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Drivers of bat activity at wind turbines advocate for mitigating bat exposure using multicriteria algorithm-based curtailment

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Abstract

Wind turbine development is growing exponentially and faster than other sources of renewable energy worldwide. While multi-turbine facilities have small physical footprint, they are not free from negative impacts on wildlife. This is particularly true for bats, whose population viability can be threatened by wind turbines through mortality events due to collisions. Wind turbine curtailment (hereafter referred to as "blanket curtailment") in non-winter periods at low wind speeds and mild temperatures (i.e. when bats are active and wind energy production is low) can reduce fatalities, but show variable and incomplete effectiveness because other factors affect fatality risks including landscape features, rain, turbine functioning, and seasonality. The combined effects of these drivers, and their potential as criteria in algorithm-based curtailment, have so far received little attention. We compiled bat acoustic data recorded over four years at 34 wind turbine nacelles in France from post-construction regulatory studies, including 8,619 entire nights (251±58 nights per wind turbine on average). We modelled nightly bat activity in relation to its multiple drivers for three bat guilds, and assessed whether curtailment based on algorithm would be more efficient to limit bat exposure than blanket curtailment based on various combinations of unique wind speed and temperature thresholds. We found that landscape features, weather conditions, seasonality, and turbine functioning determine bat activity at nacelles. Algorithm-based curtailment is more efficient than blanket curtailment, and has the potential to drastically reduce bat exposure while sustaining the same energy production. Compared to blanket curtailment, the algorithm curtailment reduces average exposure by 20 to 29% and 7 to 12% for the high-risk guilds of long- and mid-range echolocators, and by 24 to 31% for the low-risk guild of short-range echolocators. These findings call for the use of algorithm curtailment as both power production and biodiversity benefits will be higher in most situations.

Key words: acoustic monitoring; chiroptera; cut-in speed; collision risk; mitigation hierarchy; wind energy

1. Introduction

Wind power generation produces near-zero greenhouse gas emissions during the operational phase, has short greenhouse gas payback time, and constitutes an efficient and sustainable way for the transition towards reduced global greenhouse gas emissions (Dammeier et al., 2019; Veers et al., 2019). As a consequence and in line with international treaties such as the 2016 Paris agreement to reduce global greenhouse gas emissions, wind turbine installation has grown exponentially over the last 20 years and currently represents the most rapidly expanding form of renewable energy worldwide (GWEC, 2021). While wind farm installation can have a relatively small footprint in terms of land conversion compared to other development projects, it still entails negative impacts on wildlife, particularly for insectivorous bats through mortality events by collision. Such increases in mortality are likely to impinge on the viability of populations (Friedenberg and Frick, 2021; Frick et al., 2017). This is especially true for migratory and long-range echolocating bat species, which are the most sensitive to collisions as they fly more often at the height at which turbines operate (Roemer et al., 2017). In addition to mortality, some bat species avoid areas adjacent to wind turbines leading to a reduction of habitat availability (Barré et al., 2018).

In the European Union and in many countries worldwide, wind energy developers must carry out an Environmental Impact Assessment (EIA) prior to any wind farm installation to evaluate potential environmental consequences and the measures required to avoid impacts. Developers must also monitor impacts during the operational phase (e.g. decree no. 0198 of August 27, 2011, in France). However, guidelines to avoid “areas where high bat activity has been determined by impact assessment” (EUROBATS; Rodrigues et al., 2015) appear to be poorly implemented (Barré et al., 2022). When impacts cannot be avoided, measures fot their reduction or, as a last resort, offsetting, must be implemented to achieve a state of no net loss of biodiversity (i.e. the mitigation hierarchy framework; Business and Biodiversity Offsets

Programme (BBOP), 2012). Wind turbine curtailment at low wind speeds and mild temperatures – when bats are highly active and energy production is low, hereafter referred to as “blanket curtailment” – is a reduction measure that offers promising opportunities to reconcile bat conservation and wind energy (Adams et al., 2021; Whitby et al., 2021; Voigt et al., 2015; Arnett et al., 2011; Baerwald et al., 2009). One of the most common blanket curtailment strategies is based on a simple combination of a maximum wind speed threshold (most often between 3.5 and 8 m/s) and a minimum temperature threshold (most often around 10°C). Respectively below and above those thresholds, the blades are turned to a different angle (i.e. feathered) to limit their rotation rate to less than one per minute, due to expected favourable conditions for bats. Blanket curtailment is mostly limited to non-winter periods. This approach can significantly reduce the fatality risk, but shows variable and incomplete effectiveness (Voigt et al., 2022; Adams et al., 2021; Whitby et al., 2021; Măntoiu et al., 2020). Besides wind speed and temperature, landscape features and other weather factors such as rain also drive bat fatality risk (Thompson et al., 2017; Santos et al., 2013). Indeed, bat activity at wind turbine nacelles, which links to fatality risk (Peterson et al., 2021; Korner-Nievergelt et al., 2013), also depends on the weather, season, landscape features, and wind turbine dimensions and rotation speed (Roemer et al., 2019; Behr et al., 2017; Cryan et al., 2014; Brinkmann et al., 2011; Horn et al., 2008). Consequently, curtailment strategies based on multifactor algorithms have the potential to be more efficient in reducing the fatality risk. Indeed, the use of an algorithm to curtail wind turbines in real-time based on weather factors, date, and nightly time, should allow avoiding most collisions while minimizing the loss of production (Behr et al., 2017).

Behr et al. (2017) and Brinkmann et al. (2011) are two of the few studies that propose this type of multicriteria framework to curtail wind turbines. These studies were based on data sampled in 2008 in Germany covering six months at 70 wind turbine nacelles and 35 different sites. To our knowledge, no peer-reviewed study has examined simultaneously and on a spatiotemporally extensive dataset all drivers of bat exposure (i.e. landscape features, weather conditions, date, and wind turbine characteristics), nor assessed the possibility to use them in guild specific algorithms to inform wind turbine curtailment.

To assess the potential of multicriteria curtailment algorithms, we compiled bat acoustic data recorded at wind turbine nacelles in France by wind energy developers in a context of post-construction regulatory studies, while homogeneously re-analysing acoustic data (i.e. using the same automated bat call identification software). Reprocessed bat acoustic data allowed us to build a standardised bat activity metric at nacelle height known to be a good predictor of fatality risk (Peterson et al., 2021; Korner-Nievergelt et al., 2013). Given the absence of national guidelines in France concerning the characteristics and settings of bat recorders for bat monitoring at nacelles and the large number of engineering consultants involved in data collection, we expected a large variation in the methods (Coly et al., 2017). Thus, our first objective was to assess whether monitoring methods (devices and settings) or confounding effects with landscape features, date, weather and wind turbine characteristics would bias the comparison of bat activity between wind turbines. This assessment was intended to filter out data from some wind turbines if necessary, and highlight the need for better national or international cooperation in the choice of materials and parameters in the case where the current situation would not allow meta-analyses. Once any method bias was controlled for, our second objective was to determine the main factors influencing bat activity at nacelles. We expected bat activity to increase with increasing landscape quality (e.g. by an increasing amount of forests, proximity to wetlands, or land use heterogeneity; Put et al., 2019; Sirami et al., 2013; Boughey et al., 2011a) and decreasing blade rotation speed (Cryan et al., 2014; Horn et al., 2008), and to be higher during nights with good weather conditions (i.e. high temperature, low wind speed and no rain; Voigt et al., 2015; Erickson and West, 2002) and at the end of summer (Heim et al., 2016). Finally, our third objective was to compare on a per-night scale the performance of a curtailment algorithm based on multiple factors to that of a blanket curtailment method based on various combinations of unique wind speed and temperature thresholds, in terms of both bat activity exposure and energy production. We expected the algorithm-based curtailment to be more efficient in reducing bat exposure compared to blanket curtailment, by avoiding a larger percentage of bat activity occurring when blades are moving, while involving smaller losses of energy production.

