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HAL Authorization

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

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21

22 **Abstract**

23 Wind turbine development is growing exponentially and faster than other sources of renewable
24 energy worldwide. While multi-turbine facilities have small physical footprint, they are not free
25 from negative impacts on wildlife. This is particularly true for bats, whose population viability
26 can be threatened by wind turbines through mortality events due to collisions. Wind turbine
27 curtailment (hereafter referred to as “blanket curtailment”) in non-winter periods at low wind
28 speeds and mild temperatures (i.e. when bats are active and wind energy production is low) can
29 reduce fatalities, but show variable and incomplete effectiveness because other factors affect
30 fatality risks including landscape features, rain, turbine functioning, and seasonality. The
31 combined effects of these drivers, and their potential as criteria in algorithm-based curtailment,
32 have so far received little attention. We compiled bat acoustic data recorded over four years at
33 34 wind turbine nacelles in France from post-construction regulatory studies, including 8,619
34 entire nights (251 ± 58 nights per wind turbine on average). We modelled nightly bat activity in
35 relation to its multiple drivers for three bat guilds, and assessed whether curtailment based on
36 algorithm would be more efficient to limit bat exposure than blanket curtailment based on
37 various combinations of unique wind speed and temperature thresholds. We found that
38 landscape features, weather conditions, seasonality, and turbine functioning determine bat
39 activity at nacelles. Algorithm-based curtailment is more efficient than blanket curtailment, and
40 has the potential to drastically reduce bat exposure while sustaining the same energy production.
41 Compared to blanket curtailment, the algorithm curtailment reduces average exposure by 20 to
42 29% and 7 to 12% for the high-risk guilds of long- and mid-range echolocators, and by 24 to
43 31% for the low-risk guild of short-range echolocators. These findings call for the use of
44 algorithm curtailment as both power production and biodiversity benefits will be higher in most
45 situations.

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

48 **1. Introduction**

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

64 In the European Union and in many countries worldwide, wind energy developers must carry
65 out an Environmental Impact Assessment (EIA) prior to any wind farm installation to evaluate
66 potential environmental consequences and the measures required to avoid impacts. Developers
67 must also monitor impacts during the operational phase (e.g. decree no. 0198 of August 27,
68 2011, in France). However, guidelines to avoid “areas where high bat activity has been
69 determined by impact assessment” (EUROBATS; Rodrigues et al., 2015) appear to be poorly
70 implemented (Barré et al., 2022). When impacts cannot be avoided, measures for their reduction
71 or, as a last resort, offsetting, must be implemented to achieve a state of no net loss of
72 biodiversity (i.e. the mitigation hierarchy framework; Business and Biodiversity Offsets

73 Programme (BBOP), 2012). Wind turbine curtailment at low wind speeds and mild
74 temperatures – when bats are highly active and energy production is low, hereafter referred to
75 as “blanket curtailment” – is a reduction measure that offers promising opportunities to
76 reconcile bat conservation and wind energy (Adams et al., 2021; Whitby et al., 2021; Voigt et
77 al., 2015; Arnett et al., 2011; Baerwald et al., 2009). One of the most common blanket
78 curtailment strategies is based on a simple combination of a maximum wind speed threshold
79 (most often between 3.5 and 8 m/s) and a minimum temperature threshold (most often around
80 10°C). Respectively below and above those thresholds, the blades are turned to a different angle
81 (i.e. feathered) to limit their rotation rate to less than one per minute, due to expected favourable
82 conditions for bats. Blanket curtailment is mostly limited to non-winter periods. This approach
83 can significantly reduce the fatality risk, but shows variable and incomplete effectiveness
84 (Voigt et al., 2022; Adams et al., 2021; Whitby et al., 2021; Măntoiu et al., 2020). Besides wind
85 speed and temperature, landscape features and other weather factors such as rain also drive bat
86 fatality risk (Thompson et al., 2017; Santos et al., 2013). Indeed, bat activity at wind turbine
87 nacelles, which links to fatality risk (Peterson et al., 2021; Korner-Nievergelt et al., 2013), also
88 depends on the weather, season, landscape features, and wind turbine dimensions and rotation
89 speed (Roemer et al., 2019; Behr et al., 2017; Cryan et al., 2014; Brinkmann et al., 2011; Horn
90 et al., 2008). Consequently, curtailment strategies based on multifactor algorithms have the
91 potential to be more efficient in reducing the fatality risk. Indeed, the use of an algorithm to
92 curtail wind turbines in real-time based on weather factors, date, and nightly time, should allow
93 avoiding most collisions while minimizing the loss of production (Behr et al., 2017).

94 Behr et al. (2017) and Brinkmann et al. (2011) are two of the few studies that propose this type
95 of multicriteria framework to curtail wind turbines. These studies were based on data sampled
96 in 2008 in Germany covering six months at 70 wind turbine nacelles and 35 different sites. To
97 our knowledge, no peer-reviewed study has examined simultaneously and on a

98 spatiotemporally extensive dataset all drivers of bat exposure (i.e. landscape features, weather
99 conditions, date, and wind turbine characteristics), nor assessed the possibility to use them in
100 guild specific algorithms to inform wind turbine curtailment.

