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SHORT ABSTRACT FOR DISSEMINATION PURPOSES

Abstract

In line with Europe's decarbonization goals, the number and the capacity of wind-power farms is projected to increase in coming decades. However, wind farms can pose risks to biodiversity: flying animals can fatally collide with wind-farm infrastructure and bats can experience deadly barotrauma when flying close to turbines. To inform the deployment of wind farms at the European scale and minimise risks to wildlife, here we aimed to assess collision-mortality risk across European bird and bat species. We present the second version (*Version (b)*) of collision-mortality risk models, and associated estimates for 531 birds and 26 bats known to occur in Europe. To generate these, we used a compilation of recorded collisions for birds and bats from published papers and reports, which we combined with data on species traits, wind-farm characteristics, and landscape characteristics. We investigated associations between these variables and collision mortality at the species level using statistical models. We used our models' outcomes to create collision-mortality risk maps, with the aim of informing spatial deployment of wind power projects and possible mitigation measures.



TABLE OF CONTENTS

















1. INTRODUCTION	13
2. METHODS	16
2.1 Data collection	16
2.1.1 Collision data for birds and bats: Thaxter et al. (2017)	16
2.1.2 Processing and standardizing the collision data	17
2.1.3 From collision rates to counts to counts of collision victims	18
2.1.4 Trait data (species-level characteristics)	18
2.1.5 Mean wind speed at the wind-farm central locations (m/s)	20
2.1.6 Wind turbine capacity	21
2.1.7 Study quality	21
2.2 Modelling framework.....	21
2.2.1 Overview	21
2.2.2 Multicollinearity checks on the fixed predictors	22
2.2.3 Models sample sizes and spatial distribution of sampling sites.....	23
2.3 Model predictions: estimations of collision-mortality rates at the species level	24
2.3.1 Species-level predictions	24
2.4 From collision mortality to vulnerability	26
2.5 Mapping of outputs (collision mortality rates and vulnerability)	28
3. RESULTS AND OUTPUTS.....	29
3.1 Fitted models.....	29
3.2 Estimated collision-mortality rates in birds and bats	32
3.2.1 Species-level estimates of collision-mortality rates.....	32
3.2.2 Distribution of estimated collision-mortality rates among IUCN threat status groups	34
3.3 Vulnerability classes	35
3.4 Mapped estimates of collision-mortality rates and vulnerability classes.....	36
3.4.1 Summary maps of collision-mortality rates across considered bat species ...	37
3.4.2 Summary maps across all considered bird species.....	37
3.4.3 Species richness by collision vulnerability groups.....	38
3.5 Outputs.....	39
4. DISCUSSION, LIMITATIONS, AND POSSIBLE DEVELOPMENTS	41
REFERENCES	45



ANNEX.....53



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ABBREVIATIONS

Acronym	Description
GVI	Generalised Variance Inflation Factor
MW	Megawatts



LIST OF FIGURES

Figure 1: (a) Spatial distribution of all sampling sites (wind farms’ central locations) included in the fitted data of the statistical models for birds and bats. (b) Location of the European sampling sites. Country shapes were obtained from the ‘rnatualearth’ R package (Massicotte et al., 2023)..... 24

Figure 2: We derived a vulnerability score at the species-level by considering the overlap between the distributions of sensitivity and exposure, across species for which a suitability map was available (n=316). The 75% quantile of each distribution was used as a threshold above which we considered species to be highly sensitive and highly exposed. Exposure was estimated as the mean number of collisions per turbine and per year, while sensitivity was derived from combining information on generation length, litter or clutch size and geographical range area. 28

Figure 3: Estimated effects of the fixed predictors for the model fitted on (a) birds and (b) bats, mean \pm 95% credible interval. Light blue backgrounds highlight continuous predictors, while light yellow backgrounds highlight categorical predictors.31

Figure 4: Predicted number of collision victims per year-turbine (mean \pm 95% credible interval) for (a) 531 bird species and (b) 26 bat species known to occur in Europe. The predictions are plotted on the log-scale. The predictions were generated for a turbine capacity of 2 MW, a mean wind speed at 100 m of 6 m/s, and a high study quality. 33

Figure 5: Distribution of predicted number of collision victims per year-turbine within avian taxonomic Orders. Numbers on the right-hand side of the plot show the sample sizes (number of species) in each Order. The predictions are plotted on the log-scale. The predictions were generated for a turbine capacity of 2 MW, a mean wind speed at 100 m of 6 m/s, and a high study quality..... 34

Figure 6: Distribution of predicted number of collision victims per year-turbine by threat status. Numbers on the right-hand side of the plot show the sample sizes (number of species) in each threat status group. The predictions are plotted on the log-scale. The predictions were generated for a turbine capacity of 2 MW, a mean wind speed at 100 m of 6 m/s, and a high study quality..... 35

Figure 7: Estimated collision mortality rates against sensitivity index. Dashed lines represent the 75% quantiles of the distributions. Species with high sensitivity and high estimated collision mortality (i.e., falling above the 75% quantile of each distribution) were considered highly vulnerable..... 36



Figure 8: (a) Number of bat species found to occur in each grid cell (species richness, for the 22 species considered). (b)(c)(d) Summary statistics of estimated collision-mortality rates across all bat species occurring in a grid cell (sum, mean, and standard deviation).....37

Figure 9: (a) Number of bird species found to occur in each grid cell (species richness, for the 320 species considered). (b)(c)(d) Summary statistics of estimated collision-mortality rates across all bird species occurring in a grid cell (sum, mean, and standard deviation)..... 38

Figure 10: Species richness across Europe in each collision vulnerability group. Overall, we found that 8 species were classified as highly vulnerable, 71 were at high latent risk, 74 were classified as possible persisters, and 163 were classified as possible adapters..... 39

Annex

Figure A1: (a) and (b): Collision-mortality rates derived from the original compiled data, calculated after converting the original rates to counts of collision victims, either after multiplying original rates and study duration by 10 before rounding (y-axis), or rounding values directly without multiplying by 10 (x-axis). (c) and (d): Derived collision-mortality rates we used (from counts and study duration multiplied by 10; y-axis) against the original collision-mortality rates in the data..... 53

Figure A2: Mean wind speed (m/s) at 100 metres at the central wind farms’ locations calculated using various buffer sizes around the locations: 0m (no buffer), 10m, 100m, 500m, 1000m, and 5000m..... 54

Figure A3: Random-effects estimates of species identity for the model fitted on (a) birds and (b) bats, investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms’ central locations, and turbine capacity..... 57

Figure A4: Random-effects estimates of site locations (central wind farms’ locations) for the model fitted on (a) birds and (b) bats, investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms’ central locations, and turbine capacity. 58



LIST OF TABLES

Table 1: Ecological characteristics collected for birds and bats, definitions, and data sources. These characteristics were included as predictors in the models investigating associations between species-level characteristics and collision-mortality rates. 19

Table 2: Generalised Variance Inflation Factors for all fixed predictors included the models investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms' central locations, and turbine capacity.....22

Table 3: Number of bird and bat species known to occur in Europe (a), of which (b) number of species recorded in collision data, (c) number of species for which trait data was available for predictions, (d) number of species for which a suitability map was available, and (e) number of species which were both recorded in the collision data and for which a suitability map was available. 25

Table 4: Traits used to derive the sensitivity index across 316 birds.....27

Table 5: Description of the outputs and results of the task (Task 1.3). 40

Annex

Table A1: Summary of the model fitted for birds, investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms' central locations, and turbine capacity..... 55

Table A2: Summary of the model fitted for bats, investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms' central locations, and turbine capacity..... 56



EXECUTIVE SUMMARY

In line with the European Climate Law, wind-power's total installed capacity is projected to increase in the coming years. While deploying more wind-power farms is important to reducing greenhouse gas emissions, wind farms can also impact biodiversity. In particular, birds and bats can fatally collide with wind-farm turbines or turbine hubs, which can lead to decreases in the demographic rates of some species, raising questions about their impacts on the long-term viability of different animal populations. The objectives of this Deliverable are to present an assessment of collision-mortality risk for European birds and bats. We assessed collision-mortality rates in terms of number of collision victims per wind turbine and per year. We used a compilation of recorded fatal collisions for birds and bats around wind-farm sites mostly located in Europe (16 sites for birds, 41 for bats) and North America (49 sites for birds). We combined the collision data with information on individual species characteristics, wind turbine capacity, and mean wind speed at the wind-farm locations, and we assessed whether these variables were associated with collision mortality using statistical models. We then used the models' outputs to predict the mean collision-mortality rates across 531 European bird species (about 98% of 544 birds species known to occur across Europe) and 26 European bat species (about 55% of the 47 bat species known to occur in Europe). Combining the estimated rates with additional information on species life-history, we further estimated vulnerability to collisions with wind farms for 316 European birds. Using spatial data on species occurrence, we mapped estimated collision-mortality rates at the species-level and at the assemblage level, providing summary statistics of collision-mortality rates (for 320 birds and 22 bats) across all species occurring in a grid cell. Thus, we present *Version (b)* of the collision-mortality risk models and the collision-mortality risk maps for European birds and bats.