2. Methods

2.1. Acoustic data collection and processing

We compiled existing raw acoustic data (i.e. sound files in raw or wav format) of 14,937 complete recording nights at 59 wind turbine nacelles (including 20 models) located on 55 wind farms in France (Fig. 1; Table S1). These data were provided by nine wind farm developers and produced by 12 consulting firms and non-governmental organizations as part of regulatory post-implementation impact monitoring studies. Each of the 59 wind turbines was monitored on average for 251 nights (min: 103; max: 514). The monitored nights covered all months of the year and spanned four years between 2017 and 2020; 10% of the sites were monitored for more than one year. The year 2017 represents 2% of nights, 2018 18% of nights, 2019 79% of nights and 2020 0.4% of nights (Fig. S1). Depending on the analyses conducted, the complete set or subset of these data were used (see Statistical analysis section).

Three types of recorders were used: Batcorder at 18 wind turbines (versions 1, 2 and 3; ecoObs), Batmode S+ at 34 wind turbines (bat bioacoustics technology GmbH), and Song Meters at eight wind turbines (SM3BAT and SM4BAT; Wildlife Acoustics). All recorders were positioned at the bottom of the nacelle. Each was associated with one to three triggering thresholds, i.e. a built-in recording control algorithm which started the recording when a sound event exceeded a given sound level (see Supporting information S1 for more details).

Acoustic monitoring was always performed throughout the night, from sunset to sunrise. We used the number of bat passes (hereafter referred to as “activity”) or the presence/absence (hereafter referred to as “occurrence”) recorded during a night as a measure of bat visits with exposure (see section 2.3 for more details). We defined a bat pass as one or more echolocation calls within a five-second interval (Kerbiriou et al., 2019). All 731,717 bat passes were automatically classified to the closest taxonomic level using the Tadarida software (Bas et al., 2017). Since most bat species had very low occurrence (Table S1), we pooled together species into three guilds based on their similar echolocation call structures and therefore similar foraging strategies: long-range echolocators (LRE), mid-range echolocators (MRE) and short-range echolocators (SRE) (Frey-Ehrenbold et al., 2013), see Table S2 for species composition. Long-range echolocators are especially sensitive to fatality risks with wind turbines due to the great part of the time they spend at height (i.e. 20 to 45 m above ground level), followed by the mid-range echolocators (Table S2; Roemer et al., 2017). Although grouping species into these three guilds prevented misidentification problems between cryptic species, noise in the nacelle due to wind turbine functioning generated many false positives, especially at very high blade speeds. We followed the approach of Barré et al. (2019) and applied a maximum false positive tolerance of 50% to discard these interferences (see Barré et al. (2019) for more details), which reduced the dataset to 98,627 bat passes. This reduction led to discard 6.55 to 9.93% fewer false positives for Batmode data compared to other recorders.

2.2. Environmental and wind turbine variables

To determine which factors influence bat activity and occurrence at wind turbine nacelles, we collected or computed variables related to landscape composition and heterogeneity, weather conditions, and wind turbine functioning and dimensions.

Landscape variables - We considered variables representing the surface cover of five land-use types known to positively or negatively affect bats: impervious surfaces (Azam et al., 2016; Dixon, 2011), arable lands (Put et al., 2019), grasslands (Froidevaux et al., 2017; Roeleke et al., 2016; Lentini et al., 2012), forests (Heim et al., 2017; Boughey et al., 2011a) and water bodies (De Conno et al., 2018; Sirami et al., 2013). These variables were computed around the 59 wind turbines as proportions of the total area for variables presenting enough variations (impervious surfaces, arable lands, grasslands and forests), in ten area buffers around wind turbines (50, 100, 250, 500, 1000, 2000, 3000, 4000, 5000 and 10000 m radius) to use the most relevant scale for each variable (Kalda et al., 2015, see Statistical Analysis section for more details). We also calculated the Euclidean distance to the nearest impervious surfaces, forests and water bodies. Moreover, we computed landscape metrics depicting landscape configurational and compositional heterogeneity (Monck-Whipp et al., 2017), including edge density (i.e. the density of ecotones in m/ha), conditional entropy (i.e. an increasing index with increasing landscape complexity), patch richness density (i.e. the number of patch types standardised by the surface), and Shannon diversity index of habitat patches. These landscape metrics were computed using the R package *landscapemetrics* (Hesselbarth et al., 2019), for the ten radius sizes presented above. All landscape variables were extracted from the high-resolution CES OSO land cover map 2018 available at https://www.theia-land.fr/en/ceslist/land-cover-sec/ (Derksen et al., 2020).

Weather variables - We collected the average wind speed (m/s) and temperature (°C) recorded by wind turbine nacelle weather stations in 10-minute intervals and averaged them on a nightly scale at each wind turbine (i.e. on the same scale as acoustic data). Since the amount of rainfall was not recorded by the nacelle weather stations, we collected the daily cumulated rain (mm) (i.e. over the 24-hour period from midnight of the day when the recording night started) using the weather database from E-OBS (https://surfobs.climate.copernicus.eu/dataaccess/access_eobs.php#datafiles).

Wind turbines variables - We collected dimensions of wind turbines which measured 45 to 139 m (92 m on average) in nacelle height and 44 to 126 m (94 m on average) in rotor diameter (Table S1). We also collected the average rotation speed (km/h) at the tip of the blade in 10-minute intervals, and averaged it on a nightly scale at each wind turbine.

2.3. Statistical analysis

We assessed drivers of measures of bat activity and occurrence around wind turbine nacelles, including factors related to landscape composition and heterogeneity, weather conditions, the Julian day, wind turbine functioning and dimensions and recording methods (i.e. the recorder type and the trigger sensitivity). In the first step, since we compiled data produced by different contributors, we expected the existence of multiple combinations between the recorder type and the trigger sensitivity. However, these recording methods deeply affect the number of bat passes recorded (Adams et al., 2012). Confounding effects between recording methods and factors of interest (e.g. landscape composition) could prevent modeling them simultaneously. Using all compiled data, we therefore tested for trends in the landscape composition and heterogeneity, weather conditions, and wind turbine functioning and dimensions between recording methods (i.e. a discrete variable including seven combinations between the recorder type and the trigger sensitivity), using Kruskal-Wallis tests and box plots. We then computed the proportion of variance explained by each variable (*pseudo-R^2*) to assess whether the importance of the factors of interest (actual drivers of bat activity) was biased by the different recording methods. To properly study the drivers of bat activity at wind turbine nacelles, a prerequisite was that the recording methods do not capture an overwhelming part of the variance compared to the factors known to affect bat activity. To achieve this, we built one full Generalised Linear Mixed Model (GLMM, R package *glmmTMB*; Brooks et al., 2017) per bat guild, using LRE and MRE activity and SRE occurrence as response variables, and the landscape (see Supporting information S2 for landscape variable selection and composition), weather conditions (i.e. average wind speed, average temperature and cumulated rain), the Julian day, and wind turbine functioning (i.e. average blades rotation speed) and dimensions (i.e. nacelle height and rotor diameter) as fixed effects (hereafter referred to as “explanatory variables”). Since we had a relatively small number of sites, we restricted the number of landscape variables to three; i.e. the same number as the other types of variables (i.e. three weather variables and three wind turbine functioning and dimension variables available). With such approach, models were always constituted of ten variables, allowing to avoid overparameterization. For landscape variables we pre-selected the best computing area buffer and in a second step selected the three ones – within the five landscape variables – with the best conjoint contributions (see Supporting Information S2 for more details). We used the wind turbine identifier and year as random effects to account for pseudo-replication (i.e. many recording nights per wind turbine) and inter-year variations in activity, associated with a negative binomial distribution for LRE and MRE guilds and a binomial distribution for SRE guild (see Supporting information S2 and Table S4 for the composition of full models). Then, we computed the *pseudo-R^2* of each variable by subtracting the *marginal R^2* of the full model and that of the model without the target variable, using the R package *sjstats*.

