

## Risk to European birds from collisions with wind-energy facilities

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### 3 **Abstract**

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5 In line with Europe's decarbonization goals, wind-power capacity is projected to increase in future  
6 years. However, wind-energy facilities can affect biodiversity; flying animals can fatally collide with  
7 wind-energy infrastructure. Here, we assessed the reported risk posed by collisions to 108 European  
8 birds, comparatively across species. We drew risk maps to assess current hotspots of risk. We  
9 employed a customised risk approach, considering that risk emerged from the interaction between  
10 (1) reported impacts (the total estimated number of fatalities at the species-level, accounting for  
11 current exposure to wind turbines) and (2) vulnerability to these impacts (the degree to which species  
12 may be affected by collision mortality). We used a quantitative synthesis of fatality numbers at wind-  
13 energy facilities to quantify collision-mortality rates at the species-level. We derived (1) by further  
14 combining these with information on species suitable areas and on current wind-turbine deployment.  
15 We estimated species' vulnerability from ecological characteristics (generation length, clutch size, and  
16 estimates of European suitable area) assumed to reflect species' ability to cope with disturbances.  
17 Overlapping vulnerability with estimated impacts, we classified species into different risk categories,  
18 considering species to be at higher relative risk when more vulnerable and more impacted. We  
19 assessed where species falling into the risk categories might occur, and where possible conflicts with  
20 wind-energy deployment might arise. We found several risk hotspots notably located in the Iberian  
21 Peninsula and Northern Europe. Our work helps inform wind-power deployment and spatial planning  
22 at the European scale with the aim of minimising negative biodiversity impacts.

## 23           **1. Introduction**

24   With the 2021 adoption of the European Climate Law, the European Union has committed to  
25   becoming climate-neutral by 2050, i.e., to reaching net-zero greenhouse gas emissions. Key to the  
26   EU's decarbonisation is the transformation of energy systems, most notably the reduction of fossil  
27   fuels and increases in the share of renewable energy sources. In 2022, wind power alone accounted  
28   for about 16% of the electricity demand in the EU (Wind Europe, 2022). In line with the European  
29   Climate Law, the installed capacity needs to increase by more than 100% to meet the 2030 targets (to  
30   reach a total capacity of 440 GW by 2030 with regards to the REPower EU energy target; Wind Europe,  
31   2022).

32           While wind energy is a key sector for renewable energy production, wind-energy facilities can  
33   have adverse impacts on biodiversity (Loss et al., 2013; Schöll & Nopp-Mayr, 2021). These impacts can  
34   be an important barrier to the social acceptance of wind power (Voigt et al., 2019; Vuichard et al.,  
35   2022). Negative biodiversity impacts can be attributed to land-use change and habitat disturbance  
36   occurring from the construction phase of the facilities and necessary structures (e.g., roads and power  
37   lines). Habitat disturbance can lead to the direct displacement of species through the loss of suitable  
38   habitat (Marques et al., 2020), and to reductions in local abundance and population densities  
39   (Fernández-Bellon et al., 2019). For flying animals, wind turbines may present a barrier inducing  
40   avoidance behaviour and altering migratory routes (Cabrera-Cruz & Villegas-Patracá, 2016; Santos et  
41   al., 2022a). Wind-energy facilities also constitute a collision hazard for flying animals, birds and bats  
42   in particular (Smallwood, 2013; Thaxter et al., 2017), but also insects (Voigt, 2021). Collision mortality  
43   can be of concern for the long-term viability of animal populations (Duriez et al., 2023; Gómez-Catasús  
44   et al., 2018; May et al., 2019). Of particular concern are species that cumulate multiple factors  
45   rendering them vulnerable to increased mortality, such as low population densities, slow pace of life,  
46   and/or species that are already threatened (Carrete et al., 2009; Desholm, 2009; Kuvlesky Jr. et al.,  
47   2010). For instance, large soaring birds have been a group of interest since their reliance on wind  
48   resources to gain altitude (thermal and orographic updrafts in particular) can conflict with areas  
49   favourable for wind-energy developments (Farfán et al., 2023; Santos et al., 2022b; Smeraldo et al.,  
50   2020) while poor flight manoeuvrability can make them prone to colliding, and low reproductive  
51   outputs can make the species more vulnerable to added mortality (Bellebaum et al., 2013; Dahl et al.,  
52   2013). Assessing the risk posed by collision mortality to different species is therefore important to  
53   inform spatial deployment and minimise biodiversity impacts.

54           Past research has shown that collision mortality is influenced by many factors, which can be  
55   broadly classified into three categories (Marques et al., 2014): (1) site-specific factors that relate to  
56   local landscape configuration and environmental features, such as wind speed, weather, landforms,

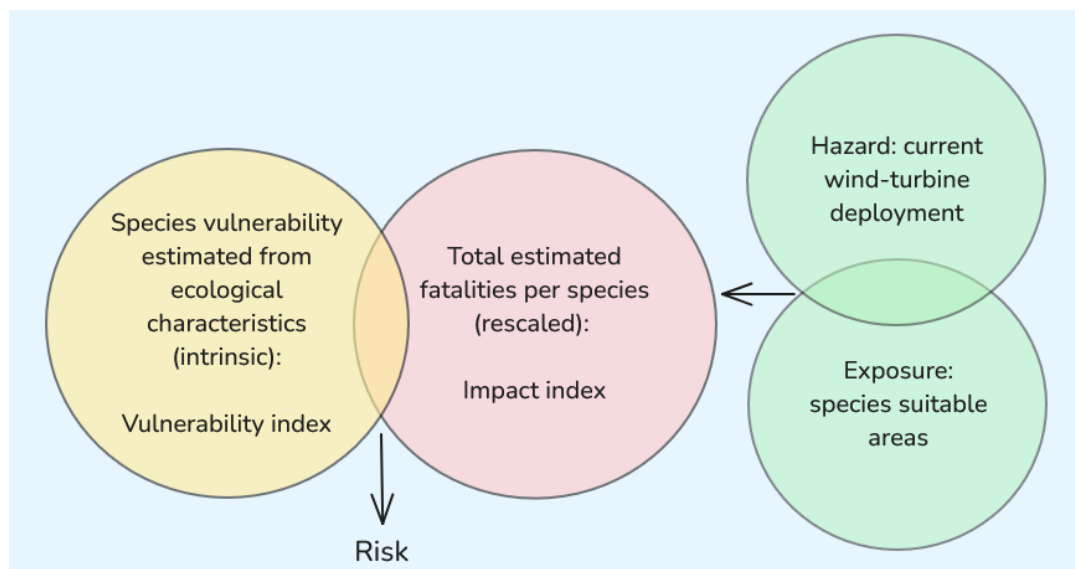
57 habitat availability for different species, etc; (2) characteristics of the wind-energy facilities, such as  
58 spatial configuration, turbine capacity, lighting, etc; and (3) species characteristics underlying  
59 vulnerability (e.g. seasonal occurrence, morphology, behaviour, etc. (May et al., 2015)). Collision  
60 mortality is influenced by complex interactions among these factors, which points to an important  
61 degree of context-specificity (Drewitt & Langston, 2008; Marques et al., 2014). Consequently, the  
62 siting of wind-energy facilities and their spatial configuration are important to reduce collision  
63 mortality (Carrete et al., 2012; Schaub, 2012). However, in a quantitative synthesis of collision-  
64 mortality data, Thaxter et al. (2017) notably showed that species' habitat preferences and dispersal  
65 distances were significantly associated with collision mortality. Using these associations, Thaxter et al.  
66 (2017) estimated the vulnerability of birds to collision at global scales, inferring collision-mortality  
67 rates for species for which there were no collision-fatality records. However, they did not investigate  
68 whether landscape characteristics were associated with collision risk; and did not consider the degree  
69 of exposure of different species to wind power.