101 To assess the potential of multicriteria curtailment algorithms, we compiled bat acoustic data
102 recorded at wind turbine nacelles in France by wind energy developers in a context of post-
103 construction regulatory studies, while homogeneously re-analysing acoustic data (i.e. using the
104 same automated bat call identification software). Reprocessed bat acoustic data allowed us to
105 build a standardised bat activity metric at nacelle height known to be a good predictor of fatality
106 risk (Peterson et al., 2021; Korner-Nievergelt et al., 2013). Given the absence of national
107 guidelines in France concerning the characteristics and settings of bat recorders for bat
108 monitoring at nacelles and the large number of engineering consultants involved in data
109 collection, we expected a large variation in the methods (Coly et al., 2017). Thus, our first
110 objective was to assess whether monitoring methods (devices and settings) or confounding
111 effects with landscape features, date, weather and wind turbine characteristics would bias the
112 comparison of bat activity between wind turbines. This assessment was intended to filter out
113 data from some wind turbines if necessary, and highlight the need for better national or
114 international cooperation in the choice of materials and parameters in the case where the current
115 situation would not allow meta-analyses. Once any method bias was controlled for, our second
116 objective was to determine the main factors influencing bat activity at nacelles. We expected
117 bat activity to increase with increasing landscape quality (e.g. by an increasing amount of
118 forests, proximity to wetlands, or land use heterogeneity; Put et al., 2019; Sirami et al., 2013;
119 Boughey et al., 2011a) and decreasing blade rotation speed (Cryan et al., 2014; Horn et al.,
120 2008), and to be higher during nights with good weather conditions (i.e. high temperature, low
121 wind speed and no rain; Voigt et al., 2015; Erickson and West, 2002) and at the end of summer
122 (Heim et al., 2016). Finally, our third objective was to compare on a per-night scale the

123 performance of a curtailment algorithm based on multiple factors to that of a blanket curtailment
124 method based on various combinations of unique wind speed and temperature thresholds, in
125 terms of both bat activity exposure and energy production. We expected the algorithm-based
126 curtailment to be more efficient in reducing bat exposure compared to blanket curtailment, by
127 avoiding a larger percentage of bat activity occurring when blades are moving, while involving
128 smaller losses of energy production.

129 **2. Methods**

130 *2.1. Acoustic data collection and processing*

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

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

147 Acoustic monitoring was always performed throughout the night, from sunset to sunrise. We
148 used the number of bat passes (hereafter referred to as “activity”) or the presence/absence
149 (hereafter referred to as “occurrence”) recorded during a night as a measure of bat visits with
150 exposure (see section 2.3 for more details). We defined a bat pass as one or more echolocation
151 calls within a five-second interval (Kerbiriou et al., 2019). All 731,717 bat passes were
152 automatically classified to the closest taxonomic level using the Tadarida software (Bas et al.,
153 2017). Since most bat species had very low occurrence (Table S1), we pooled together species

154 into three guilds based on their similar echolocation call structures and therefore similar
155 foraging strategies: long-range echolocators (LRE), mid-range echolocators (MRE) and short-
156 range echolocators (SRE) (Frey-Ehrenbold et al., 2013), see Table S2 for species composition.
157 Long-range echolocators are especially sensitive to fatality risks with wind turbines due to the
158 great part of the time they spend at height (i.e. 20 to 45 m above ground level), followed by the
159 mid-range echolocators (Table S2; Roemer et al., 2017). Although grouping species into these
160 three guilds prevented misidentification problems between cryptic species, noise in the nacelle
161 due to wind turbine functioning generated many false positives, especially at very high blade
162 speeds. We followed the approach of Barré et al. (2019) and applied a maximum false positive
163 tolerance of 50% to discard these interferences (see Barré et al. (2019) for more details), which
164 reduced the dataset to 98,627 bat passes. This reduction led to discard 6.55 to 9.93% fewer false
165 positives for Batmode data compared to other recorders.

166

167 *2.2. Environmental and wind turbine variables*

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

171 *Landscape variables* - We considered variables representing the surface cover of five land-use
172 types known to positively or negatively affect bats: impervious surfaces (Azam et al., 2016;
173 Dixon, 2011), arable lands (Put et al., 2019), grasslands (Froidevaux et al., 2017; Roeleke et
174 al., 2016; Lentini et al., 2012), forests (Heim et al., 2017; Boughey et al., 2011a) and water
175 bodies (De Conno et al., 2018; Sirami et al., 2013). These variables were computed around the
176 59 wind turbines as proportions of the total area for variables presenting enough variations
177 (impervious surfaces, arable lands, grasslands and forests), in ten area buffers around wind
178 turbines (50, 100, 250, 500, 1000, 2000, 3000, 4000, 5000 and 10000 m radius) to use the most

179 relevant scale for each variable (Kalda et al., 2015, see Statistical Analysis section for more
180 details). We also calculated the Euclidean distance to the nearest impervious surfaces, forests
181 and water bodies. Moreover, we computed landscape metrics depicting landscape
182 configurational and compositional heterogeneity (Monck-Whipp et al., 2017), including edge
183 density (i.e. the density of ecotones in m/ha), conditional entropy (i.e. an increasing index with
184 increasing landscape complexity), patch richness density (i.e. the number of patch types
185 standardised by the surface), and Shannon diversity index of habitat patches. These landscape
186 metrics were computed using the R package *landscapemetrics* (Hesselbarth et al., 2019), for
187 the ten radius sizes presented above. All landscape variables were extracted from the high-
188 resolution CES OSO land cover map 2018 available at [https://www.theia-](https://www.theia-land.fr/en/ceslist/land-cover-sec/)
189 [land.fr/en/ceslist/land-cover-sec/](https://www.theia-land.fr/en/ceslist/land-cover-sec/) (Derksen et al., 2020).