The preliminary analysis showed that recording methods resulted in confounding effects with most other variables of interest and captured the largest variance part (Table S5; Figs. 2 & S2). Thus, to model bat activity or occurrence as a function of explanatory variables, we selected in a second step only one combination between the recorder type and the trigger sensitivity that removed any variation in recording methods. We chose the combination of the Batmode set to a trigger sensitivity of 37 dBSPL which had the largest dataset resulting in 34 wind turbines, 8,619 nights and 65,775 bat passes. Based on this subset, we performed the same GLMMs workflow as presented above (see Supporting information S2 and Table S6 for more details) to assess the respective effects of explanatory variables on the LRE and MRE activity and SRE occurrence. For each explanatory variable, we checked the potential need for adding a non-linear effect by visual inspection of Generalised Additive Mixed Models (GAMM, R package *mgcv*; Wood, 2011; see Table 1 for variables that required quadratic or cubic effects). We also checked the absence of multicollinearity by calculating the Variance Inflation Factor (VIF) for each explanatory variable (R package *performance*; Lüdecke et al., 2021). All variables showed a VIF<2, implying no evidence of multicollinearity (Chatterjee and Hadi, 2006). It should be noted that wind speed and blade speed were not excessively correlated thanks to maintenance periods that stopped the turbines in all wind conditions (Fig. S3). Overall model validation was performed using diagnostic plots (R packages *DHARMa* and *performance*; Lüdecke et al., 2021). Full models were compared to null ones using the Akaike information criterion (AIC) (Burnham and Anderson, 2002), and goodness of fit was assessed using the marginal R^2 (variance explained by the fixed effects) and conditional R^2 (variance explained by both fixed and random factors) values (Nakagawa and Schielzeth, 2013). All analyses were performed using a significance threshold of 5% in R statistical software v.4.0.3 (R Core Team, 2020).

2.4. Assessing the effectiveness of using model equations to limit bat exposure compared to conventional curtailments

Using the same Batmode dataset, we assessed whether curtailment of wind turbines based on multiple-factor models could be more efficient in limiting bat activity exposure at the scale of all wind turbines than commonly used blanket curtailment methods. For that, we trained full models for each guild on a 50% fully random subset of the dataset (hereafter referred to as "training dataset") and predicted bat activity on the other 50% (hereafter referred to as "prediction dataset"), and this 100 times. Then, we computed for each prediction dataset the remaining percentage of bat activity (for LRE and MRE guilds) or occurrence (for SRE guild) (i.e. the real bat activity or occurrence recorded while the blades were moving) and the percentage of lost blade rotations (i.e. as a proxy of lost energy production) resulting of curtailing wind turbines following either of two methods: (i) curtailing above thresholds of bat activity predicted from full models (hereafter referred to as "multicriteria curtailment algorithm"), and (ii) curtailing below wind speed thresholds and this either without temperature threshold or with different minimum temperatures required from 2 to 18°C (hereafter referred to as “blanket curtailment”). Finally, we plotted the relationship between the remaining percentage of bat activity or occurrence and the percentage of lost blade rotations for both curtailment methods to evaluate their effectiveness in limiting exposure (Fig. 3A). The comparison of both curtailment methods was conducted for the non-winter periods only.

To assess whether the effectiveness was relevant for all wind turbines, we also plotted the relationship between the remaining percentage of bat activity and the percentage of lost blade rotations for each wind turbine independently. We computed Area Under Curve (AUC) values for both curtailment methods to evaluate which one was the most effective (i.e. with the highest AUC value) (R package *MESS*). We also estimated to what extent the effectiveness of curtailment methods was preserved when wind turbines included in the training dataset differed from those in the prediction dataset. For that, we repeated the procedure explained above, but using a training dataset constituted of data from 33 out of 34 wind turbines and a prediction dataset constituted of data from the 34th wind turbine, and we repeated it for each wind turbine to present its results while computing AUC values for both curtailment methods. These turbine-by-turbine assessments were only conducted for LRE and MRE guilds for which we had enough data for each wind turbines.

Finally, because the percentage of lost blade rotations did not constitute a perfect proxy of lost energy production, we assessed whether the relative comparison of lost blade rotations between curtailment methods as a proxy of energy production losses was biased (e.g. one method for a given level of lost blade rotations involving slower blade speeds, and in turn lower energy losses, than the other method). For that we compared the distribution of blade speeds inside lost blade rotations between the two curtailment methods.

3. Results

3.1. Bat monitoring

A total 98,627 bat passes were recorded at 59 wind turbines and 14,937 nights. However, as described above, in order to avoid confounding effects between recording methods and other explanatory variables, we only selected wind turbines monitored using Batmode recorders which exhibited no trigger sensitivity variation, while including most of the data (i.e. 34 wind turbines out of 59 and 8,619 nights out of 14,937). Data from Batmode resulted in a total of 65,775 bat passes recorded, with 43,519 passes of LRE, 22,135 passes of MRE and 121 passes of SRE (see Table S3 for species composition). At least one pass of LRE, MRE and SRE was recorded in 35%, 18% and 1% of nights, respectively (Table S3).

3.2. Drivers of bat activity around nacelles

Full models of bat activity and occurrence showed smaller AIC than null models (delta AIC of full models from -50 to -1468), with 33%, 55% and 51% variance explained by fixed effects and 78%, 60% and 54% by both fixed and random effects, for LRE, MRE and SRE guilds, respectively (Table S6).

Regarding landscape variables, LRE activity was positively affected by the landscape Shannon diversity index of habitat patches at the 10,000 m radius scale while MRE activity increased with increasing patch richness density at the 1,000 m radius scale and forest proportion at the 10,000 m radius scale. We also found significant positive relationships between SRE occurrence and edge density at the 10,000 m radius scale and the proportion of impervious surfaces at the 100 m radius scale (Fig. 4; Table 1). Concerning wind turbine functioning and dimensions, increasing average blade speed significantly reduced the activity/occurrence of all guilds, while no effect of nacelle height and rotor size were found (Figs. 4; Table 1). Concerning weather conditions, average temperature positively and non-linearly affected the activity of LRE and MRE guilds, while the average wind speed and the cumulated rain negatively affected (non-linearly and linearly, respectively) the activity/occurrence of all guilds (Fig. 4; Table 1). Finally, we found seasonality in the activity of the LRE and MRE guilds, manifested as a cubic and quadratic relationship, respectively, with the Julian date: increasing between January and August, and decreasing from September to December (Fig. 4; Table 1).