70 Here, building upon Thaxter et al. (2017), we aimed to assess the risk to European birds from  
71 collision mortality, and to provide a spatial assessment of risk for Europe. Our main objective was to  
72 derive risk maps at the European scale that could be integrated into decision-making tools and inform  
73 spatial deployment. To this end, we drew from past risk and vulnerability approaches (Bellard et al.,  
74 2024; Foden et al., 2013; Intergovernmental Panel on Climate Change (2007, 2014)). We devised a  
75 custom risk approach considering that risk emerged from the interaction between species intrinsic  
76 vulnerability and from collision-mortality impacts (estimated total number of fatalities), which  
77 accounted for current exposure to wind turbines (Fig. 1). We estimated these two dimensions of risk  
78 (impacts and vulnerability) separately, thus independently deriving an 'impact index' and a  
79 'vulnerability index' at the species level.

80 First, we estimated the impact index using the data from Thaxter et al. (2017). In doing so,  
81 another important question arose: whether we could consider species for which there were no fatality  
82 records in our analyses, by estimating collision-mortality rates for such species from associations with  
83 species-level characteristics, following Thaxter et al. (2017). Therefore, a secondary objective of our  
84 study was to investigate whether collision-mortality rates were associated with species- and site-level  
85 characteristics, building upon Thaxter et al. (2017). Our rationale was that, should collision mortality  
86 be associated with these characteristics, we could estimate it based on such associations (Thaxter et  
87 al. 2017), therefore expanding the risk estimation to all European species, including those that were  
88 not in the data (rather than focussing only on species for which there were reported fatalities). Thus,  
89 within our risk framework, we investigated whether species- and site-level characteristics were  
90 associated with collision-mortality rates using statistical models, and whether such characteristics

91 outperformed taxonomy only in explaining the variation in collision-mortality rates. We further used  
92 the outputs of the models to estimate the impact index, combining estimated collision-mortality rates  
93 with information on wind-turbine deployment in Europe and on species' likely habitat suitability (i.e.,  
94 exposure; Fig. 1).

95 Second, we developed a vulnerability index that accounted for additional ecological  
96 characteristics reflecting species' likely intrinsic vulnerability to disturbances. Finally, we intersected  
97 the impact index with the vulnerability index to assess the risk across species. In line with vulnerability  
98 assessments, our approach was therefore comparative, reflecting the risk of the considered species  
99 relative to one another. As wind power is likely to expand in Europe in future years, and as species are  
100 unevenly affected by wind-energy facilities, assessing which factors influence collision mortality and  
101 evaluating which species and regions might be at more risk can help putting into place appropriate  
102 mitigation measures.



103  
104 **Fig. 1. Conceptual and terminological clarifications on risk and vulnerability.** Foden et al. (2019) described a  
105 change in the terminology relating to vulnerability and risk between the 4<sup>th</sup> and the 5<sup>th</sup> Intergovernmental Panel  
106 on Climate Change (IPCC) reports. In the IPCC 4<sup>th</sup> assessment (Intergovernmental Panel on Climate Change,  
107 2007), vulnerability emerges from the interaction of sensitivity (degree to which a system is likely to be affected,  
108 intrinsic), adaptive capacity (ability of a system to adjust, intrinsic), and exposure (degree of disturbance  
109 experienced by a system, extrinsic). Vulnerability defined as such is widely employed in the field of conservation  
110 biology for vulnerability assessments (e.g. Bellard et al., 2024; Foden et al., 2013). The IPCC 5<sup>th</sup> assessment report  
111 (Intergovernmental Panel on Climate Change, 2014) presented an alternative risk framework, with differences  
112 in terminology. Risk results from the interaction of vulnerability (considered intrinsic: propensity of a system to  
113 be negatively affected; encompasses notions of sensitivity and adaptive capacity), exposure (considered  
114 intrinsic: presence of system of interest in places that could be affected), and hazard (extrinsic: presence of a  
115 particular physical threat). For further clarifications, see Foden et al. (2019). Here, we built upon these  
116 frameworks to customize a risk approach. We considered risk as emerging from the interaction between  
117 vulnerability (intrinsic ability of species to cope with disturbances, here degree to which species might be able  
118 to withstand the additive mortality) and impacts, which we defined as the total estimated number of collision  
119 fatalities at the species level, accounting for the current exposure of species to wind turbines. Note that our  
120 definition of 'impact' therefore differs from that of the IPCC 5<sup>th</sup> assessment report (Foden et al., 2019).