1. INTRODUCTION

With the adoption of the European Climate Law in 2021, the European Union has committed to becoming climate-neutral by 2050, i.e., to reaching net-zero greenhouse gas emissions. An intermediate target aims at reducing greenhouse gas emissions by 55% by 2030, compared to emission levels of 1990. Key to the EU's decarbonisation and climate-change-mitigation strategy is the transformation of European energy systems, most notably the reduction of fossil fuels in the energy mix, coupled with increases in the share of renewable energy sources. In addition to contributing to the EU's decarbonisation goals, the development of renewable energy diversifies local energy supplies and allows for a greater independence from conventional resources. Between 2000 and 2019, renewable energy consumption increased by an average 200% in the EU-27 across all sectors (Tutak & Brodny, 2022). In 2022, wind power alone accounted for about 16% of the electricity demand in the European Union (WindEurope 2022). As of 2022, with an installed capacity of 204 GW, the EU was among the biggest producers of wind energy. Most of this capacity (92%) was installed onshore (WindEurope 2022). In line with the European Climate Law, the installed capacity could need to increase by more than 100% to meet the 2030 targets (to reach a total capacity of 440 GW by 2030 with regards to the REPower EU energy target; WindEurope 2022).

While wind energy is a key sector for renewable energy production, wind-power farms can have adverse impacts on biodiversity (Loss et al., 2013; Schöll & Nopp-Mayr, 2021). These impacts can be an important barrier to the social acceptance of wind power (Voigt et al., 2019; Vuichard et al., 2022). Negative biodiversity impacts can be attributed to land-use change and habitat disturbance occurring from the construction phase of the wind farms and necessary structures (e.g., roads and power lines). Habitat disturbance can lead to the displacement of species through the loss of suitable habitat (Marques et al., 2020), and to reductions in local abundance and population densities (Fernández-Bellon et al., 2019). For flying animals, the presence of wind farms can lead to alterations of flight paths and migratory routes through a barrier or displacement effect inducing



avoidance behaviour (Cabrera-Cruz & Villegas-Patraca, 2016; Santos et al., 2022a). However, wind farms also constitute a collision hazard for flying animals, birds and bats in particular (Smallwood, 2013; Thaxter et al., 2017), but also insects (Voigt, 2021), as these animals can fatally collide with wind-farm infrastructure, and, in the case of bats, experience deadly barotrauma when flying close to rotating turbines (Baerwald et al., 2008). Negative impacts of wind-power farms on birds and bats through collision mortality can be of concern for the long-term viability of animal populations (Duriez et al., 2023; Gómez-Catasús et al., 2018; May et al., 2019; Sanz-Aguilar et al., 2015; Schippers et al., 2020). Of particular concern are species that cumulate different vulnerability factors to human pressures, such as low population densities or slow pace of life, and/or species that are already characterised as threatened (Carrete et al., 2009; Desholm, 2009; Kuvlesky Jr. et al., 2010). For instance, large soaring birds have been a group of interest since their reliance on wind resources to gain altitude (thermal and orographic updrafts in particular) can conflict with areas favourable for wind-energy developments (Farfán et al., 2023; Santos et al., 2022b; Smeraldo et al., 2020). Further, poor flight manoeuvrability can make them particularly exposed to collision mortality, while low reproductive outputs can make the species more sensitive to such added mortality (Bellebaum et al., 2013; Dahl et al., 2013). It is thus important to assess the collision-mortality risk that wind farms pose to different species, to inform wind-farm spatial deployment and to minimise biodiversity impacts.

Collision-mortality risk for onshore wind farms is typically empirically estimated from the field using search protocols around operational turbines, aiming at identifying and counting collision victims (Bernardino et al., 2013; Domínguez del Valle et al., 2020). Past research has shown that collision risk is influenced by a wide range of factors, which can be broadly classified into three categories (Marques et al., 2014): (1) site-specific factors that relate to local landscape configuration and environmental features, such as wind speed, weather, landforms, habitat availability for different species, etc; (2) characteristics of the wind farms, such as spatial configuration, turbine capacity, lighting, etc; and (3) species-specific



characteristics, such as seasonal occurrence, morphology, sensorial perception, flight strategy, migratory behaviour, behavioural plasticity and adaptability, etc (De Lucas et al., 2008; Farfán et al., 2023; May et al., 2015). Collision mortality risk is influenced by complex interactions among these factors (Drewitt & Langston, 2008). Such interactions point to an important degree of context-specificity in collision-mortality risk, supported by widespread reported estimates of collision-mortality rates at different wind farms. While low fatality numbers are reported for many wind farms, many fatal collisions have occurred at other wind farms – e.g., Altamont Pass Wind Resource Area in California or Tarifa in Southern Spain (Arnett et al., 2016; de Lucas et al., 2012; Kuvlesky Jr. et al., 2010; Marques et al., 2014; Powlesland, 2009; Rydell et al., 2012; Sebastián-González et al., 2018; Voigt et al., 2022). Consequently, the siting of wind farms and their spatial configuration are of prime importance to reduce collision-mortality risk (Carrete et al., 2012; Schaub, 2012). As species are unevenly affected by the presence of wind farms, understanding which factors explain interspecific variation in collision-mortality risk can help putting into place appropriate mitigation measures.

In a quantitative synthesis of collision-mortality data for birds and bats, Thaxter et al. (2017) investigated whether ecological characteristics measurable at the species level (also termed ‘traits’) and turbine capacity were associated with collision risk. They showed that traits relating to species’ movement (i.e., dispersal ability), migratory status, and habitat preferences were significantly associated with collision risk in birds, and that dispersal ability was significantly associated with collision-mortality risk in bats. In addition, they found that turbine capacity was positively associated with collision-mortality risk in birds and bats (although they found that deploying fewer turbines with larger capacities tended to reduce collision risk). Thaxter et al. (2017) then used information on individual species’ traits to estimate the collision-mortality risk for birds and bats globally.

In this task of the WIMBY project (T1.3), we built upon Thaxter et al. (2017) to conduct a continental-scale assessment of collision-mortality risk for European birds and bats. Using the collision-mortality data collected in



Thaxter et al. (2017), we investigated associations between species-level and site-level characteristics and collision-mortality rates using statistical models. We then used our models' outcomes to predict collision-mortality rates across 531 European bird species and 26 bat species (i.e., for about 98% of the species of birds known to occur in Europe, and for about 55% of the bat species known to occur in Europe). Collision-mortality rates were estimated as the average number of collision victims per year and per turbine (or in other words, per year-turbine), at the species level.

Combining estimated collision mortality rates with additional information on species' life history (generation length, litter/clutch size) and rarity (geographical range area), we further assessed vulnerability for 316 birds.

We mapped the collision-mortality rates at the species level and at the assemblage level (i.e., for all species found to occur at a particular location), providing summary statistics of collision-mortality rates across all species occurring in a grid cell. We also looked at the spatial distributions of species found to be highly vulnerable to collision mortality. We therefore present here *Version (b)* of the collision-mortality risk models and the collision risk maps for 531 European birds and 26 European bats.

2. METHODS

All data processing and analyses were conducted with R v.4.2.3 (R Core Team).