3.3. Effectiveness of model equations to limit bat exposure compared to conventional curtailments

For the blanket curtailment, we found that increasing wind speed thresholds below which wind turbines should be curtailed almost always linearly decreased the real remaining bat activity for all guilds (Fig. S4A-C). For the multicriteria curtailment algorithm, we found that decreasing the predicted bat activity above which wind turbines should be curtailed decreased the actual bat activity or occurrence exposed: exponentially for LRE activity, logistically for MRE activity and linearly for SRE occurrence. (Fig. S4A-C). Moreover, expanding curtailment increased the percentage of lost blade rotations differently between methods: with logistic increases when using wind speed and temperature criteria, and exponential increases when using a multicriteria curtailment algorithm. (Fig. 4D-F).

When we linked the real bat activity or occurrence exposed with the percentage of lost blade rotations, we found that the multicriteria curtailment algorithm was more efficient than the blanket curtailment for all guilds (Figs. 3B & 5). We found that the multicriteria curtailment algorithm at the scale of all wind turbines exhibited on average 20% and 9% less bat activity exposed than blanket curtailment without temperature threshold for LRE and MRE guilds, respectively, and 24% less occurrence exposed for SRE guild (Fig. 3B1). When blanket curtailment included temperature thresholds, the multicriteria curtailment algorithm exhibited on average 20 to 29%, 7 to 12% and 24 to 31% less exposure for LRE, MRE and SRE guilds, respectively, depending on the temperature threshold considered in blanket curtailment (Figs. 3B2 & 5). The higher efficiency of the multicriteria curtailment algorithm was confirmed by its AUC values which were higher than those of blanket curtailment for a 10°C threshold at 81 and 75% of wind turbines for LRE and MRE guilds, respectively (Figs. S5 & S6). Finally, when the algorithm was trained on 33 out of 34 wind turbines and predictions made on the remaining wind turbine(i.e. model training and predictions based on independent sites), algorithm curtailment had higher AUC values than blanket curtailment at 81 and 69% of wind turbines for LRE and MRE, respectively (Fig. S7 & S8).

Finally, blade speed distributions did not differ between lost blade rotations of both curtailment methods, thus suggesting that the relative comparison of lost blade rotations between curtailment methods as a proxy of energy production losses was not biased (Fig. S9).

4. Discussion

Identifying drivers of bat exposure to wind turbines from acoustic monitoring at nacelles, and the possibility of their combined use as criteria in algorithm-based curtailment, have so far received little attention in the scientific literature in the context of wind turbine impact mitigation. Our study shows that recording methods should be accounted for when using acoustic data continuously produced in post-construction regulatory studies, before analysing the drivers of bat exposure. Once detection method biases were avoided, results showed that it is possible to disentangle the main drivers. Our findings revealed that landscape features, weather conditions, seasonality, and wind turbine functioning determine the activity of all bat guilds at nacelles. Algorithms including all these drivers to curtail wind turbines above a given level of predicted bat activity are more efficient than common blanket curtailment methods based on unique wind speed and temperature thresholds on the activity period of bats, as they reduce more exposure while sustaining the same energy production.

4.1. Assessing bias in recording methods

One of the aims of this study was to take advantage of the numerous pre-existing data from post-construction monitoring studies instead of designing a field study that would require paramount monetary and time investments. A prerequisite for using all aggregated data was the absence of biases related to the recording methods. Unfortunately, when considering data collected using different recording methods, the combination of recorder type and triggering sensitivity explained much more variance than all well-known drivers of bat activity (Roemer et al., 2019; Behr et al., 2017; Cryan et al., 2014; Horn et al., 2008), minimizing their relative importance in the models. All gradients of drivers strongly varied among recorder type/trigger sensitivity combinations, thus preventing any modelling of the effects of drivers on bat activity based on the full dataset due to confounding effects. Indeed, different recorder type/trigger sensitivity combinations can lead to very different levels of bat activity between sites due to the different detection distances generated by the material specificities and settings (Darras et al., 2020; Adams et al., 2012). We opted to compensate for this problem by modelling the effect of the drivers on bat activity after separating the recorder type/trigger sensitivity combinations. However, harmonising monitoring methods across all sites would avoid such partitioning and loss of data. Alternatively, future studies could assess the possibility of using corrective coefficients of activity between different recorder type/trigger sensitivity combinations, or establish longer bat pass units, to make the sites monitored in different ways comparable.

4.2. Drivers of bat activity around nacelles

Our results highlight the high importance of accounting for all drivers (i.e. landscape, wind turbine functioning, weather, and date) to better account for the variation of bat activity at nacelle height. As expected from previous studies looking at fatality risk or bat activity at nacelle height, we found a joint effect of all types of drivers on bat activity (Behr et al., 2017; Thompson et al., 2017; Cryan et al., 2014; Santos et al., 2013; Horn et al., 2008).

Specifically, LRE and MRE activity increased with the Shannon diversity index of habitat patches and patch richness density, respectively, as previously reported by (Froidevaux et al., 2022; Mendes et al., 2017; Monck-Whipp et al., 2017). Edge density also positively affected the SRE guild occurrence, as previously documented for hedgerow density (Lacoeuilhe et al., 2016; Verboom and Huitema, 1997) or the density of all edge habitats (Ancillotto et al., 2017; Mendes et al., 2017). We also found forest cover to positively affect MRE activity, consistent with Roemer et al. (2019), who showed that bat activity at height decreased with the distance to the forest, and with Boughey et al. (2011a) who found higher bat activity at ground level with an increasing proportion of forest. Unexpectedly, our model revealed a positive effect of impervious habitat proportion on SRE activity, a relationship that is elsewhere described as negative (Gili et al., 2020). Impervious habitat in this dataset corresponds to roads and the buffer scale selected is very local (100m). This is likely an indirect positive effect related to ecotone/hedgerow associated with roads (i.e. road access to a wind turbine), a favourable context for foraging of narrow- and edge-space foragers of the SRE guild (Denzinger and Schnitzler, 2013).

Increasing blade rotation speed logistically reduced LRE activity and SRE occurrence, and linearly decreased MRE activity, in accordance with previous studies (Cryan et al., 2014; Horn et al., 2008). It should be noted that it is unlikely that this result fully mirrors the effect of wind speed because wind speed and blade speed are not fully confounded (Fig. S3). In addition, the negative effect of blade rotation speed is preserved at both high and low wind speeds (Fig. S10).

Regarding weather conditions, increasing temperatures promoted the activity of LRE and MRE guilds, while increasing wind speeds and cumulated rain suppressed the activity of all guilds. These results corroborate studies of bat activity at height, showing very similar patterns (Wellig et al., 2018; Behr et al., 2017; Horn et al., 2008; Arnett et al., 2006; Redell et al., 2006). Interestingly, both LRE and MRE guilds exhibited some tolerance to unfavourable weather conditions, with a non-negligible proportion of remaining activity in such conditions (see Fig. S11). For instance, above wind speeds of 8m/s, 9% of MRE activity and 12% of LRE activity remained; below a temperature of 10°C, 2% of MRE activity and 7% of LRE activity remained (Fig. S11), which is highly consistent with findings by Behr et al. (2017) in Germany.

With respect to seasonality, a peak in LRE and MRE activity was detected in August, thus reinforcing previous studies reporting a peak in bat fatalities at wind turbines in this period (Schuster et al., 2015; Arnett et al., 2008).