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

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

201

202 *2.3. Statistical analysis*

203 We assessed drivers of measures of bat activity and occurrence around wind turbine nacelles,
204 including factors related to landscape composition and heterogeneity, weather conditions, the
205 Julian day, wind turbine functioning and dimensions and recording methods (i.e. the recorder
206 type and the trigger sensitivity). In the first step, since we compiled data produced by different
207 contributors, we expected the existence of multiple combinations between the recorder type and
208 the trigger sensitivity. However, these recording methods deeply affect the number of bat passes
209 recorded (Adams et al., 2012). Confounding effects between recording methods and factors of
210 interest (e.g. landscape composition) could prevent modeling them simultaneously. Using all
211 compiled data, we therefore tested for trends in the landscape composition and heterogeneity,
212 weather conditions, and wind turbine functioning and dimensions between recording methods
213 (i.e. a discrete variable including seven combinations between the recorder type and the trigger
214 sensitivity), using Kruskal-Wallis tests and box plots. We then computed the proportion of
215 variance explained by each variable (*pseudo-R*²) to assess whether the importance of the factors
216 of interest (actual drivers of bat activity) was biased by the different recording methods. To
217 properly study the drivers of bat activity at wind turbine nacelles, a prerequisite was that the
218 recording methods do not capture an overwhelming part of the variance compared to the factors
219 known to affect bat activity. To achieve this, we built one full Generalised Linear Mixed Model
220 (GLMM, R package *glmmTMB*; Brooks et al., 2017) per bat guild, using LRE and MRE activity
221 and SRE occurrence as response variables, and the landscape (see Supporting information S2
222 for landscape variable selection and composition), weather conditions (i.e. average wind speed,
223 average temperature and cumulated rain), the Julian day, and wind turbine functioning (i.e.
224 average blades rotation speed) and dimensions (i.e. nacelle height and rotor diameter) as fixed
225 effects (hereafter referred to as “explanatory variables”). Since we had a relatively small
226 number of sites, we restricted the number of landscape variables to three; i.e. the same number
227 as the other types of variables (i.e. three weather variables and three wind turbine functioning

228 and dimension variables available). With such approach, models were always constituted of ten
229 variables, allowing to avoid overparameterization. For landscape variables we pre-selected the
230 best computing area buffer and in a second step selected the three ones – within the five
231 landscape variables – with the best conjoint contributions (see Supporting Information S2 for
232 more details). We used the wind turbine identifier and year as random effects to account for
233 pseudo-replication (i.e. many recording nights per wind turbine) and inter-year variations in
234 activity, associated with a negative binomial distribution for LRE and MRE guilds and a
235 binomial distribution for SRE guild (see Supporting information S2 and Table S4 for the
236 composition of full models). Then, we computed the *pseudo-R*² of each variable by subtracting
237 the *marginal R*² of the full model and that of the model without the target variable, using the R
238 package *sjstats*.

239 The preliminary analysis showed that recording methods resulted in confounding effects with
240 most other variables of interest and captured the largest variance part (Table S5; Figs. 2 & S2).
241 Thus, to model bat activity or occurrence as a function of explanatory variables, we selected in
242 a second step only one combination between the recorder type and the trigger sensitivity that
243 removed any variation in recording methods. We chose the combination of the Batmode set to
244 a trigger sensitivity of 37 dB SPL which had the largest dataset resulting in 34 wind turbines,
245 8,619 nights and 65,775 bat passes. Based on this subset, we performed the same GLMMs
246 workflow as presented above (see Supporting information S2 and Table S6 for more details) to
247 assess the respective effects of explanatory variables on the LRE and MRE activity and SRE
248 occurrence. For each explanatory variable, we checked the potential need for adding a non-
249 linear effect by visual inspection of Generalised Additive Mixed Models (GAMM, R package
250 *mgcv*; Wood, 2011; see Table 1 for variables that required quadratic or cubic effects). We also
251 checked the absence of multicollinearity by calculating the Variance Inflation Factor (VIF) for
252 each explanatory variable (R package *performance*; Lüdtke et al., 2021). All variables showed

253 a $VIF < 2$, implying no evidence of multicollinearity (Chatterjee and Hadi, 2006). It should be
254 noted that wind speed and blade speed were not excessively correlated thanks to maintenance
255 periods that stopped the turbines in all wind conditions (Fig. S3). Overall model validation was
256 performed using diagnostic plots (R packages *DHARMA* and *performance*; Lüdtke et al.,
257 2021). Full models were compared to null ones using the Akaike information criterion (AIC)
258 (Burnham and Anderson, 2002), and goodness of fit was assessed using the marginal R^2
259 (variance explained by the fixed effects) and conditional R^2 (variance explained by both fixed
260 and random factors) values (Nakagawa and Schielzeth, 2013). All analyses were performed
261 using a significance threshold of 5% in R statistical software v.4.0.3 (R Core Team, 2020).

262

263 *2.4. Assessing the effectiveness of using model equations to limit bat exposure compared to* 264 *conventional curtailments*

265 Using the same Batmode dataset, we assessed whether curtailment of wind turbines based on
266 multiple-factor models could be more efficient in limiting bat activity exposure at the scale of
267 all wind turbines than commonly used blanket curtailment methods. For that, we trained full
268 models for each guild on a 50% fully random subset of the dataset (hereafter referred to as
269 “training dataset”) and predicted bat activity on the other 50% (hereafter referred to as
270 “prediction dataset”), and this 100 times. Then, we computed for each prediction dataset the
271 remaining percentage of bat activity (for LRE and MRE guilds) or occurrence (for SRE guild)
272 (i.e. the real bat activity or occurrence recorded while the blades were moving) and the
273 percentage of lost blade rotations (i.e. as a proxy of lost energy production) resulting of
274 curtailing wind turbines following either of two methods: (i) curtailing above thresholds of bat
275 activity predicted from full models (hereafter referred to as “multicriteria curtailment
276 algorithm”), and (ii) curtailing below wind speed thresholds and this either without temperature
277 threshold or with different minimum temperatures required from 2 to 18°C (hereafter referred

278 to as “blanket curtailment”). Finally, we plotted the relationship between the remaining
279 percentage of bat activity or occurrence and the percentage of lost blade rotations for both
280 curtailment methods to evaluate their effectiveness in limiting exposure (Fig. 3A). The
281 comparison of both curtailment methods was conducted for the non-winter periods only.