## 121 **2. Materials and methods**

### 122 **2.1. Overview of the workflow**

123 Fig. S1 describes the conceptual framework and objectives for this work. Our aim was to assess the  
124 relative risk for European species, based on an estimation of vulnerability and of estimated impacts.  
125 A key consideration was whether we could extend the risk estimation to species for which there were  
126 no fatality records. Thus, a secondary aim was to assess whether collision-mortality rates were  
127 associated with species- and site-level characteristics, therefore investigating if collision-mortality  
128 rates could be estimated for all European species based on such possible associations (decision tree  
129 on Fig. S1; Section 2.2). The methodology behind the risk assessment (Section 2.3) was therefore partly  
130 informed by the Results from 2.2. in defining the taxonomic scope and modelling approach. In brief,  
131 we (1) estimated an index of collision-mortality impacts across species; impacts were quantified as  
132 the total number of fatalities estimated for each species. This index accounted for exposure and  
133 hazard (wind turbines overlapping with species suitable habitats), combined with estimated collision-  
134 mortality rates at the species level to estimate fatality numbers (2.2). (2) We built the vulnerability  
135 index by considering species' life history (generation length and clutch size) and rarity (European  
136 suitable range area), assuming such characteristics to be proxies for vulnerability, expressed as the  
137 species' ability to withstand the additional collision mortality. The rationale was that species with  
138 longer generation lengths and/or with fewer offsprings, and (geographically) rarer species, might be  
139 more vulnerable because, from a demographic point of view, it might take such species longer to  
140 recover from decreases in population size than species with shorter generation lengths, a larger clutch  
141 size, or than more (geographically) common species (Foden et al., 2019). (3) Finally, combining the  
142 impact index with the vulnerability index (Hyman et al., 2025), we assessed the comparative, relative  
143 risk across species and assessed which European regions harboured species at higher risk.

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### 145 **2.2. Are species- and site-level characteristics associated with collision-mortality rates?**

#### 146 **2.2.1. Fatality-count data**

147 We used data from Thaxter et al. (2017), in which peer-reviewed and non-peer-reviewed studies and  
148 reports that estimated collision mortality at wind-energy facilities were compiled. Thaxter et al. (2017)  
149 identified 88 sources for birds suitable for inclusion, spanning locations biased towards Europe and  
150 North America. The studies were heterogenous, e.g. varying in the number of wind turbines, sampling  
151 year(s), or search protocols. Thaxter et al. (2017) compiled estimates at the wind-energy facility level,  
152 also reporting turbine capacity, number of wind turbines, central location of the facility (central  
153 longitude and latitude of turbines), and study duration. In addition, Thaxter et al. (2017) estimated  
154 the quality of each study, e.g., whether studies corrected for carcass detectability (Huso & Dalthorp,

155 2014; Nilsson et al., 2023; Domínguez del Valle et al., 2020), characterising study quality as “very low”,  
156 “low”, “medium”, or “high”, depending on the application of correction factors. For further  
157 methodological details, see Thaxter et al. (2017).

158 Over 90% of the records reported either (annual) collision-mortality rates or fatality counts,  
159 depending on the study. We subset the data to include only such records (e.g., described as “annual  
160 mortality per turbine”, “total fatalities”) and for which study duration and number of turbines were  
161 known. We standardised the values across studies to obtain annual mortality rates throughout (i.e.,  
162 number of fatalities per year-turbine). These rates were converted back to count data prior to fitting  
163 the models, as required by Poisson models (thus we refer to these data to as ‘fatality-count data’;  
164 Supporting Information S2; Fig. S2).

165 Although our assessment focussed on European species, we considered sites located in other  
166 regions (e.g. North America), because we had no expectation that ecological characteristics should  
167 influence collision mortality differently in different regions. In addition, some species were sampled  
168 across several continents, so retaining all sites increased sample size. Despite this, the data remained  
169 biased, not only geographically (Fig. S3), but also taxonomically, with some species sampled only a few  
170 times (Fig. S4; 66% of the species were recorded at least twice, 47% at least three times, and 16%  
171 more than 10 times).

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### 173 **2.2.2. Investigating associations with species- and site-level characteristics**

174 We combined the fatality-count data with species-level ecological characteristics (Table 1a), targeting  
175 traits that related to movement (i.e., hand-wing index, migratory status) and species habitat  
176 preferences (Thaxter et al. 2017).

177 At the central location of the wind-energy facilities, we obtained four environmental  
178 characteristics: mean wind speed at 100 m, elevation, terrain roughness, and topographic index.  
179 Roughness reflected the variability in elevation around a location, while topographic index reflected  
180 whether a location was relatively lower or higher than its surroundings. We obtained mean wind  
181 speed from the Global Wind Atlas (<https://globalwindatlas.info/en>; data downloaded 23/10/2023 and  
182 aggregated at 1 x 1 km using an arithmetic mean). Elevation, roughness, and topographic index were  
183 derived from a global digital elevation model (Amatulli et al. (2018);  
184 <http://www.earthenv.org/topography>). We used different buffer sizes (0, 10, 100, 500, and 1000 m)  
185 to capture the landscape context around each location (extracting values around the locations falling  
186 within each buffer area, then using the mean across the buffer cells), but since the estimations were  
187 overall congruent across buffer sizes (Fig. S5) we used a buffer of 1 km around each location  
188 throughout.

189 First, we investigated whether species' ecological characteristics (Table 1a), site-level  
190 characteristics, turbine capacity and study quality were associated with collision-mortality rates. Study  
191 quality was specifically included to control for the degree to which corrections for carcass detectability  
192 were applied across studies (Thaxter et al., 2017). We fitted generalized linear mixed-effects models,  
193 using a Bayesian framework implemented with the R-package 'brms' (Bürkner, 2017, 2018, 2021). We  
194 fitted fatality counts (per record within each study) as the response, using a zero-inflated Poisson error  
195 distribution to account for excess-zeroes, using an offset variable to control for study duration and  
196 varying number of turbines within wind-energy facilities. Random intercepts accounted for variation  
197 in experimental design across studies and for the spatial structuring of sites and studies; another  
198 random intercept accounted for the identity of species, controlling for repeated observations and  
199 taxonomic non-independence. We fitted an observation-level random effect to control for  
200 overdispersion (Harrison, 2014). Drawing on Thaxter et al. (2017)'s findings that species with  
201 intermediate dispersal distances had significantly higher collision-mortality rates, and on the  
202 association between hand-wing index and dispersal (Sheard et al., 2020; Weeks et al., 2022), we  
203 treated hand-wing index as a continuous predictor with a quadratic effect. In the first iteration of this  
204 model (referred to as 'trait model'), we considered the effects of habitat openness, but we further  
205 tested if using habitat categories instead of openness (Table 1a) improved the model. The initial trait  
206 model considered the effects of mean wind speed, and we further tested whether adding the other  
207 site-level variables (terrain roughness, elevation, topographic index) improved the model.

208 Second, we fitted an alternative model, whereby species identity was fitted as a fixed effect, while  
209 other species- and site-level characteristics were removed (except for turbine capacity and study  
210 quality). This model (referred to as 'taxonomic model') was used to assess whether species- and site-  
211 level characteristics outperformed taxonomy in explaining the variation in collision-mortality rates  
212 across species.