2.1 Data collection

2.1.1 Collision data for birds and bats: Thaxter et al. (2017)

Thaxter et al. (2017) investigated whether species ecological characteristics and wind-turbine capacity (in Megawatts, MW) were associated with collision risk in birds and bats. To this end, they compiled data from a range of peer-reviewed and non-peer-reviewed studies and reports that recorded or estimated collision mortality at wind farms for birds and bats. They used a literature search on the terms: "(bird* OR avian OR bat) AND wind AND (farm* OR energy OR windfarm* OR industry* OR wind-farm* OR park* OR



development OR facilit*)” to identify relevant sources, using Web of Science, Google[®] and Google Scholar[®]. Thaxter et al. (2017) identified 88 sources for birds and 87 studies for bats that were suitable for inclusion, spanning a range of countries with a bias towards European and North American locations. The compiled data included 93 and 134 onshore and coastal wind farms for birds and bats respectively (several wind farms being sometimes considered in a single study). Wind farms varied in the number of operational wind turbines, with some wind farms consisting of single wind turbines while others consisted of several turbines. The sampling year(s), the employed search protocol or methodology, as well as the duration of each study were varied. Thaxter et al. (2017) reported mortality estimates at the wind-farm level, along with turbine capacity, number of wind turbines within each wind farm, location of the wind farm (central longitude and latitude of all wind turbines within a wind farm), and the duration of each study. In addition, Thaxter et al. (2017) estimated the quality of each study, that is, whether studies corrected for the detectability of collision victims after field searches (Huso & Dalthorp, 2014; Nilsson et al., 2023), characterising study quality as “very low”, “low”, “medium”, or “high”, depending on if and how correction factors were applied. For further methodological details on the collision-mortality data collection, see Thaxter et al. (2017).*

2.1.2 Processing and standardizing the collision data

We used the collision data for birds and bats from Thaxter et al. (2017), accessible at:

<https://datadryad.org/stash/dataset/doi:10.5061/dryad.h9s55>

(retrieved 10/05/2023). As the collected data came from diverse sources that used different methods to estimate mortality, the metrics reported in the data varied. >80% of the records reported (annual) mortality per turbine; and about 2% of the records reported counts of collision (or barotrauma) victims. We subset the data to include records that reported mortality rates (e.g., “annual mortality per turbine”) or counts of collision victims (e.g., “total fatalities”) and for which study duration and number of turbines were known. We standardised the values across all studies to obtain annual mortality rates per turbine (collisions victims.year⁻¹.turbine⁻¹). These rates were



converted back to count data prior to fitting the models (see section 2.1.3 Modelling framework), as Poisson models require count data as dependent variables. The use of an offset variable then allowed to control for uneven study duration and varying number of turbines (see section 2.2.1).

2.1.3 From collision rates to counts to counts of collision victims

We converted the standardised collision rates (number of collision victims per year-turbine) to counts of collision victims, by multiplying the standardised rates in the original data with study duration and number of turbines within each wind farm. Since doing so did not necessarily generate integers – required to fit the models with a Poisson error distribution–, we rounded the estimates to the nearest integers. To get more precise estimates of the number of collision victims with a more accurate rounding, we increased the study duration by 10 years, multiplying both estimated rates and study duration by 10 before rounding. This allowed by a better estimation of rounded counts since initial counts of e.g., 0.2 over 1 year became 2 over 10 years, without affecting the rate itself. We further verified that this rounding procedure did not affect the estimated rates, by comparing the initial standardised collision rates with collision rates derived from the rounded counts (Figure A1). We filtered out species that were never recorded to be collision victims (0 collision victim reported across all sampled locations).

2.1.4 Trait data (species-level characteristics)

We combined the collision data with species-level trait data and ecological characteristics for birds and bats (Thaxter et al. (2017) showed that traits related to species movement (i.e., dispersal distance for birds and bats, as well as migratory status for birds and habitat affinity) were associated with collision risk. Thus, we targeted traits that related to species movement, as well as habitat affinity for birds.

The set of traits we collected for birds and bats differed in part, since these two taxonomic groups have distinct characteristics that are not always directly comparable. For both groups, we obtained traits that related to species morphology, movement, and ecology, targeting characteristics

that could be associated with collision risk, and that were available for a maximum of species occurring in the collision data. We excluded traits that were too strongly associated with each other, checking both Pearson’s correlation coefficients among continuous traits, as well as Generalised Variance Inflation factors among continuous and categorical traits (GVIF; Dormann et al. (2013)), to avoid multicollinearity issues in the models (see section 2.2). For instance, in bats, forearm length and body mass were too highly correlated to be considered simultaneously (Pearson’s correlation coefficient >0.9). We further excluded variables with GVIF >5. The resulting sets of selected species-level ecological characteristics that we considered in the models are defined in Table 1.

Table 1: Ecological characteristics collected for birds and bats, definitions, and data sources. These characteristics were included as predictors in the models investigating associations between species-level characteristics and collision-mortality rates.

Taxon	Ecological characteristic	Definition	Sources
Birds	Migratory status (categorical)	Species classified as: <ul style="list-style-type: none"> - migratory (long-distance migration occurs across most of the species' population) - partially migratory (short-distance migration occurs across most of the species' population) - sedentary. 	Tobias et al. (2022)
	Hand-wing index (HWI) (continuous, unitless)	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)
	Species’ habitat density (categorical)	Description of species’ preferred habitat’s density: <ul style="list-style-type: none"> - open (e.g., grassland) - semi-open (e.g., shrubland) - dense (e.g., forest) 	Tobias et al. (2022)

	Flight mode (categorical)	Following (Watanabe, 2016), we classified species as soaring when belonging to the following Families: <i>Accipitridae</i> , <i>Cathartidae</i> , <i>Ciconiidae</i> , <i>Diomedeidae</i> , <i>Pandionidae</i> , and <i>Procellariidae</i> ; flapping when belonging to any other family. Soaring species mainly rely on thermal updrafts to gain altitude, while flapping species use flap-powered flight (Santos et al., 2020); some species are able to use both modes, but we do not account for this here.	Ad-hoc classification
Bats	Adult body mass (g) (continuous)	Species-level average for adult body mass (not sex-specific).	Etard et al. (2020) and Froidevaux et al. (2023)
	Home range (ha) (continuous)	Mean area used to satisfy daily individual needs (foraging, etc)	Froidevaux et al. (2023)
	Max recorded movement (km) (continuous)	Maximum seasonal movement recorded (including migration distances)	Froidevaux et al. (2023)

2.1.5 Mean wind speed at the wind-farm central locations (m/s)

At the central location of the wind farms, we obtained mean wind speed at a height of 100 metres from the Global Wind Atlas (<https://globalwindatlas.info/en>; spatial data downloaded 23/10/2023 and aggregated at a resolution of 1 km by 1 km). We initially used different buffer sizes (0, 10, 100, 500, 1000, and 5000 metres) around each wind-farm location to estimate mean wind speed across the buffer cells, and we assessed whether the estimations were sensitive to buffer size. Mean wind speed was not sensitive to the choice of buffer size (Figure A2), and we used a buffer of 1 km around each point to estimate mean wind speed.

2.1.6 *Wind turbine capacity*

Turbine capacity (in MW) was directly obtained from the data compiled by Thaxter et al. (2017).

2.1.7 *Study quality*

The quality of each original data source in the collision dataset was estimated by Thaxter et al. (2017) as “very low”, “low”, “medium”, “high”. This classification reflected whether collision–mortality data collected from the field were corrected for carcass detectability. Data collected from the field not corrected for carcass detectability typically tend to underestimate counts of collision victims (Domínguez del Valle et al., 2020).

2.2 **Modelling framework**

2.2.1 *Overview*

We investigated whether species’ ecological characteristics, mean wind speed at wind farms’ locations, and wind turbine capacity were associated with collision–mortality rates using generalized linear mixed-effects models, fitted with a Bayesian framework implemented with the R package ‘brms’ (Bürkner, 2017, 2018, 2021). We fitted counts of collision victims as the response variable, using a zero-inflated Poisson error distribution (zero-inflation occurred as collision–mortality counts were reported as 0 for some species). We created an offset variable to control for uneven study duration and varying number of turbines within a wind farm.

Thaxter et al. (2017) showed that study quality influenced collision risk, with lower-quality studies (that is, those that didn’t correct collision counts for carcass detectability) underestimating the number of collision victims. Thus, we included study quality as a fixed predictor in the models. In all models, two random intercepts accounted for the identity of studies and of sites, to control for variation in experimental design across studies and for the spatial structuring of sites within studies; another random intercept accounted for the identity of species, to control for repeated observations among species and for taxonomic non-independence. In addition, we fitted

an observation-level random effect for birds to control for overdispersion (Harrison, 2014). We fitted separate models for birds and bats. The general form of the models was:

Number of collision victims ~
 Species-level predictors +
 Mean wind speed +
 Turbine capacity +
 Study quality +
 Offset variable +
 1|Study ID +
 1|Site ID +
 1|Species identity
 (+ 1|Observation ID - *birds only*)

The offset used was: $\log(\text{study duration} * \text{number of turbines})$. We ran the Bayesian models using 4 chains, 5000 warm-up iterations, 50,000 sampling iterations, and thinning intervals of 10. We used non-informative priors.