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

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

300 **3. Results**

301 *3.1. Bat monitoring*

302 A total 98,627 bat passes were recorded at 59 wind turbines and 14,937 nights. However, as
303 described above, in order to avoid confounding effects between recording methods and other
304 explanatory variables, we only selected wind turbines monitored using Batmode recorders
305 which exhibited no trigger sensitivity variation, while including most of the data (i.e. 34 wind
306 turbines out of 59 and 8,619 nights out of 14,937). Data from Batmode resulted in a total of
307 65,775 bat passes recorded, with 43,519 passes of LRE, 22,135 passes of MRE and 121 passes
308 of SRE (see Table S3 for species composition). At least one pass of LRE, MRE and SRE was
309 recorded in 35%, 18% and 1% of nights, respectively (Table S3).

310

311 *3.2. Drivers of bat activity around nacelles*

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

316 Regarding landscape variables, LRE activity was positively affected by the landscape Shannon
317 diversity index of habitat patches at the 10,000 m radius scale while MRE activity increased
318 with increasing patch richness density at the 1,000 m radius scale and forest proportion at the
319 10,000 m radius scale. We also found significant positive relationships between SRE
320 occurrence and edge density at the 10,000 m radius scale and the proportion of impervious
321 surfaces at the 100 m radius scale (Fig. 4; Table 1). Concerning wind turbine functioning and
322 dimensions, increasing average blade speed significantly reduced the activity/occurrence of all
323 guilds, while no effect of nacelle height and rotor size were found (Figs. 4; Table 1). Concerning

324 weather conditions, average temperature positively and non-linearly affected the activity of
325 LRE and MRE guilds, while the average wind speed and the cumulated rain negatively affected
326 (non-linearly and linearly, respectively) the activity/occurrence of all guilds (Fig. 4; Table 1).
327 Finally, we found seasonality in the activity of the LRE and MRE guilds, manifested as a cubic
328 and quadratic relationship, respectively, with the Julian date: increasing between January and
329 August, and decreasing from September to December (Fig. 4; Table 1).

330

331 *3.3. Effectiveness of model equations to limit bat exposure compared to conventional* 332 *curtailments*

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

342 When we linked the real bat activity or occurrence exposed with the percentage of lost blade
343 rotations, we found that the multicriteria curtailment algorithm was more efficient than the
344 blanket curtailment for all guilds (Figs. 3B & 5). We found that the multicriteria curtailment
345 algorithm at the scale of all wind turbines exhibited on average 20% and 9% less bat activity
346 exposed than blanket curtailment without temperature threshold for LRE and MRE guilds,
347 respectively, and 24% less occurrence exposed for SRE guild (Fig. 3B1). When blanket
348 curtailment included temperature thresholds, the multicriteria curtailment algorithm exhibited

349 on average 20 to 29%, 7 to 12% and 24 to 31% less exposure for LRE, MRE and SRE guilds,
350 respectively, depending on the temperature threshold considered in blanket curtailment (Figs.
351 3B2 & 5). The higher efficiency of the multicriteria curtailment algorithm was confirmed by its
352 AUC values which were higher than those of blanket curtailment for a 10°C threshold at 81 and
353 75% of wind turbines for LRE and MRE guilds, respectively (Figs. S5 & S6). Finally, when
354 the algorithm was trained on 33 out of 34 wind turbines and predictions made on the remaining
355 wind turbine(i.e. model training and predictions based on independent sites), algorithm
356 curtailment had higher AUC values than blanket curtailment at 81 and 69% of wind turbines
357 for LRE and MRE, respectively (Fig. S7 & S8).

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

361 **4. Discussion**

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

374

375 *4.1. Assessing bias in recording methods*

376 One of the aims of this study was to take advantage of the numerous pre-existing data from
377 post-construction monitoring studies instead of designing a field study that would require
378 paramount monetary and time investments. A prerequisite for using all aggregated data was the
379 absence of biases related to the recording methods. Unfortunately, when considering data
380 collected using different recording methods, the combination of recorder type and triggering
381 sensitivity explained much more variance than all well-known drivers of bat activity (Roemer
382 et al., 2019; Behr et al., 2017; Cryan et al., 2014; Horn et al., 2008), minimizing their relative
383 importance in the models. All gradients of drivers strongly varied among recorder type/trigger
384 sensitivity combinations, thus preventing any modelling of the effects of drivers on bat activity
385 based on the full dataset due to confounding effects. Indeed, different recorder type/trigger

386 sensitivity combinations can lead to very different levels of bat activity between sites due to the
387 different detection distances generated by the material specificities and settings (Darras et al.,
388 2020; Adams et al., 2012). We opted to compensate for this problem by modelling the effect of
389 the drivers on bat activity after separating the recorder type/trigger sensitivity combinations.
390 However, harmonising monitoring methods across all sites would avoid such partitioning and
391 loss of data. Alternatively, future studies could assess the possibility of using corrective
392 coefficients of activity between different recorder type/trigger sensitivity combinations, or
393 establish longer bat pass units, to make the sites monitored in different ways comparable.

394

395 *4.2. Drivers of bat activity around nacelles*

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

401 Specifically, LRE and MRE activity increased with the Shannon diversity index of habitat
402 patches and patch richness density, respectively, as previously reported by (Froidevaux et al.,
403 2022; Mendes et al., 2017; Monck-Whipp et al., 2017). Edge density also positively affected
404 the SRE guild occurrence, as previously documented for hedgerow density (Lacoeuilhe et al.,
405 2016; Verboom and Huitema, 1997) or the density of all edge habitats (Ancillotto et al., 2017;
406 Mendes et al., 2017). We also found forest cover to positively affect MRE activity, consistent
407 with Roemer et al. (2019), who showed that bat activity at height decreased with the distance
408 to the forest, and with Boughey et al. (2011a) who found higher bat activity at ground level
409 with an increasing proportion of forest. Unexpectedly, our model revealed a positive effect of
410 impervious habitat proportion on SRE activity, a relationship that is elsewhere described as

411 negative (Gili et al., 2020). Impervious habitat in this dataset corresponds to roads and the buffer
412 scale selected is very local (100m). This is likely an indirect positive effect related to
413 ecotone/hedgerow associated with roads (i.e. road access to a wind turbine), a favourable
414 context for foraging of narrow- and edge-space foragers of the SRE guild (Denzinger and
415 Schnitzler, 2013).