213 Each model was fitted through Markov-Chain Monte Carlo, using 4 chains, 5000 warm-up  
214 iterations, 50,000 sampling iterations, and thinning intervals of 10 with weakly informative priors to  
215 improve sampling convergence. We compared all six models using the '*loo\_compare*' function of the  
216 brms package, using 'elpd' differences (Vehtari et al., 2017).

217

218 **Table 1. Ecological characteristics considered (a) in the models investigating associations between**  
 219 **species-level characteristics, site-level characteristics, and collision-mortality rates; (b) in the**  
 220 **comparative assessment of species vulnerability: definitions and sources.**

	Ecological characteristic	Definition	Sources
(a) Used in the 'Trait' model	<b>Migratory status</b> (categorical)	Species classified as: <ul style="list-style-type: none"> <li>- migratory (long-distance migration occurs across most of the species' population)</li> <li>- partially migratory (population composed of both migratory and resident individuals (Chapman et al., 2011)).</li> <li>- sedentary.</li> </ul>	Tobias et al. (2022) Note: the migratory status for <i>Gyps fulvus</i> was changed from sedentary to partially migratory <sup>1,2</sup> .
	<b>Hand-wing index (HWI)</b> (continuous; log)	HWI is a standardisation of Kipp's distance (distance between tip of 1st secondary feather to tip of the longest primary feather) with wing length. It is a widely-used proxy for dispersal ability (Sheard et al., 2020; Weeks et al., 2022).	Tobias et al. (2022)
	<b>Species' preferred habitat openness and preferred habitat</b> (categorical)	Description of species' preferred habitat (e.g. forest, grassland, shrubland, wetland, coastal, marine, human modified) and habitat openness (one of open, semi-open or dense)	Tobias et al. (2022)
	<b>Flight mode</b> (categorical): soaring species versus others	Following Santangeli et al. (2018), Shiomi, (2022) and Watanabe (2016), species classified as soaring when part of the following Orders: Accipitriformes (22 species), Cathartiformes (1), Falconiformes (7), and Pelecaniformes (10). We additionally considered species in the Gruidae Family (2), in the Procellariidae Family (2), in the Ciconiidae Family (2) and in the Laridae Family (18). Finally, one species of the <i>Corvus</i> genus was considered as soaring. See Supporting Information (S5) for more details.	Ad-hoc classification
(b) Used in vulnerability estimation	<b>Generation length (GL)</b> (continuous)	Average age of parents of the current cohort (Pacifi et al., 2013)	BirdLife; Bird et al., (2020)
	<b>Clutch size (CS)</b> (continuous)	Number of eggs (species-level average)	Myhrvold et al. (2015)
	<b>Area of habitat suitability (SA)</b> (continuous)	From habitat suitability maps: surface area where habitat suitability >0, weighted by habitat suitability ( $SA = \sum_i^n area_i * suitability_i$ where $i...n$ are grid cells). Suitability maps were derived from an integrated species distribution modelling approach; see 2.3.1.	See 2.3.1.

221 <sup>1</sup><https://datazone.birdlife.org/species/factsheet/griffon-vulture-gyps-fulvus>

222 <sup>2</sup><https://birdsoftheworld.org/bow/species/eurgr1/cur/movement>.

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## 227 **2.3. Risk estimation**

### 228 **2.3.1. Impact index**

229 We used the database from Fischereit et al. (in preparation), in which publicly available and  
230 commercial datasets (including <https://www.thewindpower.net/>) were combined to create a  
231 European wind-turbine database. We combined wind-turbine locations and capacity (i.e., hazard; Fig.  
232 1) with species habitat suitability maps (i.e., exposure; Fig. 1) and with the fitted models to quantify  
233 the total number of fatalities for each species within their suitable habitat (i.e., impact index). For each  
234 species, a habitat suitability map was estimated using the modelling approach developed by Jung  
235 (2023). Suitability maps were derived from an integrated species distribution modelling approach,  
236 combining a range of biodiversity datasets (from GBIF, eBIRD and Natura 2000) and environmental  
237 variables (e.g., climate and land-cover variables) into an ensemble-modelling framework to predict  
238 how suitable the local environmental conditions might be for a species. A weighted ensemble  
239 prediction from multiple ‘engines’ was calculated and a threshold based on the True Skill Statistics  
240 obtained. For each ensemble prediction, values below the threshold were set to 0, and we considered  
241 as suitable all pixels where suitability was above the threshold. More details about the maps can be  
242 found in the supplementary materials of Chapman et al. (2023) and in Visconti et al. (2024) in which  
243 similar maps were used. All available maps were projected with the Lambert azimuthal equal-area  
244 projection, with a resolution of 10 km by 10 km.

245 In each suitable grid-cell where turbines were detected, fatality counts were estimated as a  
246 function of species identity and turbine capacities, using the taxonomic model (which had a similar  
247 predictive performance to the trait model; see Results), and therefore not expanding the analysis to  
248 species for which there were no fatality records (Fig. S1). Estimations were obtained for the highest  
249 study quality and were made marginal to location (site) and study identity. To this end, we linearised  
250 the relationship between turbine capacity and fatality counts for each species, instead of using the  
251 exponential relationship estimated from the Poisson model. We did this because the turbine capacity  
252 in the fitted data ranged between 0.015MW and 2.5MW, while turbines with a capacity of up to 8MW  
253 occurred in Europe. Assuming an exponential relationship would lead to unrealistic estimations of  
254 fatality counts for large capacities (Fig. S6). For each species, we used the model to predict values for  
255 capacities of 0.015MW and 2.5MW (range of values in the fitted data) and estimated the slope  
256 assuming a linear relationship. We then used the estimated slopes to predict fatality counts given  
257 turbine capacities, weighting the estimation by the suitability value of each relevant grid cell. We thus  
258 derived estimations of fatality counts per year across all turbines falling within the suitable habitat of  
259 each species (i.e., total fatalities per year). The impact index was then rescaled between 0 and 1 across

260 species, to provide a relative impact index with higher values reflecting higher relative impacts and  
261 lower values reflecting lower relative impacts.