2.2.2 Multicollinearity checks on the fixed predictors

We ran multicollinearity checks before fitting the models, using Generalised Variance Inflation Factors (GVIFs). The selected predictors all had GVIF <5, indicating that multicollinearity was not an issue in the models (Table 2).

Table 2: Generalised Variance Inflation Factors for all fixed predictors included the models investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms’ central locations, and turbine capacity.

Taxon	Predictor	GVIF	Type
Birds	Flight mode	1.08	Species-level characteristic
	Migration	1.24	Species-level characteristic
	Study quality	1.37	Study-level characteristic
	Hand-wing index (log)	1.37	Species-level characteristic
	Habitat density	1.77	Species-level characteristic
	Mean wind speed	1.81	Site-level characteristic
	Turbine capacity	2.25	Wind-turbine characteristic
Bats	Mean wind speed	1.02	Site-level characteristic
	Turbine capacity	1.11	Wind-turbine characteristic
	Study quality	1.13	Study-level characteristic

	Recorded movement (log)	1.25	Species-level characteristic
	Home range (log)	1.82	Species-level characteristic
	Body mass (log)	1.86	Species-level characteristic

2.2.3 Models sample sizes and spatial distribution of sampling sites

For birds, the fitted data included 2204 records of collision counts from 330 species spanning 65 avian families, including 124 bird species known to occur in Europe from 39 families and 16 orders (note that these were species figuring in the fitted data, but we further generated predictions from the models for more species, see section 2.3.1). These records were compiled from 80 different sources across 68 sampling sites distributed worldwide (Figure 1). There are about 544 species of birds known to occur regularly across Europe (European Red List of Birds, BirdLife International, <http://datazone.birdlife.org/info/euroredlist2021>), so about 22% of the European bird species occurred in the collision data (124 over 544).

For bats, the fitted data included 356 records of collision counts from 12 species, spanning 3 taxonomic families. These records were compiled from 11 different sources across 42 sampling sites located in Europe (Figure 1). There are about 47 species of bats occurring across Europe (Froidevaux et al., 2023), so about 26% of the European bat species occurred in the collision data (12 over 47).



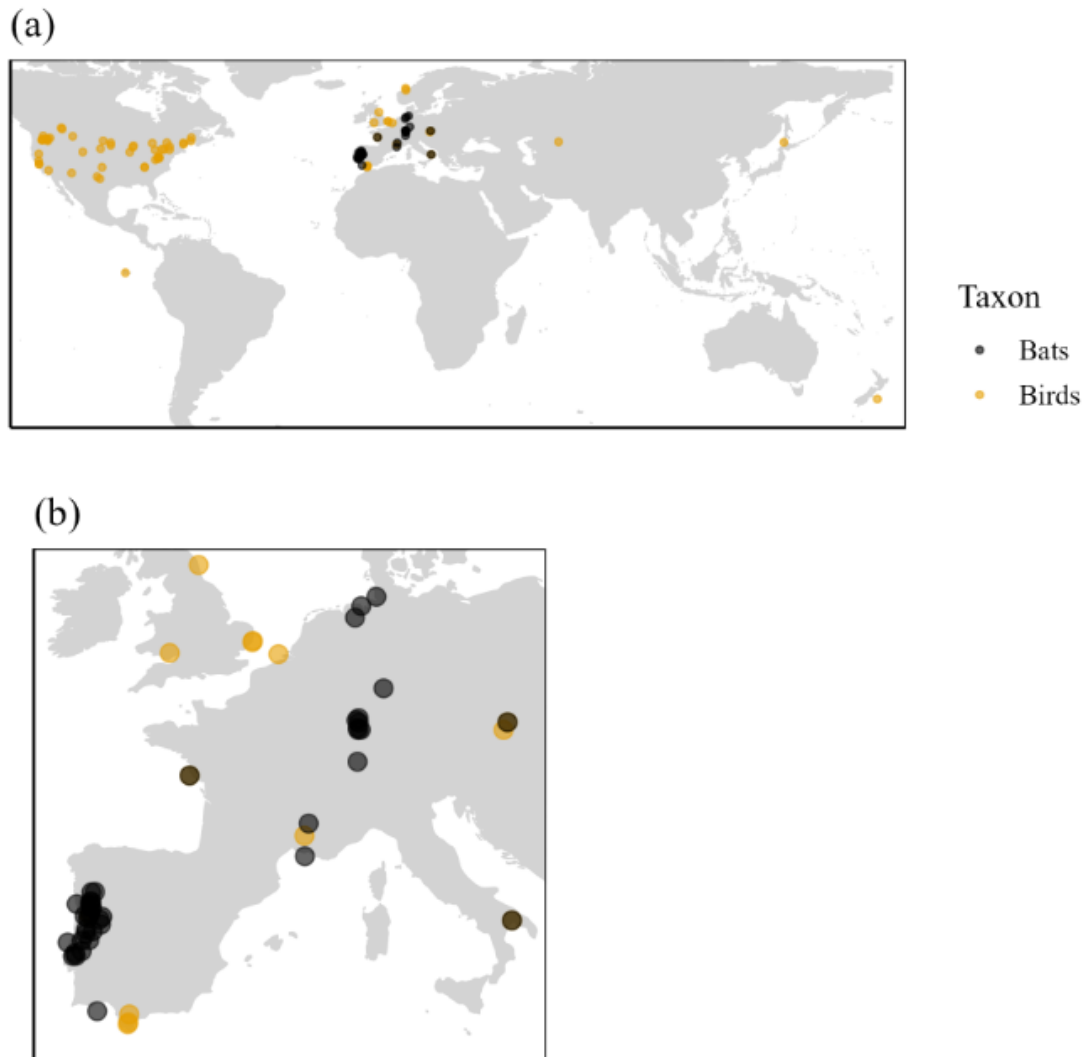


Figure 1: (a) Spatial distribution of all sampling sites (wind farms' central locations) included in the fitted data of the statistical models for birds and bats. (b) Location of the European sampling sites. Country shapes were obtained from the 'rnaturl-earth' R package (Massicotte et al., 2023).

2.3 Model predictions: estimations of collision-mortality rates at the species level

2.3.1 Species-level predictions

From the fitted models, we generated species-level estimates of collision-mortality rates for 531 European bird species and 26 bat species, known to occur in Europe regularly. However, not all these species were represented in the fitted data (Table 5); we only used information on species traits for the species that were not represented in the collision data; and we used

additional random effects on species identity for all other species that were represented in the data.

For some species, we obtained a suitability map from Jung (2023) that described where the species may occur in Europe; the maps were available for a fraction of the species (Table 5). The maps showed the degree of suitability of a particular location (grid cell) for a species, with an index varying between 0 and 1 (0: not suitable for the species; 1: entirely suitable for the species). We assumed occurrence wherever the suitability index was >0 (therefore obtaining the potential geographical range of each species). The suitability maps were obtained using an integrated species distribution modelling approach (Jung, 2023), which combined a range of biodiversity datasets and environmental variables (e.g., climate and land-cover variables) into an ensemble-modelling framework, to predict where the species occurred and how suitable the local environmental conditions might be for the species. The methodology behind the obtention of the maps is fully described in Chapman et al. (2023). All available maps were projected with the Lambert azimuthal equal-area projection, with a resolution of 10 km by 10 km.

Table 3: Number of bird and bat species known to occur in Europe (a), of which (b) number of species recorded in collision data, (c) number of species for which trait data was available for predictions, (d) number of species for which a suitability map was available, and (e) number of species which were both recorded in the collision data and for which a suitability map was available.

	(a) Occurs in Europe	(b) Recorded in collision data	(c) Data available for predictions	(d) Map available	(e) Recorded in collision data + map available
Birds	544	124	531	320	105
Bats	47	12	26	22	10

For the species identified to occur in Europe, we estimated the number of collision victims per year-turbine (mean \pm 95% credible interval) from the models. We used information on individual species traits to estimate

species-level collision-mortality rates from the effects of the fitted models. We generated predictions of collision-mortality rates at the species level for a turbine capacity of 2MW, a wind speed of 6 m/s at 100 metres, and for the highest study quality. For species that figured in the fitted data (124 species for birds, and 14 species for bats), we included the random effects of species identity in the predictions. For other additional species (407 species for birds and 16 species for bats), we used the models fixed effects only to generate the predictions. All predictions were made marginal to location (site) identity.