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

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

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

433

434 *4.3. Assessing the effectiveness of using model equations to limit bat exposure compared to*
435 *conventional curtailments*

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

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

456

457 *4.4. Limitations and recommendations*

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

466 To go further in the modelling of bat exposure, the curtailment algorithm method we propose
467 should be adapted on an intra-night scale to account for the variation of bat activity during the
468 night and thus minimise even more production losses (Behr et al., 2017). In addition, our
469 efficiency assessment does not rely on a real loss of energy production as such information is
470 rarely available from wind energy developers. However, as blade speed distributions do not
471 differ between lost blade rotations of both curtailment methods, the relative comparison of lost
472 blade rotations between curtailment methods as a proxy of energy production losses is not
473 biased. Bat activity around nacelles was reported to be a good proxy for fatality risk (Peterson
474 et al., 2021; Korner-Nievergelt et al., 2013), but we encourage further research on the
475 relationship between activity and mortality to refine algorithms towards an explicit reduction
476 of the real collision risk, either by giving more weight to conditions in which activity is most
477 strongly correlated with mortality or by using mortality data directly. Acoustic-informed
478 blanket curtailment is another method practised in North America, notably using the Turbine
479 Integrated Mortality Reduction (TIMR) system which, in addition to a wind-speed threshold,
480 integrates a real-time bat activity criterion. Although this system is not directly comparable to
481 our algorithm (intra-night timescale, effectiveness assessed using daily fatality surveys), it
482 seems to show similar effectiveness (i.e. a 37% reduction in exposure compared to blanket

483 curtailment) (Rabie et al., 2022; Hayes et al., 2019). Future studies could therefore compare
484 these two types of curtailment strategies on an equivalent basis to highlight the strengths and
485 weaknesses of each, especially regarding technological constraints. Finally, the baseline data
486 used to train the algorithm should be updated on a regular basis with data from the latest wind
487 turbine models in order to explicitly incorporate their dimensional changes into the modelling.