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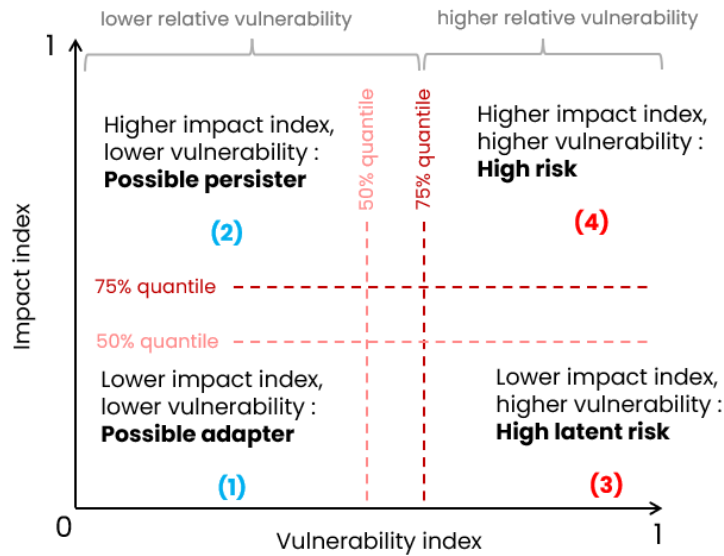
### 263 **2.3.2. Vulnerability index**

264 The vulnerability index accounted for three ecological characteristics: generation length (GL), clutch  
265 size (CS), and area of habitat suitability (SA; Table 1b). Drawing from vulnerability analyses (Bellard et  
266 al., 2024), the vulnerability index was calculated as a composite index, by summing of the  
267 characteristic values, after rescaling each characteristic across species for comparability, as  $GL_{\text{rescaled}} +$   
268  $(1-CS_{\text{rescaled}}) + (1-SA_{\text{rescaled}})$ . We took the opposite of CS and SA to reflect the higher vulnerability of  
269 species with smaller clutch sizes or areas of habitat suitability, compared to species with larger clutch  
270 sizes or areas of habitat suitability. The vulnerability dimensions were not too highly correlated (Table  
271 S1). We then rescaled the final vulnerability index, so that it ranged between 0 and 1 with lower values  
272 reflecting lower relative vulnerability and higher values reflecting higher relative vulnerability.

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### 274 **2.3.3. Risk categories**

275 We assessed species risk by considering the relative position of species in the risk space (vulnerability  
276 index against impact index; Fig. 2). We considered species to be at 'high risk' when exhibiting higher  
277 relative vulnerability and higher relative impacts, species to be at 'high latent risk' when exhibiting  
278 higher relative vulnerability but lower relative impacts (meaning that species could be negatively  
279 affected if more impacted), species to be 'possible persisters' when exhibiting lower relative  
280 vulnerability with higher relative mortality impacts (species possibly able to persist despite high  
281 impacts), and species to be 'possible adapters' when exhibiting lower relative vulnerability with lower  
282 relative mortality impacts (species that currently have low mortality impacts, but could be able persist  
283 if cumulative collision mortality increased; note that the terms were adapted from Foden et al. (2013)  
284 for the purpose of this work and of defining risk categories here). In absence of specific demographic  
285 information to set ecologically-informed thresholds, we used the 75% quantiles of the distributions of  
286 the impact index and of the vulnerability index as threshold values, considering species to be highly  
287 vulnerable and highly impacted when falling above these quantiles (overlapping top 25% species in  
288 both dimensions). Because using different threshold values could influence the results, we also  
289 considered 50% quantiles to investigate the congruence of the results. We thus classified species into  
290 the different risk categories (Fig. 2).



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**Fig. 2. We derived a risk category at the species-level by considering the overlap between the vulnerability index and the impact index. Terminology adapted from Foden et al. (2013). The 75% quantile of each distribution was used as a threshold above which we considered species to be highly vulnerable and highly impacted (species classified as “high risk” when falling above both thresholds), and we used 50% quantiles to check the congruence of the results when using lower threshold values. We also highlight relative vulnerability groupings (i.e. grouping species into lower/higher relative vulnerability based on the chosen quantile).**

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#### **2.3.4. Mapping risk**

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To assess hotspots of risk, we mapped pseudo-species richness in each risk category, for the two threshold values applied to classify species into the risk categories (75% and 50%). We also grouped high risk and high latent risk species on the one hand; and possible persisters and possible adapters on the other hand (i.e., lower versus higher vulnerability groupings). Pseudo-richness maps were derived by stacking the suitability maps.

Further, combining the richness maps with the current wind-turbine locations, we assessed the spatial overlap between wind-turbine locations and local pseudo-richness in the different risk categories and groupings. We derived bivariate plots highlighting areas with both high turbine densities and a relatively higher number of species in each group ('biscale' package, Prener et al. (2022)). Turbine kernel densities were derived using the 'st\_kde' function of the ibis.iSDM package (Jung, 2023).

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All data processing and analyses were conducted with R v.4.2.3 (R Core Team). The output pseudo-species richness maps were made available at [10.5281/zenodo.14717411](https://zenodo.org/record/14717411).

### 316 **3. Results**

#### 317 **3.1. Species- and site-level characteristics did not outperform taxonomy in explaining variation** 318 **in collision-mortality rates**

319 The fitted data in the trait and taxonomic models included 2,212 records from 330 species, including  
320 124 species known to occur in Europe. These records were compiled from 81 sources spanning 69  
321 locations (Fig. S3). 63% of the fitted records were categorised as ‘high’ or ‘medium’ quality (meaning  
322 that group- or species-specific corrections for detectability were applied; see Thaxter et al. (2017)),  
323 and 37% of the records as ‘low’ quality (some corrections applied). The fitted data did not include any  
324 study whose quality was classified as ‘very low’ (i.e., no study where no form of detectability  
325 correction was applied).

326 We found that collision-mortality rate was positively associated with turbine capacity (trait model,  
327 Fig. S7: estimated slope: 1.1; 95% CI: 0.74-1.4; taxonomic model: 1.1 [0.80;1.4]). However, we did not  
328 find any association between species-level characteristics and collision-mortality rate (Fig. S7).  
329 Although low study quality had a negative effect on estimated rates, there was no significant  
330 difference between the effects of medium and high-quality studies. Further, model comparisons  
331 (Table S2) showed that the different fitted models did not differ from each other in terms of predictive  
332 performance, even when considering landscape predictors and despite negative associations of both  
333 terrain roughness (estimate: -0.53[-0.97;-0.10]) and elevation (-0.33[-0.58;-0.09]) with collision-  
334 mortality rates (note that roughness and elevation were positively correlated with Pearson’s  $r=0.55$ ).

335 In the trait model, the fixed effects explained a small proportion of the overall variation in collision  
336 mortality, while the random effects (including taxonomy) explained an important part of the variation  
337 (marginal pseudo- $R^2$ : 0.064; conditional pseudo- $R^2$ : 0.96). In the taxonomic model, the variation  
338 explained by the fixed effects was higher (marginal pseudo- $R^2$ : 0.53; conditional pseudo- $R^2$ : 0.96).