Additionally, we extracted the current threat status of each species from the IUCN Red List of Threatened Species, using the 'iucn_status' function of the 'taxize' R package (Chamberlain & Szöcs, 2013).

2.4 From collision mortality to vulnerability

Collision-mortality rates estimated from the statistical models represent the average number of individual birds and bats expected to die from wind-turbine collision, per year and per turbine (of 2 MW capacity). Therefore, these estimations reflect the average known **exposure** of the different species to collision mortality. These rates, however, do not reflect how sensitive a species might be to this additional, human-induced (non-natural) source of mortality.

Species with longer generation lengths, species with fewer offsprings, and rarer species, might be more sensitive to this added mortality, because, from a demographic point of view, it might take such species longer to recover from decreases in population size than species with shorter generation lengths, with a larger number of offsprings, or than more common species (Foden et al., 2013). Accounting for such differences in species life history might help understand which species could be more vulnerable to collision mortality.

To assess vulnerability, we developed a species-level sensitivity index that factored in three additional life-history and ecological traits (Table 4). We restricted this analysis to birds for which data on the three sensitivity traits were available (316 species). For comparability, each trait was normalised and rescaled between 0 and 1 across all species for which distribution maps were available (Table 3). Because species with shorter generation length were considered less sensitive, while species with smaller

litter or clutch sizes and with smaller geographical range area were considered more sensitive, we used the inverse of generation length. The sensitivity index was then obtained by summing the values for all three normalised traits. We then took the inverse and normalised the index, so that the sensitivity index ranged between 0 and 1, with low values reflecting low sensitivity and high values reflecting high sensitivity.

Table 4: Traits used to derive the sensitivity index across 316 birds.

Taxon	Ecological characteristic	Definition	Sources
Birds	1/Generation length (inverse of generation length)	Average age of parents of the current cohort (reflects the turnover rate of breeding individuals in a population; Pacifici et al. (2013))	Etard et al. (2020) –
	Litter or clutch size	Number of offspring (litter size) or eggs (clutch size)	Etard et al. (2020)
	Geographical range area	From the suitability maps, surface area where suitability >0	Suitability maps described in section 2.5

Combining the estimated collision mortality rates with the sensitivity index for each species ([Figure 2](#)), we derived a score reflecting species' vulnerability. Building upon the vulnerability framework (Foden et al., 2013), we considered species to be highly vulnerable when exhibiting high sensitivity and high exposure (score of 4), species to be at high latent risk when exhibiting high sensitivity but low exposure (score of 3), and species to be possible adapters/persisters when exhibiting low sensitivity with low/high exposure (score of 1 & 2; [Figure 2](#)). We used the 75% quantile of each distribution as a threshold value. We considered species to be highly sensitive and highly exposed when falling above the 75% quantiles. Thus, our analysis is comparative and highlights which species are at relatively higher risk within the considered pool of species.

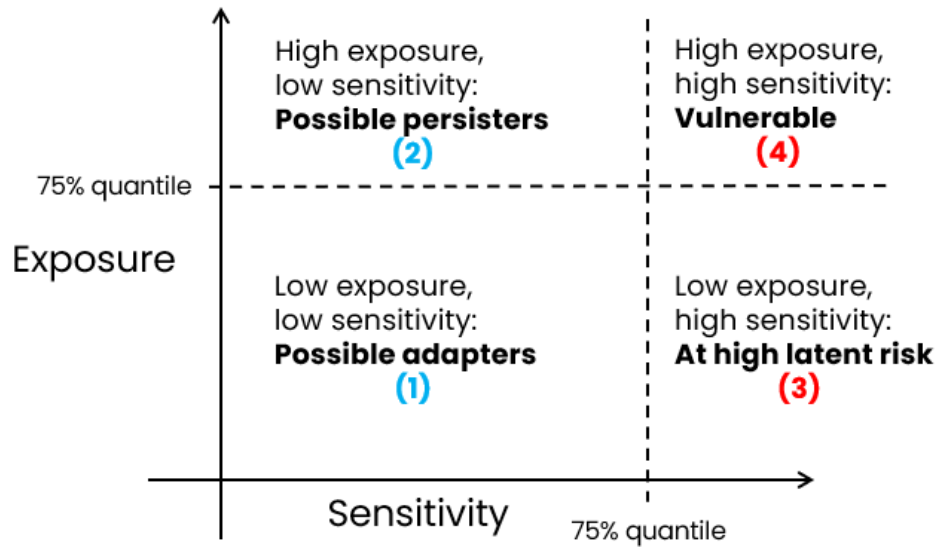


Figure 2: We derived a vulnerability score at the species-level by considering the overlap between the distributions of sensitivity and exposure, across species for which a suitability map was available (n=316). The 75% quantile of each distribution was used as a threshold above which we considered species to be highly sensitive and highly exposed. Exposure was estimated as the mean number of collisions per turbine and per year, while sensitivity was derived from combining information on generation length, litter or clutch size and geographical range area.

2.5 Mapping of outputs (collision mortality rates and vulnerability)

For each species, we mapped the estimated collision-mortality rate by transferring the predicted value onto the species suitability map (when available). As there was no variation in estimated collision-mortality rate within species and given that we generated predictions for a fixed wind speed value and a fixed turbine capacity, the mapped estimates are spatially uniform at the species level.

At the grid-cell level, we obtained summary statistics of collision-mortality rates and vulnerability scores across species. Specifically, by stacking the maps for a specified group of species, we calculated:

- The cumulative collision-mortality rate (sum of estimated collision-mortality rates across all species occurring in a grid cell; in other words, total predicted number of collision-mortality victims per year-turbine across all species occurring in a grid cell).



- The mean collision-mortality rate (mean and median of estimated collision-mortality rates across all species occurring in a grid cell).
- The standard deviation in collision-mortality rate (standard deviation in estimated collision-mortality rates across all species occurring in a grid cell).
- The species richness (number of species occurring in each grid cell).

The summary statistics can be obtained for any subsets of species that are of interest. Here, we present summary statistics across all the bird and bat species we considered.

Further, to assess where the most vulnerable species are likely to occur, we mapped species richness within each of the vulnerability group (highly vulnerable species, species at high latent risk, possible adapters, possible persisters).

3. RESULTS AND OUTPUTS

3.1 Fitted models

In birds, turbine capacity was significantly positively associated with the number of collision victims (Figure 3; Table A1; note that model coefficients are presented on the log-scale); species' hand-wing index and migratory status had near-significant effects. The mean number of collision victims (back-transformed estimate of the model's intercept) was 0.024 collision victims per year-turbine (95% credible interval: 0.0034-0.17). However, the fixed effects explained only a small proportion of the overall variation in the number of collision victims, partly because the random effects explained an important part of the variation (conditional pseudo- R^2 : 0.96; marginal pseudo- R^2 : 0.064). There were significant differences in the estimated random-effects estimates of species' identity, showing that the mean number of collision victims varied significantly among species (Figure A3).

In bats, we did not detect significant associations between species ecological characteristics and the number of collision victims (Figure 3;



Table A2). The mean number of collision victims (back-transformed estimate of the model's intercept) was 1.7 collision victims per year-turbine, with a large variation around the mean (95% credible interval: 0.027-98). The fixed effects explained only a small proportion of the overall variation in the number of collision victims, while the random effects explained only slightly more variation (conditional pseudo- R^2 : 0.20; marginal pseudo- R^2 : 0.057). There were few significant differences among the random-effects estimates of species' identity (Figure A3), but bigger differences among the random-effects estimates of site location (Figure A4).