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

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

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516

517 **Author's contribution**

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

522

523 **Data accessibility**

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

525

526 **Conflict of Interest**

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

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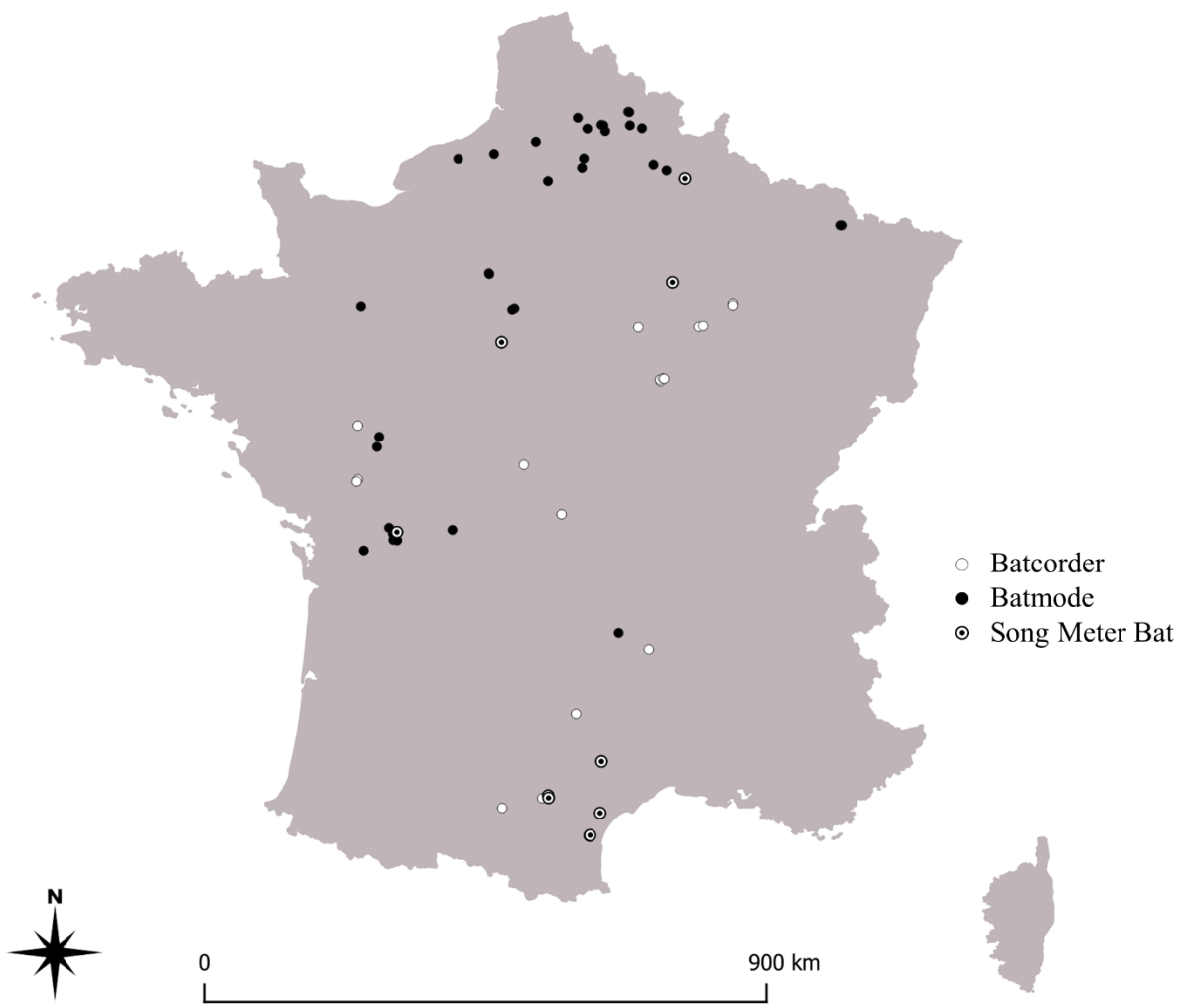
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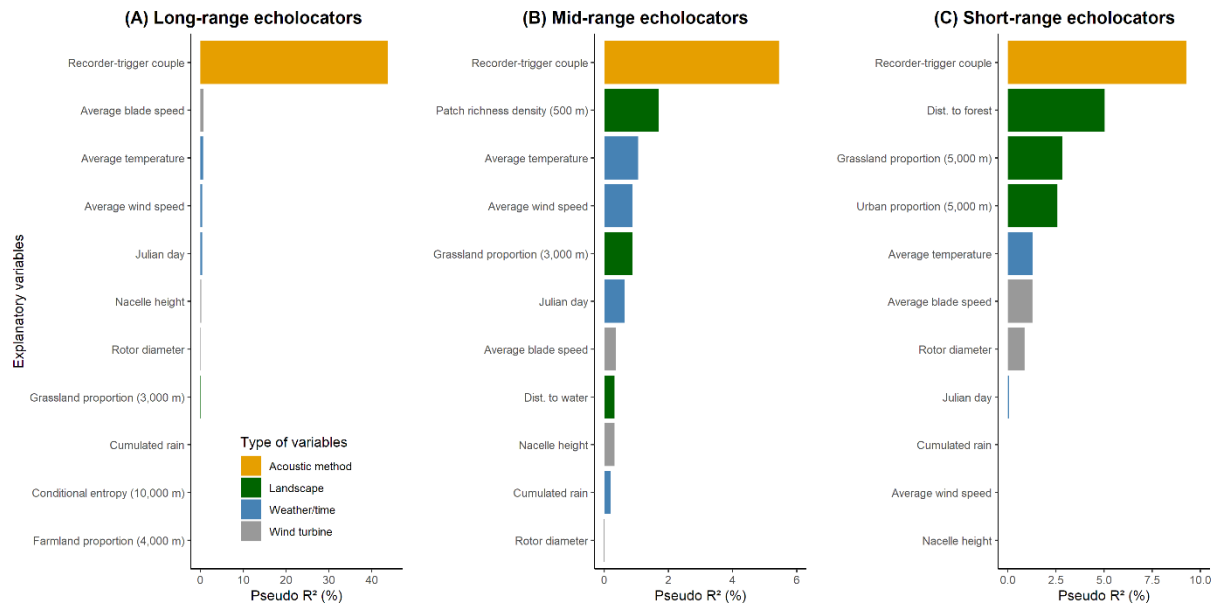
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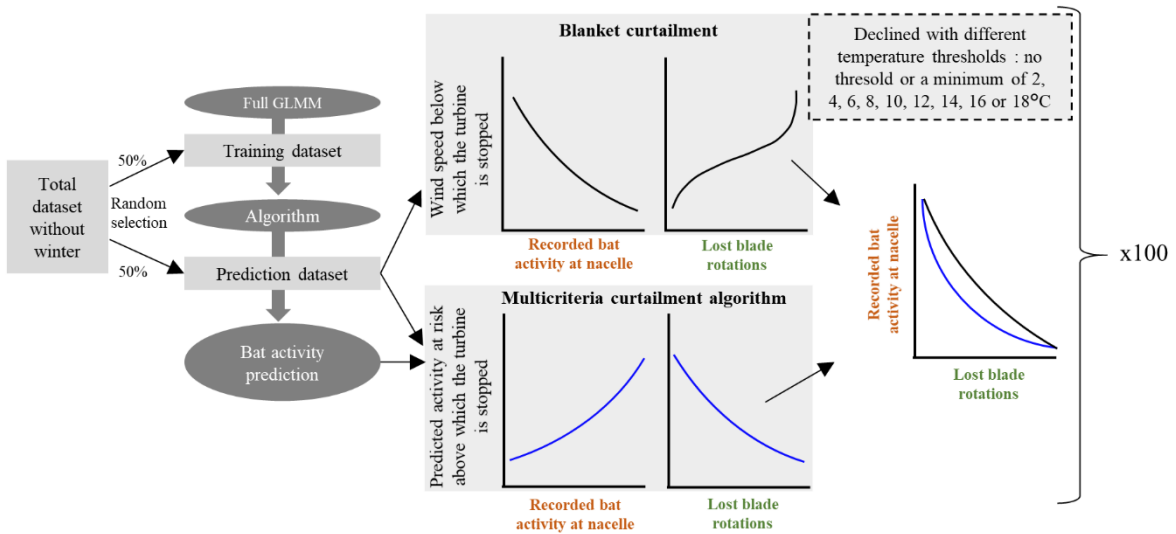
774 Figure 1. Location of monitoring sites in France according to bat recorder types.