4.3. Assessing the effectiveness of using model equations to limit bat exposure compared to conventional curtailments

The multifactor responses of bat activity and occurrence at wind turbine nacelles reported in this study highlight the crucial need for curtailment strategies based on all possible combinations of the driving factors, while proving that curtailment based on fixed environmental thresholds such as cut-in wind speed and temperature is not fully effective in avoiding bat exposure.

Based on the relationship between the percentage of recorded bat activity or occurrence and the percentage of lost blade rotations entailed by each curtailment threshold (i.e. wind speed and temperature values for blanket curtailment and a predicted bat activity and occurrence value for multicriteria curtailment algorithm), multicriteria curtailment algorithm will save many more bats from exposure to spinning blades (i.e. on average 20 to 29%, 7 to 12% and 24 to 31% less exposure for LRE, MRE and SRE guilds, respectively, depending on temperature threshold considered in blanket curtailment). This result corroborates conclusions from Behr et al. (2017) who performed a similar assessment using the real loss of energy production and curtailment thresholds based on a mean number of fatalities per turbine and per year. The fact that the difference in efficiency is smaller for the MRE than for the LRE guild (both being at high risk of collision; Roemer et al., 2017), is mainly due to the fact that blanket curtailment is significantly less efficient for LREs as they are more tolerant to non-optimal weather conditions (Fig. S11). The increased effectiveness on LRE (the most collision-sensitive guild) reinforces the importance of moving from current blanket curtailments to a multi-criteria algorithm-based approach.

4.4. Limitations and recommendations

The study calls for prudence when using data from different recording methods that should be controlled before any modelling as they could strongly bias the algorithm to use for curtailment. This requires regulatory databases (as is the case with the DEPOBIO tool in France; https://depot-legal-biodiversite.naturefrance.fr/) to demand the input of metadata related to the methods used, or ideally to harmonise these methods. Thus, in order to be generalised to all types of material and settings, the algorithm should either be adapted to each type using appropriate data, or a ratio of equivalence in activity between pairs of material/settings should be defined in future studies.

To go further in the modelling of bat exposure, the curtailment algorithm method we propose should be adapted on an intra-night scale to account for the variation of bat activity during the night and thus minimise even more production losses (Behr et al., 2017). In addition, our efficiency assessment does not rely on a real loss of energy production as such information is rarely available from wind energy developers. However, as blade speed distributions do not differ between lost blade rotations of both curtailment methods, the relative comparison of lost blade rotations between curtailment methods as a proxy of energy production losses is not biased. Bat activity around nacelles was reported to be a good proxy for fatality risk (Peterson et al., 2021; Korner-Nievergelt et al., 2013), but we encourage further research on the relationship between activity and mortality to refine algorithms towards an explicit reduction of the real collision risk, either by giving more weight to conditions in which activity is most strongly correlated with mortality or by using mortality data directly. Acoustic-informed blanket curtailment is another method practised in North America, notably using the Turbine Integrated Mortality Reduction (TIMR) system which, in addition to a wind-speed threshold, integrates a real-time bat activity criterion. Although this system is not directly comparable to our algorithm (intra-night timescale, effectiveness assessed using daily fatality surveys), it seems to show similar effectiveness (i.e. a 37% reduction in exposure compared to blanket curtailment) (Rabie et al., 2022; Hayes et al., 2019). Future studies could therefore compare these two types of curtailment strategies on an equivalent basis to highlight the strengths and weaknesses of each, especially regarding technological constraints. Finally, the baseline data used to train the algorithm should be updated on a regular basis with data from the latest wind turbine models in order to explicitly incorporate their dimensional changes into the modelling.

The strategy of algorithm-based curtailment should be conceived on a large scale to save a global percentage of the bat community from exposure, although on some sites the method may currently be less effective. In the future, to capitalise on large-scale data, algorithms could be developed using national data and applied site by site as it accounts for the landscape context, and could be regularly updated with data from new post-construction monitoring. This will require more years and sites of monitoring to account for the inter-annual stochasticity of the responses and to cover larger landscape gradients, respectively, and would also require updating algorithms with the most recent data to consider climate change and especially the gradual increase in temperature. The large amount of regulatory post-implementation acoustic monitoring performed each year could be included annually to update algorithms so that the exposure threshold defined by the central authority is continuously based on a predictive tool accounting for climate change. Since temperate insectivorous bat species respond to a documented set of landscape characteristics, weather conditions and seasonality, we expect the development of such curtailment algorithms to be efficient and of great relevance in most temperate ecosystems.

Finally, our study calls for the use of multicriteria curtailment algorithms instead of basic blanket curtailments as power production is clearly predicted to be higher and the benefit for bats is high in most situations (Behr et al., 2017).

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Author's contribution

K.B. with the support of C.K. conceived the ideas, designed the methodology, collected and processed the data, and analysed the data; K.B. led the writing of the manuscript with the support of all authors. JSPF computed landscape variables. All authors critically contributed to the drafts and gave their final approval for publication.

Data accessibility

Data used for analyses will be available on a dedicated platform.

Conflict of Interest

France Energie Eolienne (FEE) is an association of more than 300 members, professionals of the wind energy sector in France, who have built more than 90% of the turbines installed on the French territory and operate more than 85% of them. The scientific question was defined with FEE whose members provided the data. FEE had no role in data preparation and analysis,

interpretation and discussion of the results, and decision to publish. The Office Français de la Biodiversité (OFB) is a public institution dedicated to the protection and restoration of biodiversity in metropolitan and overseas France, under the authority of the French Ministry of Ecological Transition and Agriculture and Food. OFB and FEE proofread an early version of the manuscript and this proofreading did not influence the interpretations, discussions and conclusions of the study. Corrections made to the first draft following these proofreadings can be found at https://doi.org/10.5281/zenodo.6818161. 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.