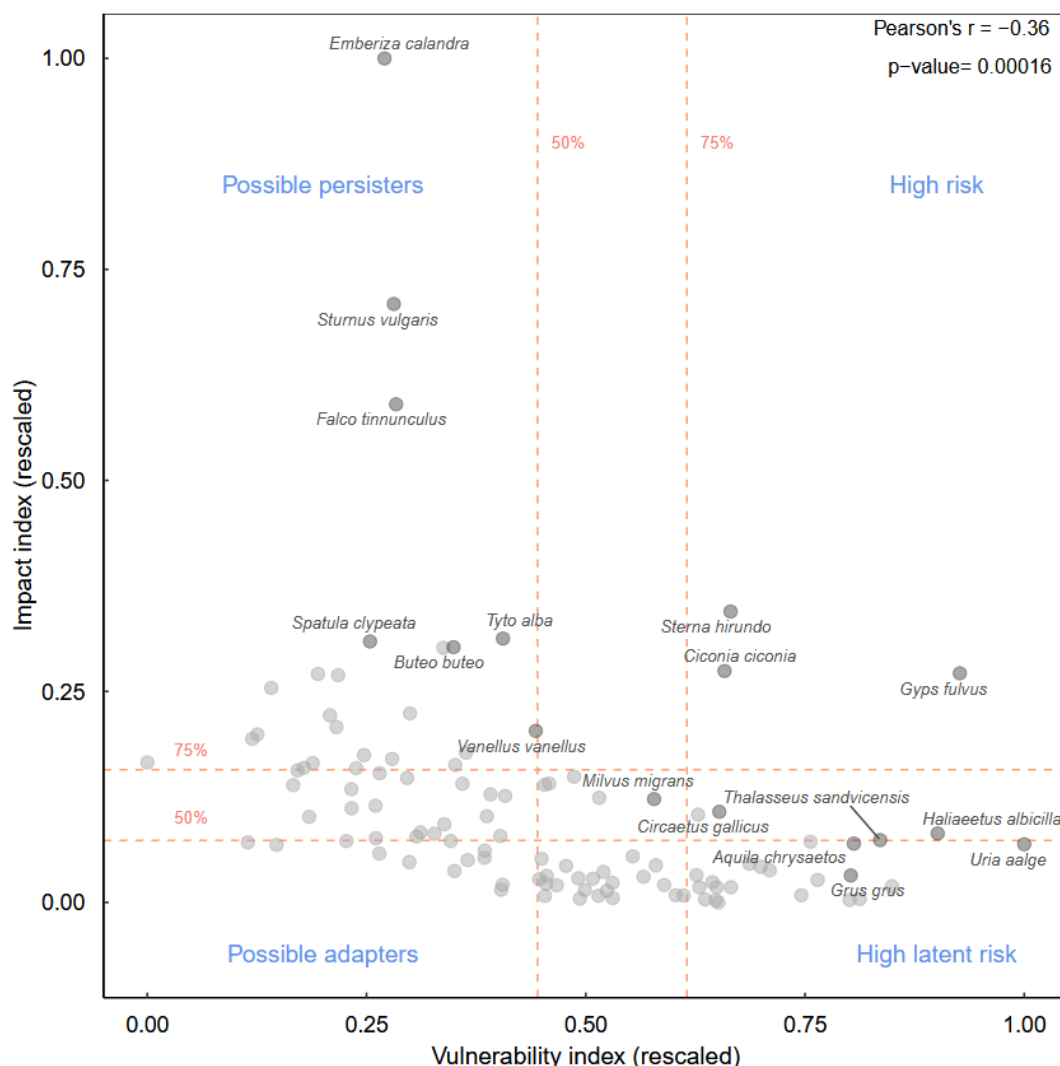
339 Given that species- and site-level characteristics did not explain an important part of the variation  
340 in collision-mortality rates and given that the trait models did not outperform the taxonomic model,  
341 we retained the taxonomic model for all further analyses, and we did not make inferences for  
342 additional European species based on trait values (Fig. S1); the taxonomic model was therefore  
343 employed to estimate the impact index at the species level (Fig. S8).

344

#### 345 **3.2. Risk estimation and patterns of risk**

346 Among the 124 European species that figured in the fitted data, 108 had enough information to  
347 quantify vulnerability and therefore risk (Fig. S8). Across species, we found that the vulnerability and  
348 impact indices were negatively correlated (Pearson’s  $r$ : -0.36;  $p$ -value<0.001; Fig. 3), with average  
349 impacts decreasing significantly with increasing vulnerability. The species with the highest impact