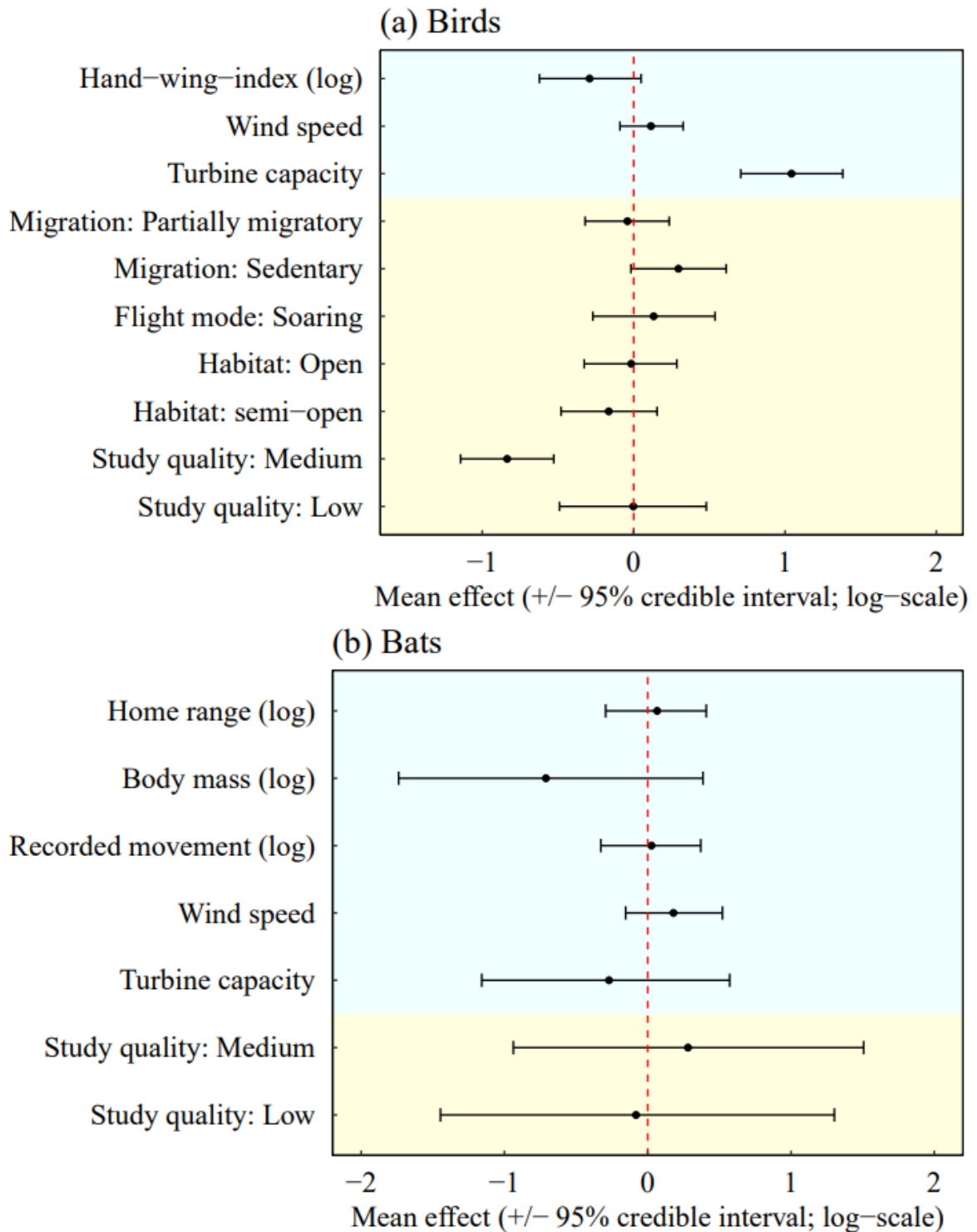


Figure 3: Estimated effects of the fixed predictors for the model fitted on (a) birds and (b) bats, mean \pm 95% credible interval. Light blue backgrounds highlight continuous predictors, while light yellow backgrounds highlight categorical predictors.

3.2 Estimated collision-mortality rates in birds and bats

3.2.1 Species-level estimates of collision-mortality rates

For 531 birds found to occur in Europe, mean estimated collision-mortality rates ranged between 0.018 victims per year-turbine (95% credible interval: 0.0065 – 0.040) for the black-crowned night-heron (*Nycticorax nycticorax*), to 1.6 victims per year-turbine (95% credible interval: 0.54 – 3.9) for the griffon vulture (*Gyps fulvus*). For 95% of the species, the mean estimated collision-mortality rate fell between 0.078 and 0.28 victims per year-turbine. 2.5% of the species (i.e., 14 species) had an estimated collision rate >0.28 (Figure 4; estimates are presented on the log-scale). There were differences in collision-mortality rates among avian taxonomic Orders (Figure 5). *Piciformes* (Order including woodpeckers and their relatives) had the highest median collision-mortality rate (0.17 victims per year-turbine). *Accipitriformes* (Order including eagles, hawks, kites, and vultures) had the second highest mean collision-mortality rate (0.185 victims per year-turbine) after *Columbiformes* (Order including doves and pigeons; mean collision-mortality rate: 0.189 victims per year-turbine).

For bats, mean estimated collision-mortality rates ranged between 0.062 victims per year-turbine (95% credible interval: 0.012 – 0.20) for Geoffroy's bat (*Myotis emarginatus*), to 1.7 victims per year-turbine (95% credible interval: 0.34 – 5.3) for the common pipistrelle (*Pipistrellus pipistrellus*). For 95% of the species, the mean estimated collision mortality fell between 0.11 and 1.4 victims per year-turbine. One species (*Pipistrellus pipistrellus*) had an estimated collision-mortality rate >1.4 (Figure 4; estimates are presented on the log-scale).

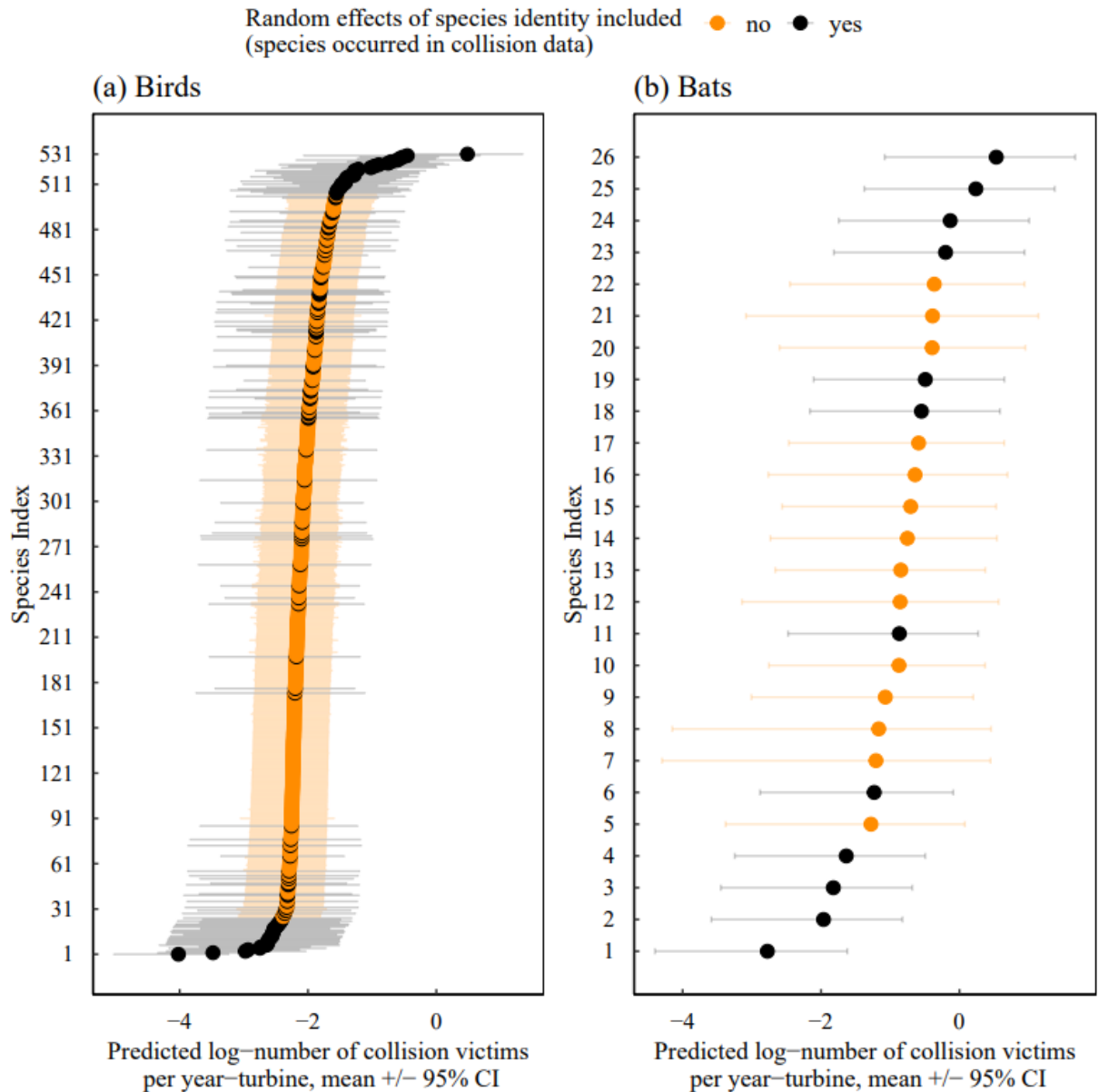


Figure 4: Predicted number of collision victims per year-turbine (mean \pm 95% credible interval) for (a) 531 bird species and (b) 26 bat species known to occur in Europe. The predictions are plotted on the log-scale. The predictions were generated for a turbine capacity of 2 MW, a mean wind speed at 100 m of 6 m/s, and a high study quality.

