anaïs Pessato:** Writing – review & editing. **Andréas Ravache:** Writing – review & editing, Methodology, Conceptualization. **Elise Sivault:** Writing – review & editing, Methodology, Conceptualization. **Cassandre Treyvaud:** Writing – review & editing, Data curation. **Fabien Verniest:** Writing – review & editing, Methodology, Conceptualization. **Christian Kerbiriou:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Christian E. Vincenot:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The data acquisition was funded by France Renouvelables (FR), an association of >300 members, professionals of the wind energy sector in France, who have built >90 % of the turbines installed on the French territory and operate >85 % of them. FR had no role in data preparation and analysis, interpretation and discussion of the results, and decision to publish. Authors take complete responsibility for the accuracy of their analysis and their interpretations and discussions. None of the authors was employed by any of the funders prior to, or at the time of the submission of the article. We declare having no other competing interest.

Acknowledgments

Data acquisition was funded by France Renouvelables, and data analysis and their interpretations and discussions are product of the project “Win-Wind” funded by the Luxembourg National Research Fund (FNR-CORE C24/SR/18980316/), the "BRIBAT" project funded by the French Foundation for Research on Biodiversity (FRB; www.fondationbiodiversite.fr) and MIROVA Foundation, the project “RIDE” funded by the French National Centre for Scientific Research (CNRS), and the project “AlgoChiro” funded by the French Office for Biodiversity (OFB). We thank all participants which provided acoustic and weather/wind turbine operation data. We also thank CC-IN2P3 and PCIA-MNHN for providing computing and storage facilities, and Didier Bas for his help in this process. Finally, we also thank Paul Franc, Thomas Eglin, and Aurélien Besnard for their advice.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2026.130829.

Data availability

Data used in the study are available at https://doi.org/10.48579/PRO/DJD158, and codes used for analysis are available at https://github.com/KevBarre/Optimising-Bat-Friendly-Curtailment-Algorithms-for-Wind-Turbines-.git.

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 Ecol. Evol. 3 (6), 992–998. https://doi.org/10.1111/j.2041-210X.2012.00244.x.

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. https://doi.org/10.1371/journal.pone.0256382.

Arnett, E.B., Hayes, J., Huso, M.M.P., 2006. Patterns of pre-construction bat activity at a proposed wind facility in south-central Pennsylvania 2005 annual report. Bat Conservation International. Austin, Texas, USA (Number August).

Arnett, E.B., Huso, M.M.P., Schirmacher, M.R., Hayes, J.P., 2011. Altering turbine speed reduces bat mortality at wind-energy facilities. Front. Ecol. Environ. 9 (4), 209–214. https://doi.org/10.1890/100103.

Bailey, L.D., Pol, M. van de, 2016. Climwin: an R toolbox for climate window analysis. PLOS ONE 11 (12), e0167980. https://doi.org/10.1371/journal.pone.0167980.

Barré, K., Froidevaux, J.S.P., Leroux, C., Mariton, L., Fritze, M., Kerbiriou, C., Le Viol, I., Bas, Y., Roemer, C., 2022. Over a decade of failure to implement UNEP/EUROBATS guidelines in wind energy planning: a call for action. Conservation Science and Practice 4 (11), e12805. https://doi.org/10.1111/csp2.12805.

Barré, K., Froidevaux, J.S.P., Sotillo, A., Roemer, C., Kerbiriou, C., 2023. Drivers of bat activity at wind turbines advocate for mitigating bat exposure using multicriteria algorithm-based curtailment. Sci. Total Environ. 866, 161404. https://doi.org/10.1016/j.scitotenv.2023.161404.

Barré, K., Le Viol, I., Julliard, R., Pauwels, J., Newson, S.E., Julien, J., Claireau, F., Kerbiriou, C., Bas, Y., 2019. Accounting for automated identification errors in acoustic surveys. Methods Ecol. Evol. 10 (8), 1171–1188. https://doi.org/10.1111/2041-210X.13198.

Bas, Y., Bas, D., Julien, J., 2017. Tadarida: a toolbox for animal detection on acoustic recordings. J. Open Res. Software 5 (6), 1–8. https://doi.org/10.5334/jors.154.

Behr, O., Brinkmann, R., Hochradel, K., Mages, J., Korner-nievergelt, F., Niermann, I., Reich, M., Simon, R., Weber, N., Nagy, M., 2017. Wind energy and wildlife interactions. In: Wind Energy and Wildlife Interactions. https://doi.org/10.1007/978-3-319-51272-3.

Beucher, Y., Matutini, F., Nardou, X., Besnard, A., Albespy, F., Langlois, A., Illac, P., 2022. Programme OPRECh, Optimisation des Processus de Régulation des Eoliennes en faveur des Chiroptères : analyse des pratiques nationales. In: Tests Expérimentaux Etrecommandations, p. 243.