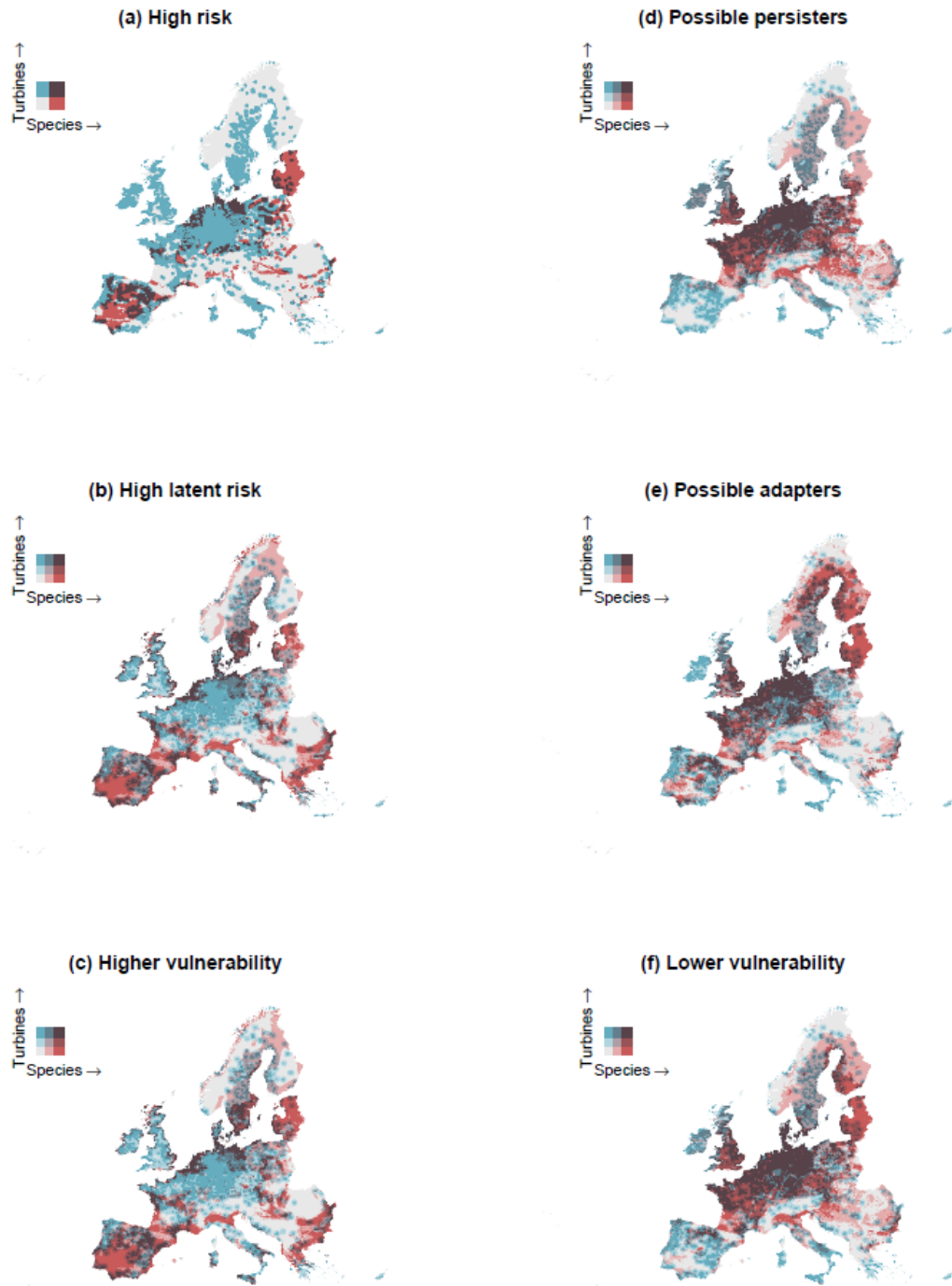
350 index (i.e. total estimated fatalities) was *Emberiza calandra* (corn bunting), while the species with the  
351 highest vulnerability index was *Uria aalge* (common murre). Median vulnerability and impact differed  
352 across taxonomic Orders (Fig. S9). The distribution of the impact index was right-skewed (Fig. S9), with  
353 many species exhibiting lower relative impacts and few species exhibiting higher relative impacts.  
354 Using 75% quantiles as thresholds (overlapping top 25% species in both dimensions), we found 3  
355 species to be at high risk (Fig. 3), and 24 species to be at high latent risk. 81 species were classified as  
356 potential adapters or potential persisters. Using 50% quantiles meant an additional 9 species were  
357 considered at high risk, and an additional 18 species were considered at high latent risk (54 species in  
358 total at high (latent) risk when using 50% quantile thresholds).  
359



360  
361 **Fig. 3. Estimated impact index against vulnerability index, and classification into risk categories, for**  
362 **108 species that figured in the fatality-count data. Dashed lines represent 75% and 50% quantiles of**  
363 **the distributions for each axis of risk. We highlight some of the species in the data, but not all, for**  
364 **readability.**

365

366 Plotting pseudo-species richness in the different risk categories highlighted hotspots of risk in  
367 Europe (Fig. S10). Parts of the Iberian Peninsula, of Northern Europe, and of the Balkans notably  
368 tended to concentrate more species at high (latent) risk. Using 50% quantiles for the classification of  
369 species into different risk categories did not affect the spatial patterns overall (Fig. S9; Fig. S10),  
370 although the number of species considered at high risk and high latent risk increased, therefore also  
371 expanding areas concentrating more species at higher risk into other regions. Combining information  
372 on wind turbine locations with the pseudo-species richness in the different risk categories, we  
373 obtained bivariate plots (Fig. 4; Fig. S12) showing regions which had both a higher density of turbines  
374 and a higher number of species at high risk or high latent risk, highlighting possible areas of conflict.  
375 Overall, the current turbine deployment had a higher degree of overlap with suitable habitats of  
376 species at lower relative vulnerability than with those of species at higher relative vulnerability (Fig.  
377 S13). For instance, turbine density was lower around central areas of the Iberian Peninsula, which also  
378 concentrated some of the species at higher risk (e.g. the Griffon vulture, *Gyps fulvus*). On the other  
379 hand, Germany tended to harbour a higher number of species at lower relative vulnerability and  
380 exhibited a higher density of turbines, but fewer species at higher relative vulnerability.



381

382 **Fig. 4. Spatial overlap between suitable habitats for species in the different risk categories or**  
383 **vulnerability groupings and current wind-turbine locations; (a) & (b) high risk and high latent risk**  
384 **species; (c) higher relative vulnerability (i.e., high risk and high latent risk species considered**  
385 **together); (d) & (e) possible persisters and possible adapters; (f) lower relative vulnerability (i.e.,**  
386 **possible persisters and possible adapters considered together). Red areas harbour a larger number**  
387 **of species in a given risk category; blue areas harbour a larger number of turbines; purple areas**  
388 **indicate overlaps between areas of higher pseudo-species richness and higher turbine density. Here,**  
389 **risk categories were derived using the 75% quantiles of the distribution of the vulnerability and**  
390 **impact indices as thresholds. Note that we used only two breaks in (a) because no more than 3 high-**  
391 **risk species occurred simultaneously in any given grid cell, while most often only 2 species occurred.**

## 392 4. Discussion

### 393 4.1. Key results and interpretations

394 Here, using a risk assessment approach built upon two dimensions (impact and vulnerability), we  
395 evaluated the current risk to 108 European birds from collisions with wind-energy facilities. Our  
396 estimation of the impact index relied on fatality counts which can be biased (e.g. with more detectable  
397 species more frequently reported; Nilsson et al. (2023)). Therefore, we emphasize that our results  
398 reflected the 'reported' risk; true risk might be underestimated for species for which fatalities remain  
399 underreported. However, although data biases may influence our results, all fatality records we  
400 considered were corrected for detectability in some way, with over 60% of the records including  
401 species- or group-specific corrections (Thaxter et al., 2017), and we found no evidence of further bias  
402 in the data (S10). This suggests that our results were robust to potential data biases. Further, the  
403 vulnerability index was estimated independently from the impact index, so the relative vulnerability  
404 groupings were unaffected by possible biases in the fatality-count data. Our study therefore provides  
405 a proof-of-concept for applying a risk framework to wind-turbine collisions at macroecological scales,  
406 which future studies can build upon, refine further and validate.