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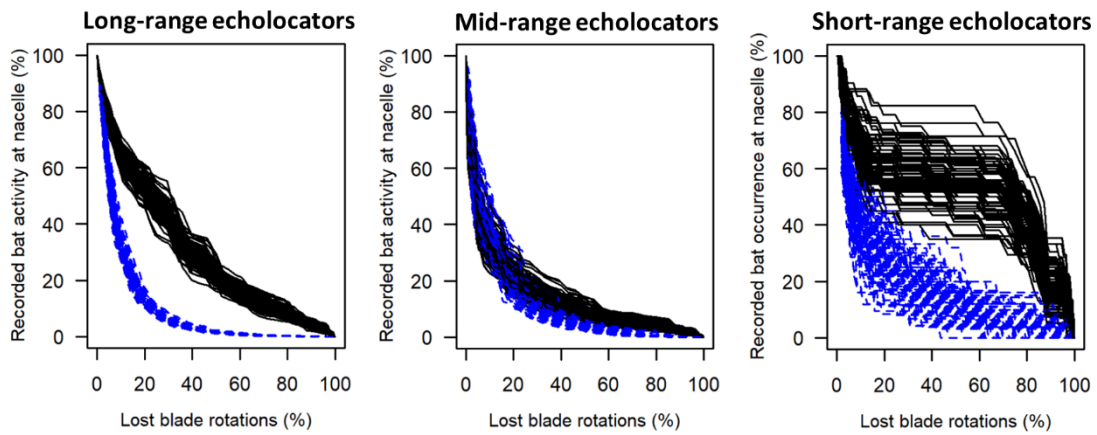
776 Figure 2. Percentage of bat activity and occurrence variance explained by each variable (i.e.
 777 pseudo- R^2) related to acoustic method, landscape, weather and time, and wind turbine features
 778 from generalized linear mixed models based on data from all recorder types (i.e. 59 sites, 14,937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

(A) Method for assessing the effectiveness of curtailment methods

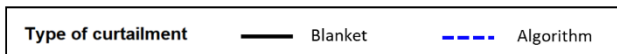
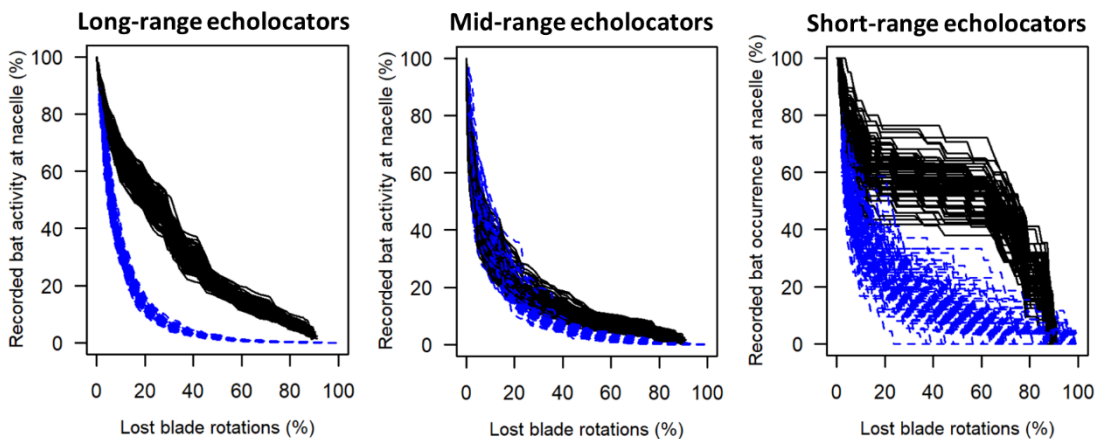