Brabant, R., Laurent, Y., Poerink, B., Degraer, S., 2020. Activity and behaviour of nathusius' pipistrelle Pipistrellus nathusii at low and high altitude in a north sea offshore wind farm. Acta Chiropt. 21, 341–348. https://doi.org/10.3161/15081109ACC2019.21.2.009.

Burke, M.J., Stephens, J.C., 2018. Political power and renewable energy futures: a critical review. Energy Research & Social Science, Energy and the Future 35, 78–93. https://doi.org/10.1016/j.erss.2017.10.018.

Carrete, M., Sánchez-Zapata, J.A., Benítez, J.R., Lobón, M., Donázar, J.A., 2009. Large scale risk-assessment of wind-farms on population viability of a globally endangered long-lived raptor. Biol. Conserv. 142 (12), 2954–2961. https://doi.org/10.1016/j.biocon.2009.07.027.

Collins, J., Jones, G., 2009. Differences in bat activity in relation to bat detector height: implications for bat surveys at proposed windfarm sites. Acta Chiropt. 11 (2), 343–350.

Cryan, P.M., Gorresen, P.M., Hein, C.D., Schirmacher, M.R., Diehl, R.H., Huso, M.M., Hayman, D.T.S., Fricker, P.D., Bonaccorso, F.J., Johnson, D.H., Heist, K., Dalton, D. C., 2014. Behavior of Bats at wind turbines. In: Proceedings of the National Academy of Sciences, pp. 1–6. https://doi.org/10.1073/pnas.1406672111.

Darras, K.F.A., Deppe, F., Fabian, Y., Kartono, A.P., Angulo, A., Kolbrek, B., Mulyani, Y. A., Prawiradilaga, D.M., 2020. High microphone signal-to-noise ratio enhances acoustic sampling of wildlife. PeerJ 8, e9955. https://doi.org/10.7717/peerj.9955.

Duriez, O., Pilard, P., Saulnier, N., Boudarel, P., Besnard, A., 2023. Windfarm collisions in medium-sized raptors: even increasing populations can suffer strong demographic impacts. Anim. Conserv. 26 (2), 264–275. https://doi.org/10.1111/acv.12818.

Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37 (12), 4302–4315. https://doi.org/10.1002/joc.5086.

Frey-Ehrenbold, A., Bontadina, F., Arlettaz, R., Obrist, M.K., 2013. Landscape connectivity, habitat structure and activity of bat guilds in farmland-dominated matrices. J. Appl. Ecol. 50 (1), 252–261. https://doi.org/10.1111/1365-2664.12034.

Frick, W.F., Baerwald, E.F., Pollock, J.F., Barclay, R.M.R., Szymanski, J.A., Weller, T.J., Russell, A.L., Loeb, S.C., Medellin, R.A., McGuire, L.P., 2017. Fatalities at wind turbines May threaten population viability of a migratory bat. Biol. Conserv. 209, 172–177. https://doi.org/10.1016/j.biocon.2017.02.023.

Friedenberg, N.A., Frick, W.F., 2021. Assessing fatality minimization for hoary Bats amid continued wind energy development. Biol. Conserv. 262 (August), 109309. https://doi.org/10.1016/j.biocon.2021.109309.

Froidevaux, J.S.P., Le Viol, I., Barré, K., Bas, Y., Kerbiriou, C., 2025. A modeling framework for biodiversity assessment in renewable energy development: a case study on european Bats and wind turbines. Renew. Sustain. Energy Rev. 211, 115323. https://doi.org/10.1016/j.rser.2024.115323.

Gaultier, S.P., Blomberg, A.S., Ijäs, A., Vasko, V., Vesterinen, E.J., Brommer, J.E., Lilley, T.M., 2020. Bats and wind farms: the role and importance of the Baltic sea countries in the European context of power transition and biodiversity conservation. Environmental Science & Technology 54 (17), 10385–10398. https://doi.org/10.1021/acs.est.0c00070.

Guest, E.E., Stamps, B.F., Durish, N., Hale, A., Hein, C.D., Morton, B., Weaver, S., Fritts, S., 2022. An updated review of hypotheses regarding bat attraction to wind turbines. Animals 12 (3), 343. https://doi.org/10.3390/ani12030343.

Heim, O., Treitler, J.T., Tschapka, M., Knörnschild, M., Jung, K., 2015. The importance of landscape elements for bat activity and species richness in agricultural areas. PLoS One 10 (7), 1–13. https://doi.org/10.1371/journal.pone.0134443.

Horn, J.W., Arnett, E.B., Kunz, T.H., 2008. Behavioral responses of Bats to operating wind turbines. J. Wildl. Manag. 72 (1), 123–132. https://doi.org/10.2193/2006-465.

Hurme, E., Lenzi, I., Wikelski, M., Wild, T.A., Dechmann, D.K.N., 2025. Bats surf storm fronts during spring migration. Science 387 (6729), 97–102. https://doi.org/10.1126/science.ade7441.