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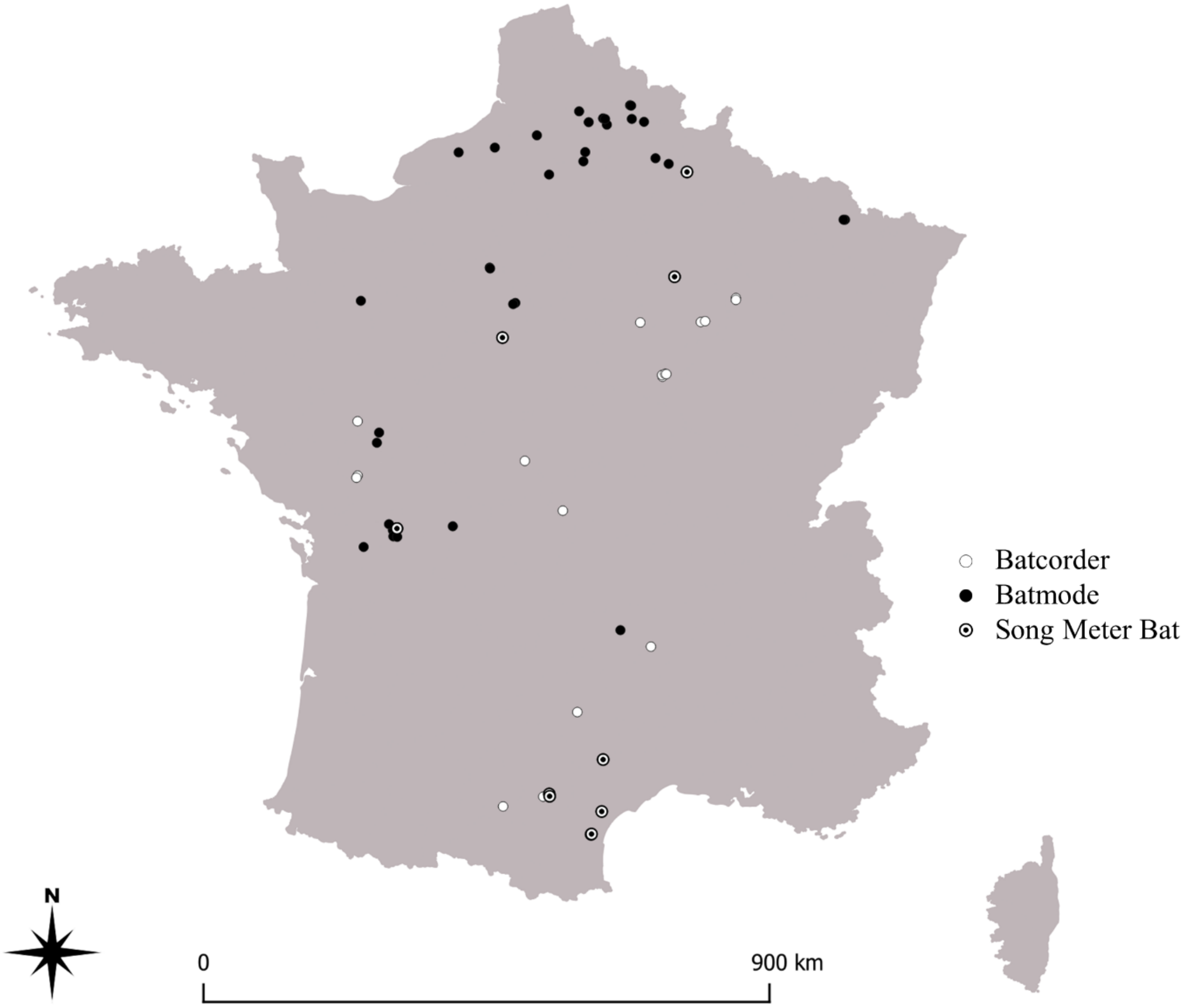


Figure 1. Location of monitoring sites in France according to bat recorder types.

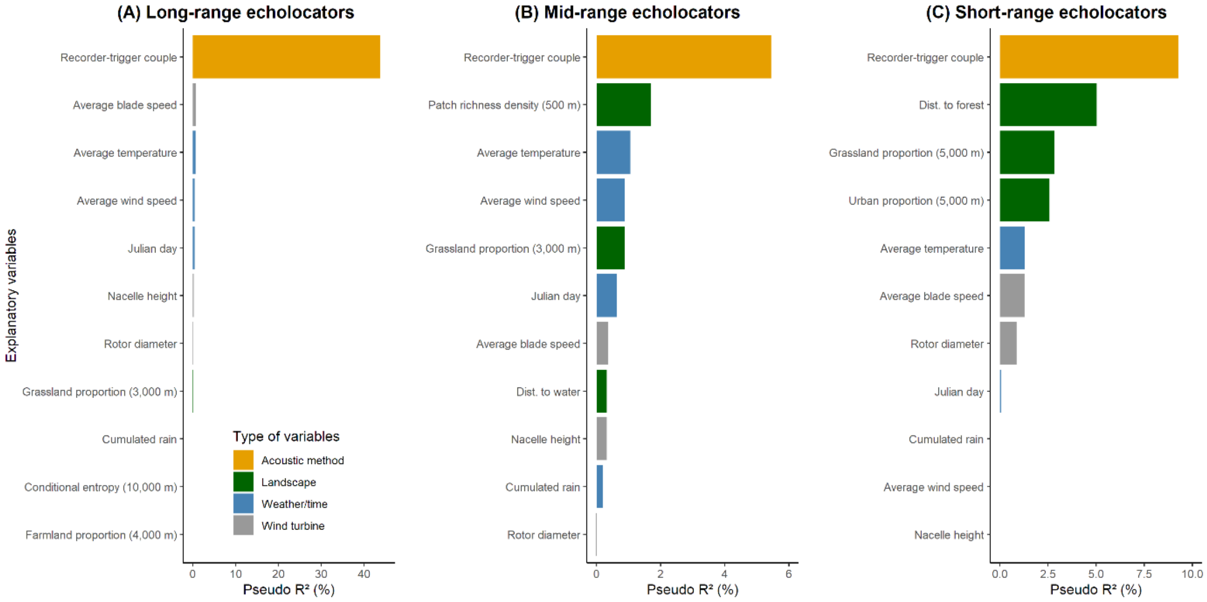
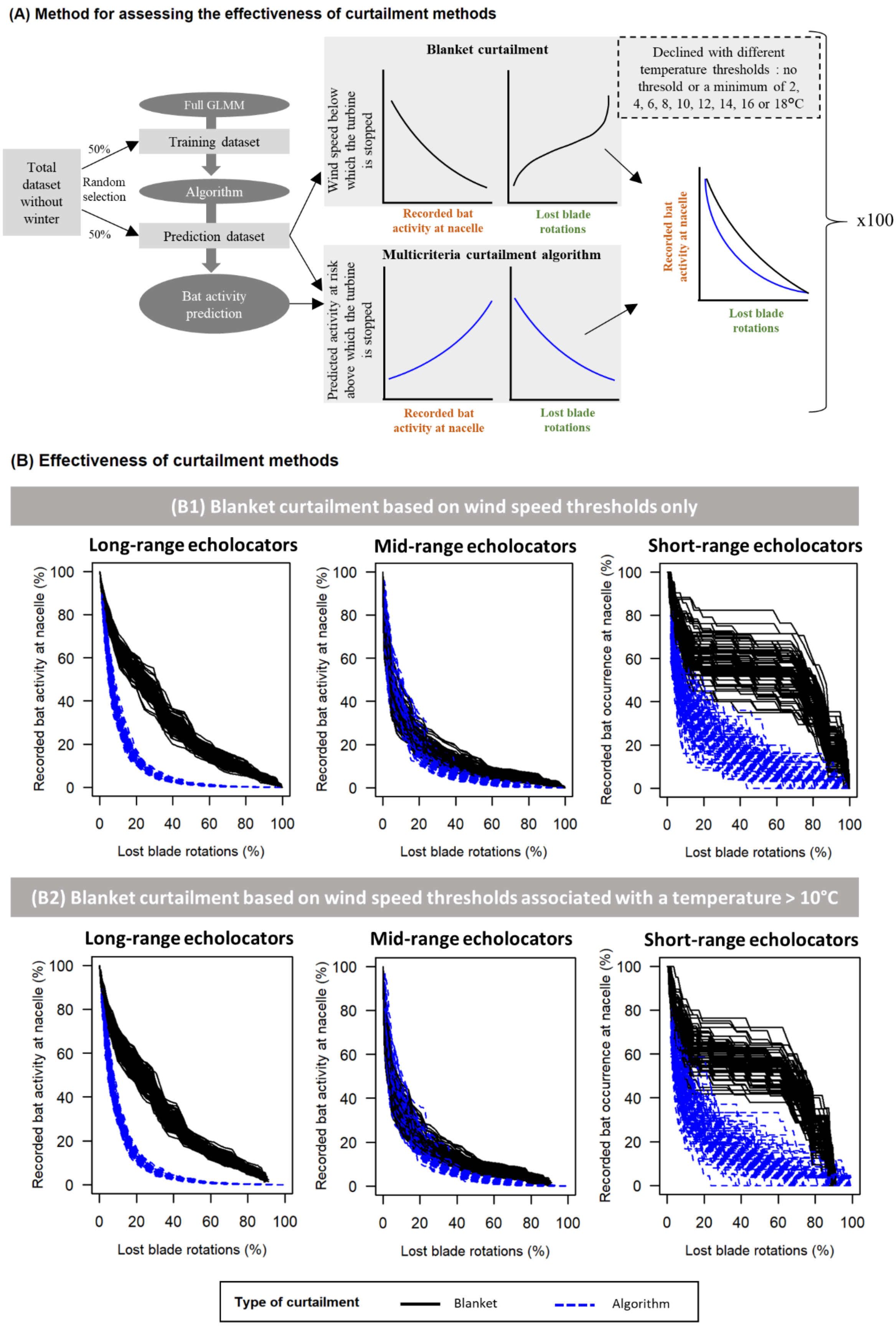
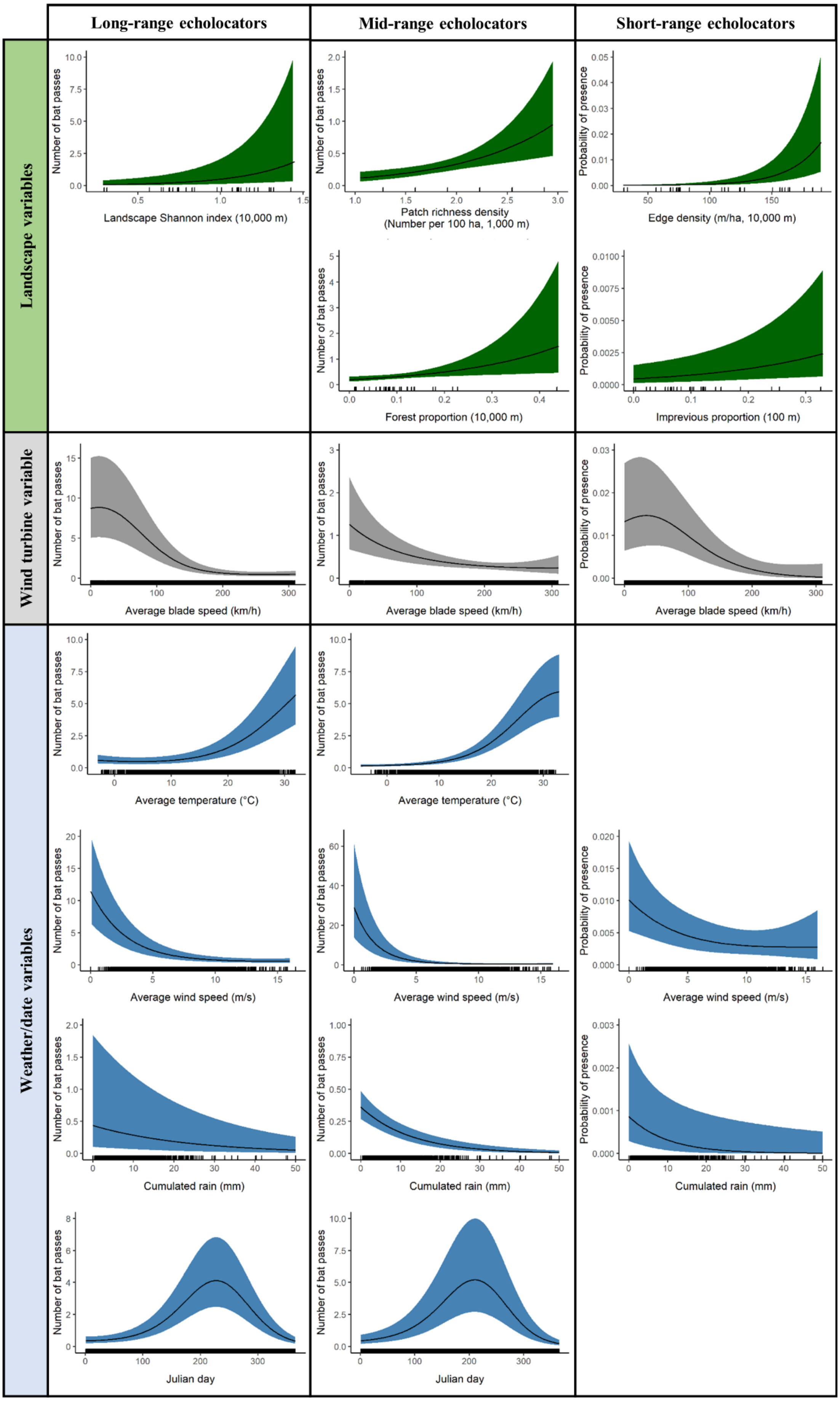