(B) Effectiveness of curtailment methods

(B1) Blanket curtailment based on wind speed thresholds only

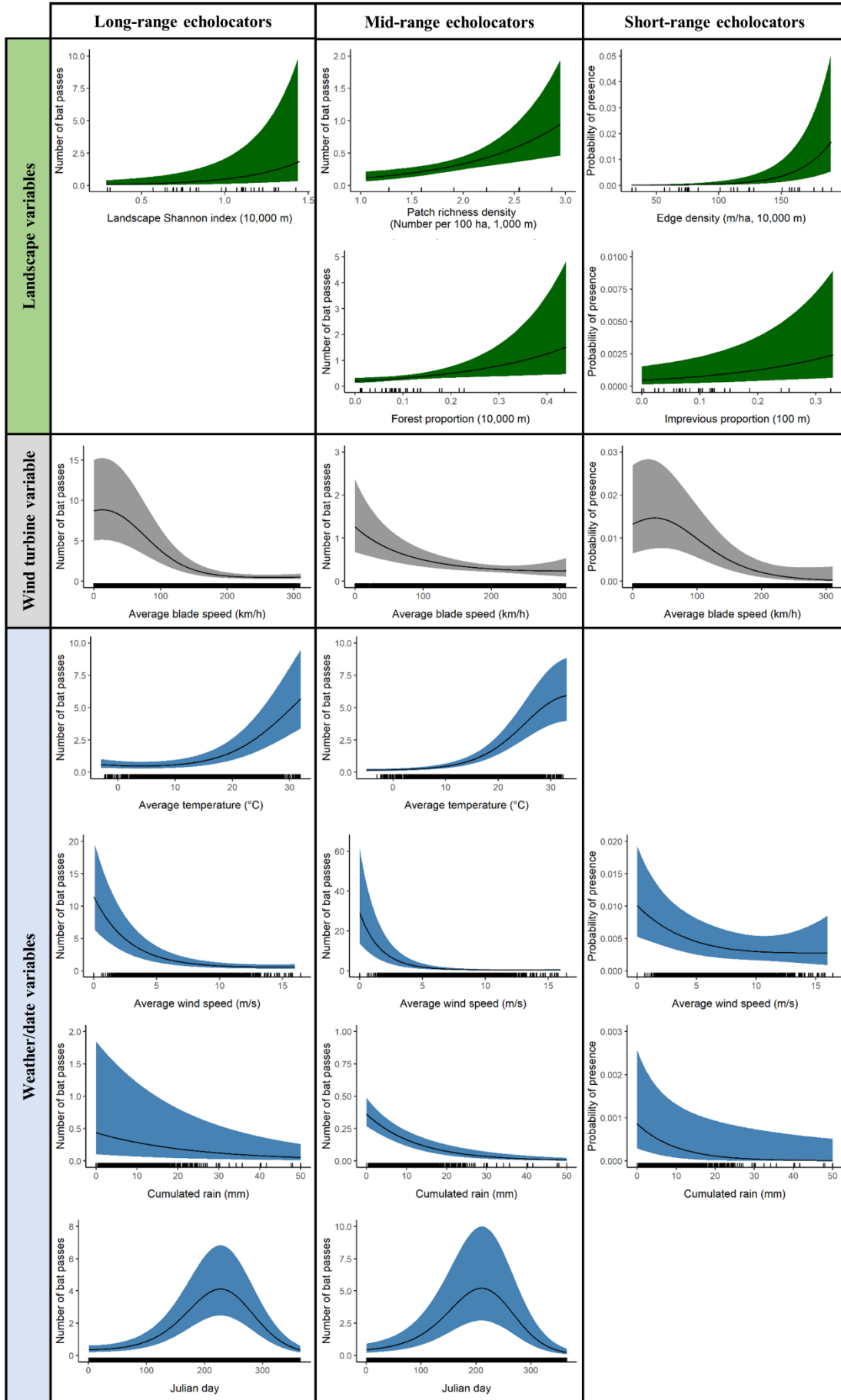


(B2) Blanket curtailment based on wind speed thresholds associated with a temperature > 10°C



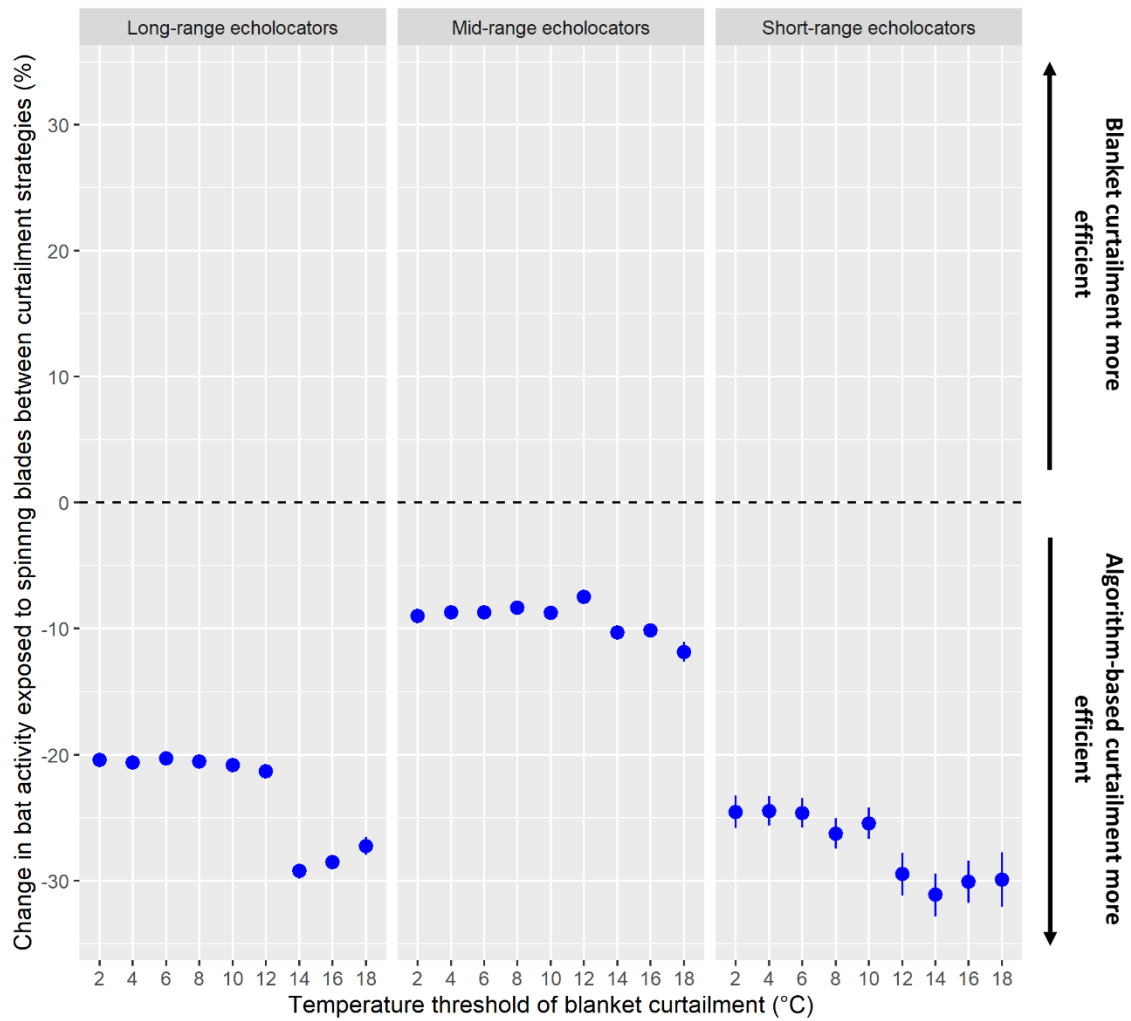
781 Figure 3. Panel A depicts the method to compare blanket (black) and algorithm-based (blue)
782 curtailment methods' effectiveness to limit bat activity exposure. One hundred iterations were
783 performed to train generalized linear mixed models (GLMM) on a random selection of 50% of
784 the Batmode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

795



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

801



802

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

807 Table 1. Estimates, standard errors and p-values from full models testing the effect of landscape,
808 wind turbine and weather/time variables on LRE and MRE activity and SRE occurrence.
809 Missing values indicate that the landscape variable was not selected in full models (only the
810 three best explaining ones per guild were included, see Statistical analysis section for more
811 details) or the no need for quadratic or cubic effects on weather/date variables. Significant
812 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
<i>Landscape variables</i>						
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	-	-
<i>Wind turbine variables</i>						
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
<i>Weather/date variables</i>						
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

813