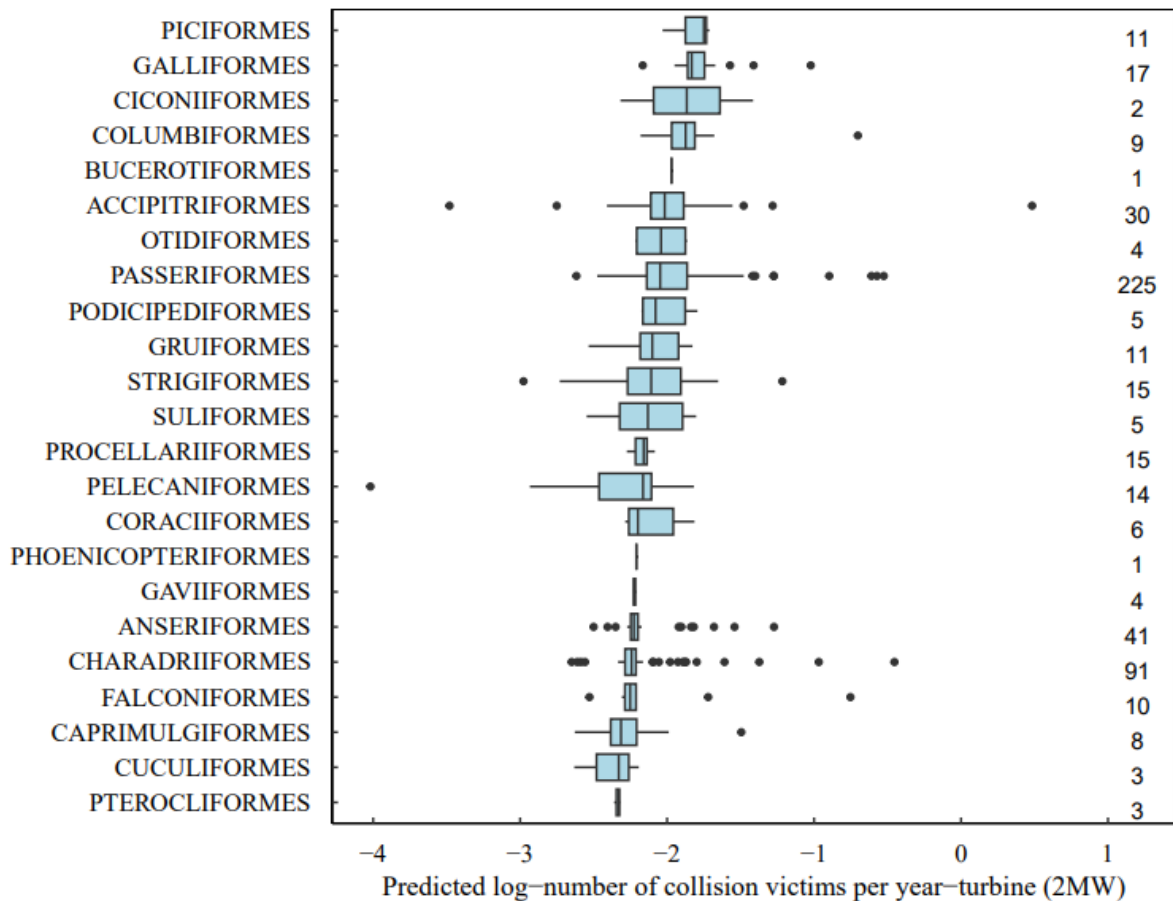


Figure 5: Distribution of predicted number of collision victims per year-turbine within avian taxonomic Orders. Numbers on the right-hand side of the plot show the sample sizes (number of species) in each Order. The predictions are plotted on the log-scale. The predictions were generated for a turbine capacity of 2 MW, a mean wind speed at 100 m of 6 m/s, and a high study quality.

3.2.2 Distribution of estimated collision-mortality rates among IUCN threat status groups

Among the species of birds we considered, 39 were listed as threatened (i.e., vulnerable, endangered, or critically endangered) according to the IUCN Red List of Threatened Species; two species of bats were listed as vulnerable (Figure 6).

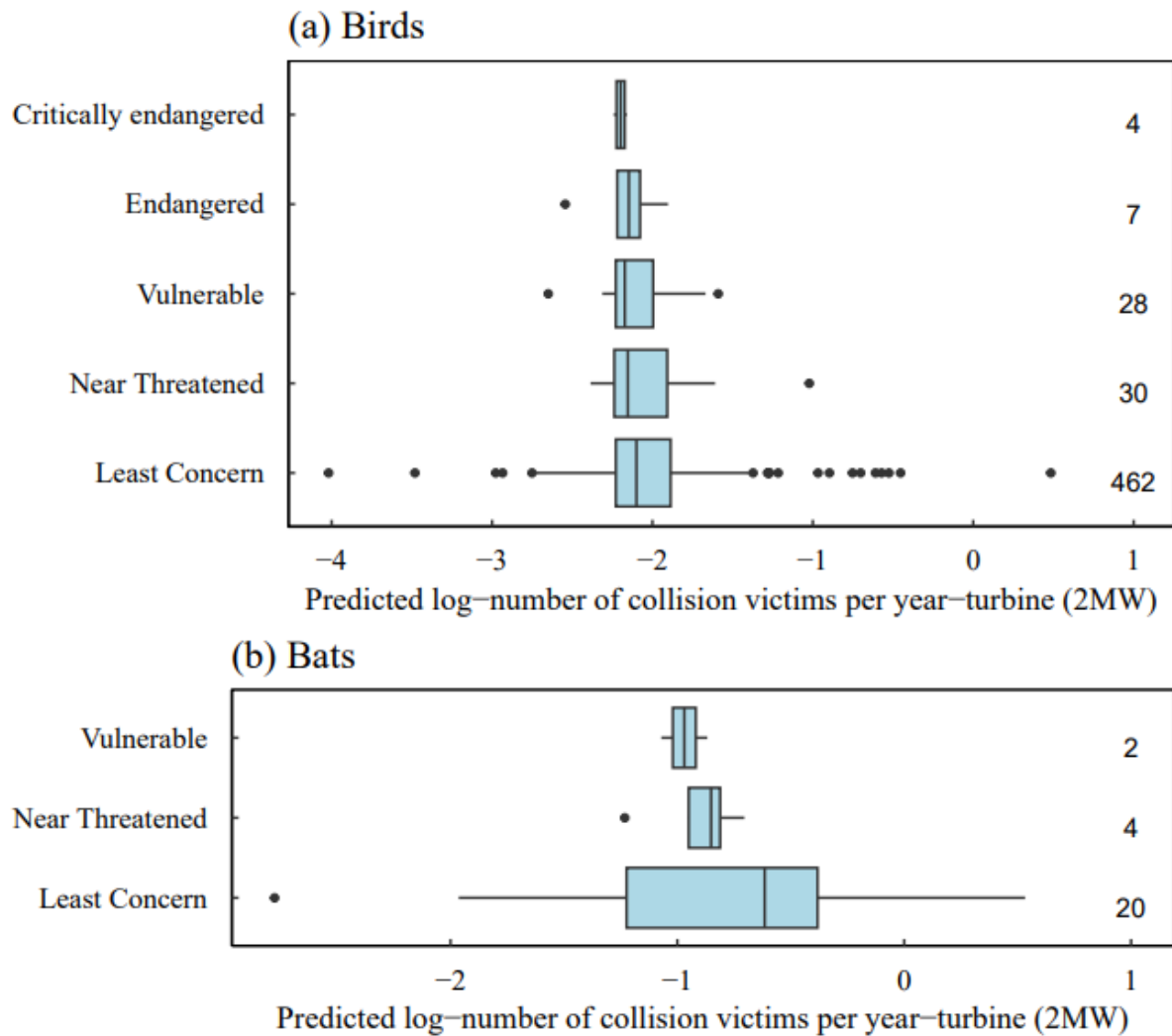


Figure 6: Distribution of predicted number of collision victims per year-turbine by threat status. Numbers on the right-hand side of the plot show the sample sizes (number of species) in each threat status group. The predictions are plotted on the log-scale. The predictions were generated for a turbine capacity of 2 MW, a mean wind speed at 100 m of 6 m/s, and a high study quality.