Figure 2. Percentage of bat activity and occurrence variance explained by each variable (i.e. pseudo-R^2) related to acoustic method, landscape, weather and time, and wind turbine features from generalized linear mixed models based on data from all recorder types (i.e. 59 sites, 14,937 nights and 98,627 bat passes).



(A) Method for assessing the effectiveness of curtailment methods
Total dataset without winter
Random selection
50%
50%
Full GLMM
Training dataset
Algorithm
Prediction dataset
Bat activity prediction
Blanket curtailment
Wind speed below which the turbine is stopped
Recorded bat activity at nacelle
Lost blade rotations
Declined with different temperature thresholds : no thresold or a minimum of 2, 4, 6, 8, 10, 12, 14, 16 or 18°C
Multicriteria curtailment algorithm
Predicted activity at risk above which the turbine is stopped
x100
(B) Effectiveness of curtailment methods
(B1) Blanket curtailment based on wind speed thresholds only
(B2) Blanket curtailment based on wind speed thresholds associated with a temperature > 10°C
Long-range echolocators
Mid-range echolocators
Short-range echolocators
Recorded bat activity at nacelle (%)
Recorded bat occurrence at nacelle (%)
Lost blade rotations (%)
Type of curtailment
Blanket
Algorithm

Figure 3. Panel A depicts the method to compare blanket (black) and algorithm-based (blue) curtailment methods' effectiveness to limit bat activity exposure. One hundred iterations were performed to train generalized linear mixed models (GLMM) on a random selection of 50% of the Batmode dataset and predict bat activity (for LRE and MRE guilds) and occurrence (for SRE guild) as well as computing remaining recorded bat activity and lost blade rotations on the remaining 50% (see section 2.4). The method first links the percentage of recorded bat activity and the percentage of lost blade rotations, respectively, to the wind speed threshold below which the turbine is curtailed when no temperature threshold and various minimum temperature thresholds were applied (blanket curtailment, black) and the predicted bat activity above which the turbine is curtailed (curtailment algorithm, blue). Then the method links the percentage of remaining recorded bat activity and the percentage of lost blade rotations for both curtailment methods to compare their effectiveness presented for the three guilds in panel B. For the blanket curtailment, panel B shows the effectiveness of the method when no temperature threshold (B1) and a minimum temperature of 10°C (B2) were applied.