407 We found that reported risk was unevenly distributed in Europe, with risk hotspots in the Iberian  
408 Peninsula, in Northern Europe, in the Balkans, and in parts of Western and central Europe. The overlap  
409 between wind-turbine locations and species at higher relative vulnerability highlighted regions where  
410 conflicts between wind-energy facilities and bird conservation might currently arise. Our results  
411 however showed that the current deployment of wind turbines overlapped more with the suitable  
412 areas of species at lower relative risk than with that of species at higher relative risk, signalling that to  
413 now, turbine deployment may have avoided some areas harbouring relatively more vulnerable  
414 species.

415 Of the 108 considered species, we found 27 species to be at higher relative vulnerability, of which  
416 6 belonged to the *Accipitriformes* Order (birds of prey), and 12 belonged to the *Charadriiformes* Order  
417 (shorebirds), when using a more conservative threshold value for the groupings (75% quantiles). Most  
418 species classified as possible persisters (i.e., higher relative impacts, but lower relative vulnerability)  
419 belonged to the *Passeriformes* Order (perching birds), suggesting that such species possibly sustain  
420 high impacts on their populations. Altogether, this highlights the effects of wind-energy developments  
421 on such bird Orders, in line with previous studies (Desholm, 2009; Erickson et al., 2014; Estellés-  
422 Domingo & López-López, 2024; Thaxter et al., 2017).

423 Unlike Thaxter et al. (2017), we found that the interspecific variation in collision-mortality rates  
424 could not be attributed to the ecological characteristics considered (but Thaxter et al. (2017)  
425 considered categorised dispersal distances, i.e, dispersal bands, whereas we used a continuous proxy

426 of dispersal ability). Further, species- and site-level characteristics did not outperform taxonomy in  
427 estimating collision-mortality rates; and most of the variation explained in the different models was  
428 attributable to taxonomy. It could be that collision mortality is influenced by factors that we did not  
429 capture here, and possibly challenging to account for at large scales. For instance, weather, species  
430 behavioural plasticity, flight height, or fine-scale landscape variables (e.g., distance to breeding  
431 grounds) were difficult to capture in a quantitative synthesis such as ours but likely play an important  
432 role in collision mortality; it could also be that a high degree of context specificity hampers our ability  
433 to detect some effects.

434 Finally, species face multiple anthropogenic pressures. In a study of mortality causes for large birds  
435 over the Eurasian-African flyway, Serratos et al. (2024) showed that mortality events related to  
436 energy infrastructure represented 49% of human-induced mortality events, but only a small  
437 proportion of these were attributed to collisions with wind-energy facilities; electrocutions and  
438 collisions with power lines represented most mortality events. In vultures, direct and indirect  
439 poisoning is a major source of human-induced mortality, and vulture protection may require curbing  
440 poisoning as well as collision mortality (Posillico et al., 2023; Sanz-Aguilar et al., 2015). Thus, as species  
441 face multiple pressures, ensuring that the risk posed by wind-energy facilities does not exacerbate the  
442 threats on populations is important to their long-term viability.

443

#### 444 **4.2. Possible applications**

445 Our maps could be employed in decision-making tools, e.g. to constrain future scenarios of wind-  
446 power deployment at the European scale in energy-systems modelling, to improve biodiversity-  
447 inclusive spatial planning, to mitigate potential adverse impacts on birds, or to assess possible areas  
448 of conflicts and biodiversity impacts of different deployment scenarios. Our outputs could also be  
449 combined with other assessments of wind-power impacts (e.g. land-use change, noise, shadow flicker;  
450 McKenna et al., (2025)) for exploring spatial trade-offs and synergies of different impacts (social &  
451 ecological). However, we caution that our mapped outputs are not appropriate for fine-scale  
452 downscaling or local prioritisations, given that we could not capture some of the likely context  
453 specificity.

454

#### 455 **4.3. Research priorities**

456 The amount of readily available collision-mortality data was an important limiting factor. We relied on  
457 data previously compiled by Thaxter et al. (2017). While there are recent initiatives aiming at  
458 centralising fatality records (e.g., see [https://oscars-project.eu/projects/risky-wildlife-mortality-  
energy-and-transport-infrastructure](https://oscars-project.eu/projects/risky-wildlife-mortality-energy-and-transport-infrastructure); [https://spbt.gr/en/database\\_victims\\_wind\\_turbines/](https://spbt.gr/en/database_victims_wind_turbines/)), there is

460 currently no protocol at the European scale for the collection and processing of such data. Unravelling  
461 the factors that influence collision risk at large scales may require developing frameworks for  
462 systematic processing of such data, which are currently scattered across studies and technical reports,  
463 implying important and possibly duplicated collection efforts for use in quantitative syntheses. Such  
464 systematically processed data, possibly enhanced with information on local conditions, would be  
465 valuable not only to understand what shapes collision mortality at large scales, but also to inform  
466 mitigation strategies and spatial planning. Standardised protocols for data collection would also  
467 enhance comparability across studies (Conkling et al., 2021) and help reduce potential sampling biases  
468 in quantitative synthesis such as ours. Systematically processed data could allow to further investigate  
469 seasonal, spatial or intraspecific variation in collision-mortality rates (which we did not consider here;  
470 our analyses considered species-level yearly averages, with data limitations also precluding the  
471 inclusion of interactions in the models). Thus, additional data could allow for further validation of our  
472 results and further characterisation of the inter- and intra-specific variation in collision mortality.

473 Finally, an important question is how collision mortality may impact species populations and  
474 demographic trends over large spatiotemporal scales (Duriez et al., 2023; May et al., 2019), and which  
475 collision-mortality rates we can consider as “acceptable” thresholds for the long-term viability of  
476 populations. Investigating such a question requires using mechanistic demographic models, which rely  
477 on demographic information that can be challenging to obtain across many species. By adapting a risk  
478 framework here which used readily available information across many species, we were able to assess  
479 which species were at higher relative risk; our approach, however, could not estimate an acceptable  
480 level of risk within a species.

481

#### 482 **4.4. Conclusion**

483 Our work highlights the uneven spatial and taxonomic distribution of risk and can help identify areas  
484 of possible higher risk at the European scale. As more wind-energy facilities are deployed in the coming  
485 decades, mitigating the risk they pose to birds, particularly to species at higher risk, may be important  
486 for the long-term viability of the species.

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