Kerbiriou, C., Bas, Y., Le Viol, I., Lorrilliere, R., Mougnot, J., Julien, J.F., 2018. Potential of bat pass duration measures for studies of bat activity. Bioacoustics 4622, 1–16. https://doi.org/10.1080/09524622.2017.1423517.

Leroux, C., Kerbiriou, C., Le Viol, I., Valet, N., Barré, K., 2022. Distance to hedgerows drives local repulsion and attraction of wind turbines on Bats: implications for spatial siting. J. Appl. Ecol. 59 (8), 2142–2153. https://doi.org/10.1111/1365-2664.14227.

Mariton, L., Le Viol, I., Bas, Y., Kerbiriou, C., 2023. Characterising diel activity patterns to design conservation measures: case study of European bat species. Biol. Conserv. 277, 109852. https://doi.org/10.1016/j.biocon.2022.109852.

Marques, A.T., Batalha, H., Rodrigues, S., Costa, H., Pereira, M.J.R., Fonseca, C., Mascarenhas, M., Bernardino, J., 2014. Understanding bird collisions at wind farms: an updated review on the causes and possible mitigation strategies. Biol. Conserv. 179, 40–52. https://doi.org/10.1016/j.biocon.2014.08.017.

Martin, C.M., Arnett, E.B., Stevens, R.D., Wallace, M.C., 2017. Reducing bat fatalities at wind facilities while improving the economic efficiency of operational mitigation. J. Mammal. 98 (2), 378–385. https://doi.org/10.1093/jmammal/gyx005.

Peterson, T., Rusk, A., Byrne, C., Aghababian, S., Edwards, S., 2025. Acoustic exposure reveals variation in curtailment effectiveness at reducing bat fatality at wind turbines. Ecosphere 16 (5), e70277. https://doi.org/10.1002/ecs2.70277.

Put, J.E., Fahrig, L., Mitchell, G.W., 2019. Bats respond negatively to increases in the amount and homogenization of agricultural land cover. Landsc. Ecol. 2. https://doi.org/10.1007/s10980-019-00855-2.

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. https://doi.org/10.1371/journal.pone.0266500.

Rodrigues, Bach L., Dubourg-Savage, M., Karapandza, B., Kovac, D., Kervyn, T., Dekker, J., Kepel, A., Bach, P., Collins, J., Harbusch, C., Park, K., Micevski, B., Minderman, J., 2015. Guidelines for Consideration of Bats in Wind Farm projects—Revision 2014. UNEP/EUROBATS Secretariat, p. 133 (EUROBATS Publication Series No. 6 (English Version).

Roemer, C., Disca, T., Coulon, A., Bas, Y., 2017. Bat flight height monitored from wind masts predicts mortality risk at wind farms. Biol. Conserv. 215 (August), 116–122. https://doi.org/10.1016/j.biocon.2017.09.002.

Santos, H., Rodrigues, L., Jones, G., Rebelo, H., 2013. Using species distribution modelling to predict bat fatality risk at wind farms. Biol. Conserv. 157, 178–186. https://doi.org/10.1016/j.biocon.2012.06.017.

Staid, A., Guikema, S.D., 2013. Statistical analysis of installed wind capacity in the United States. Energy Policy 60, 378–385. https://doi.org/10.1016/j.enpol.2013.05.076.

Thompson, M., Beston, J.A., Etterson, M., Diffendorfer, J.E., Loss, S.R., 2017. Factors associated with bat mortality at wind energy facilities in the United States. Biol. Conserv. 215, 241–245. https://doi.org/10.1016/j.biocon.2017.09.014.

Voigt, C.C., Bernard, E., Huang, J.C.-C., Frick, W.F., Kerbiriou, C., MacEwan, K., Mathews, F., Rodríguez-Durán, A., Scholz, C., Webala, P.W., Welbergen, J., Whitby, M., 2024. Toward solving the global green–green dilemma between wind energy production and bat conservation. Bioscience 74 (4), 240–252. https://doi.org/10.1093/biosci/biae023.

Voigt, C.C., Lehnert, L.S., Petersons, G., Adorf, F., Bach, L., 2015. Wildlife and renewable energy: german politics cross migratory Bats. Eur. J. Wildl. Res. 61 (2), 213–219. https://doi.org/10.1007/s10344-015-0903-y.

Voigt, C.C., Russo, D., Runkel, V., Goerlitz, H.R., 2021. Limitations of acoustic monitoring at wind turbines to evaluate fatality risk of Bats. Mamm Rev. 51 (4), 559–570. https://doi.org/10.1111/mam.12248.

Wellig, S., Nusslé, S., Miltner, D., Kohle, O., Glaizot, O., Braunisch, V., Obrist, M.K., Arlettaz, R., 2018. Mitigating the negative impacts of tall wind turbines on Bats: vertical activity profiles and relationships to wind speed. PLoS One 13 (3), 1–16.

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 the National Renewable Energy Laboratory. Bat Conservation International. Austin, Texas.