Long-range echolocators
Mid-range echolocators
Short-range echolocators
Landscape variables
Wind turbine variable
Weather/date variables
Number of bat passes
Probability of presence
Landscape Shannon index (10,000 m)
Patch richness density
(Number per 100 ha, 1,000 m)
Edge density (m/ha, 10,000 m)
Forest proportion (10,000 m)
Imprevious proportion (100 m)
Average blade speed (km/h)
Average temperature (°C)
Average wind speed (m/s)
Cumulated rain (mm)
Julian day

Figure 4. Predicted number of bat passes or probability of presence from generalized linear mixed models and 95% confidence intervals as a function of significant variables related to landscape (green), wind turbine (grey), and weather and date (blue), based on the Batmode dataset.

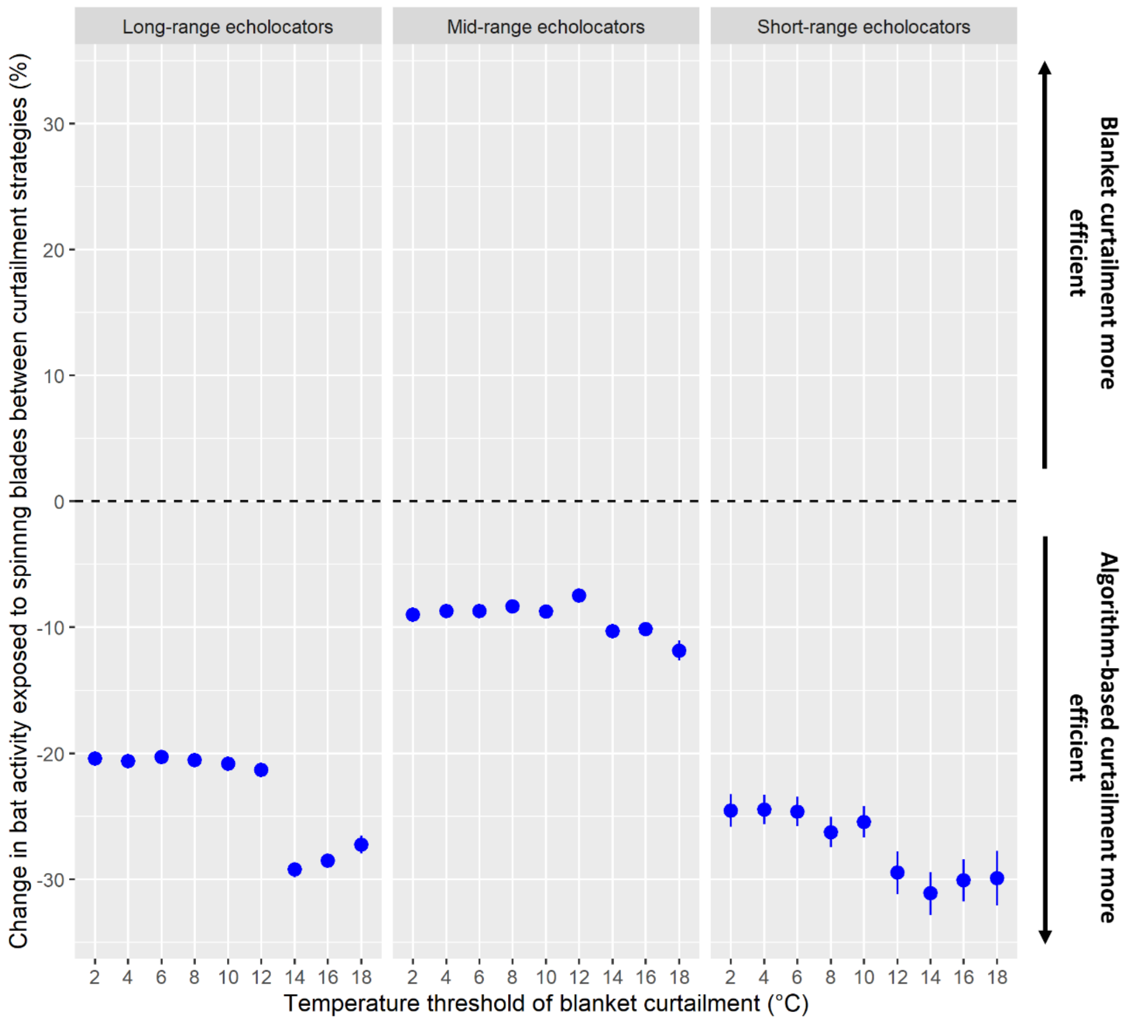


Figure 5. Average change in remaining percentage of bat activity exposed to spinning blades and associated 95% intervals between blanket and algorithm-based curtailments for various temperature thresholds in the blanket curtailment. Average change was computed using each intra-iteration difference between curtailment methods.

Table 1. Estimates, standard errors and p-values from full models testing the effect of landscape, wind turbine and weather/time variables on LRE and MRE activity and SRE occurrence. Missing values indicate that the landscape variable was not selected in full models (only the three best explaining ones per guild were included, see Statistical analysis section for more details) or the no need for quadratic or cubic effects on weather/date variables. Significant effects ($P<0.05$) are shown in bold.

Variable	LRE		MRE		SRE	
	Estimate±SE	P	Estimate±SE	P	Estimate±SE	P
Intercept	-0.670±0.733	0.361	-0.492±0.122	<0.001	-6.614±0.537	<0.001
Landscape variables						
Edge density (m/ha, 10,000 m)	-	-	-	-	**1.884±0.304**	**<0.001**
Patch richness density (Number per 100 ha, 1,000 m)	-	-	**0.608±0.175**	**0.001**	-	-
Arable land proportion (10,000 m)	-	-	-	-	0.674±0.378	0.075
Shannon diversity index (10,000 m)	**0.894±0.283**	**0.002**	-	-	-	-
Distance to impervious (m)	-0.257±0.416	0.537	-0.194 ±0.204	0.342	-	-
Impervious proportion (100 m)	-	-	-	-	**0.355±0.137**	**0.010**
Distance to forest (m)	-0.227±0.312	0.467	-	-	-	-
Forest proportion (10,000 m)	-	-	**0.313±0.119**	**0.008**	-	-
Wind turbine variables						
Rotor diameter (m)	0.162±0.270	0.549	0.037±0.151	0.805	0.532±0.344	0.122
Nacelle height (m)	0.153±0.270	0.572	0.192±0.145	0.185	-0.064±0.331	0.845
Average blade speed (km/h)	0.155±0.128	0.223	**-0.751±0.221**	**<0.001**	**-1.148±0.508**	**0.024**
Average blade speed^2	**-0.761±0.155**	**<0.001**	0.402±0.259	0.120	**1.775±0.513**	**<0.001**
Weather/date variables						
Julian day	**0.227±0.040**	**<0.001**	**-1.516±0.364**	**<0.001**	0.121±0.137	0.377
Julian day^2	0.028±0.052	0.585	**1.736±0.365**	**<0.001**	-	-
Julian day^3	**-0.417±0.035**	**<0.001**	**-**	**-**	-	-
Average temperature (°C)	**-0.507±0.133**	**<0.001**	**2.030±0.222**	**<0.001**	0.225±0.141	0.112
Average temperature^2	**1.044±0.126**	**<0.001**	**-1.055±0.201**	**<0.001**	-	-
Average wind speed (m/s)	**-1.988±0.159**	**<0.001**	**-3.272±0.269**	**<0.001**	**-1.868±0.584**	**0.001**
Average wind speed^2	**1.963±0.155**	**<0.001**	**2.751±0.272**	**<0.001**	**1.630±0.438**	**<0.001**
Cumulated rain (mm)	**-0.178±0.031**	**<0.001**	**-0.330±0.052**	**<0.001**	**-0.422±0.185**	**0.022**