3.3 Vulnerability classes

Combining estimated collision rates with the sensitivity index, we found 8 species to be highly vulnerable, 71 species to be at high latent risk, 163 species to be potential adapters, and 74 species to be potential persisters (Figure 7).

The highly vulnerable species were the cinereous vulture (*Aegypius monachus*), the golden eagle (*Aquila chrysaetos*), the short-toed snake eagle (*Circaetus gallicus*), the griffon vulture (*Gyps fulvus*), the white-tailed

eagle (*Haliaeetus albicilla*), as well as the sandwich tern (*Thalasseus sandvicensis*), the common tern (*Sterna hirundo*), and the common murre (*Uria aalge*). Species at high latent risk notably included the bearded vulture (*Gypaeetus barbatus*), the Egyptian vulture (*Neophron percnopterus*), and the red kite (*Milvus milvus*).

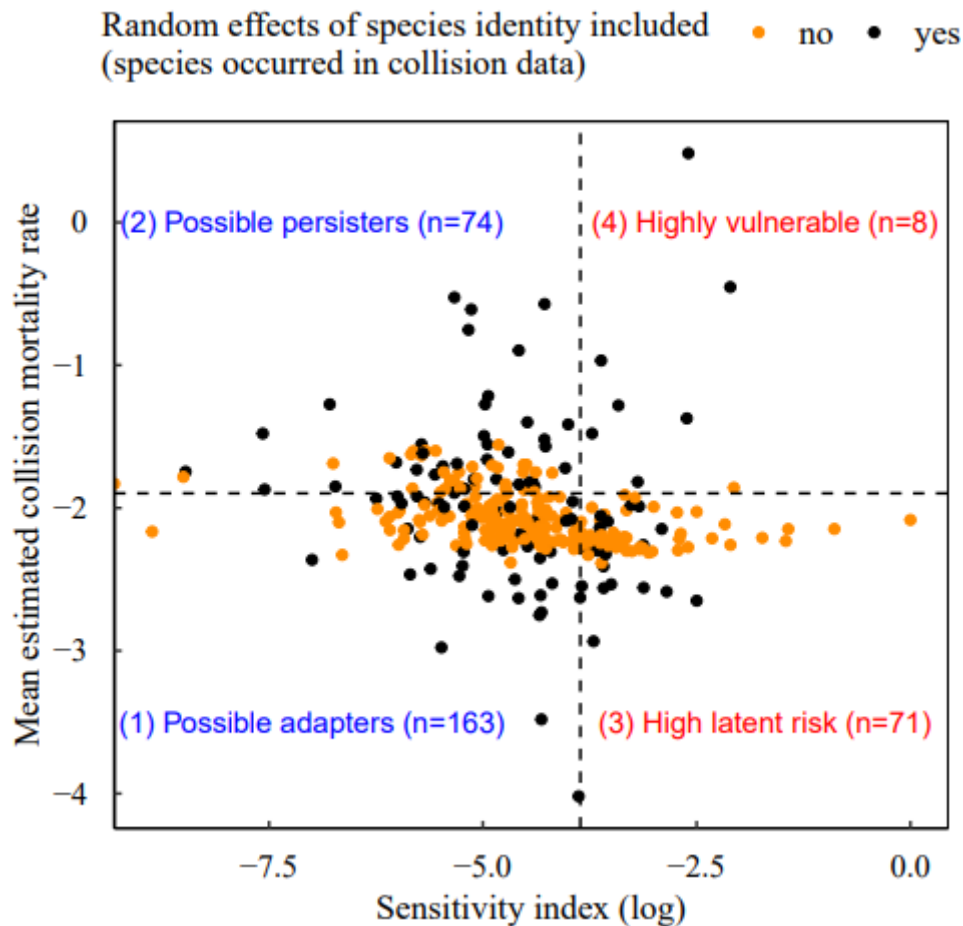


Figure 7: Estimated collision mortality rates against sensitivity index. Dashed lines represent the 75% quantiles of the distributions. Species with high sensitivity and high estimated collision mortality (i.e., falling above the 75% quantile of each distribution) were considered highly vulnerable.

3.4 Mapped estimates of collision-mortality rates and vulnerability classes

For each species, we transferred the value of the estimated collision-mortality rate onto the species range. By stacking the maps across species, we obtained summary statistics (sum, mean, and standard deviation of

estimated collision–mortality rates across all species occurring in a grid cell). Here, we provide examples of summary maps for all considered bats and birds, but summary maps can be obtained for any taxonomic group of species of interest.

3.4.1 Summary maps of collision–mortality rates across considered bat species

In bats, the cumulative mortality rate (sum of collision–mortality rates across all species occurring in a grid cell) reflected patterns of bat species richness for the considered species (Figure 8), likely because there were few significant differences in estimated collision–mortality rates across the 22 species. Consequently, there was little spatial variation in mean and standard deviation in estimated collision–mortality rates.

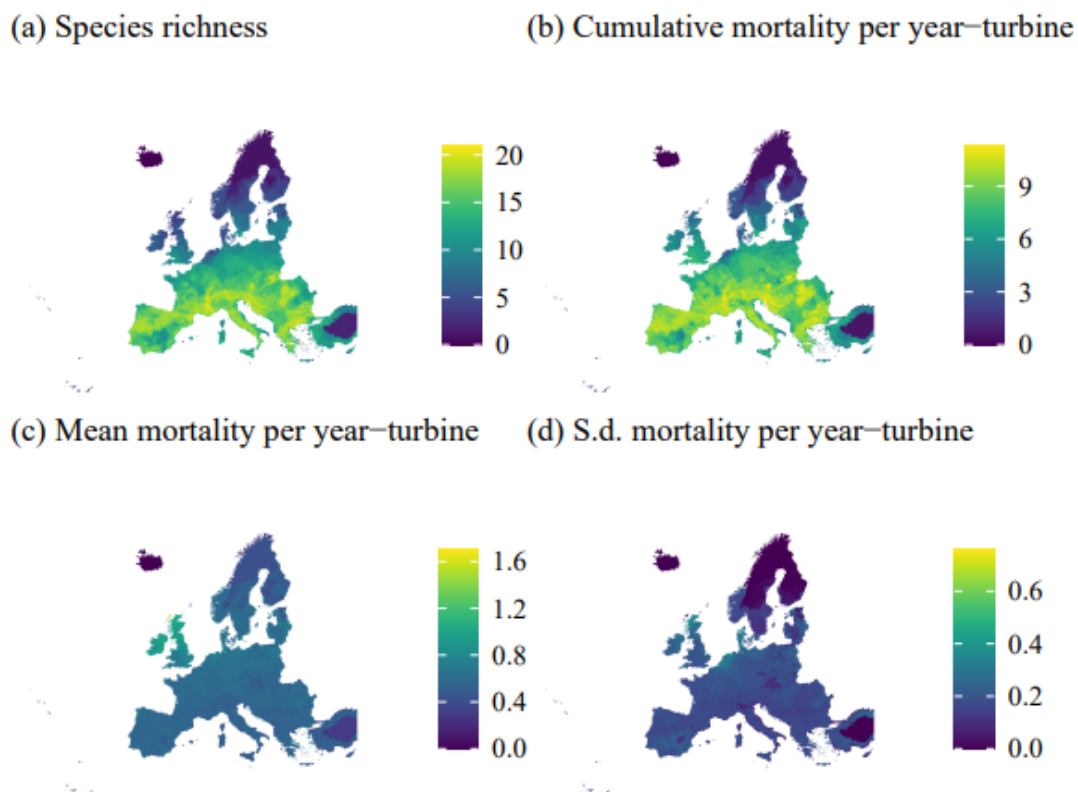


Figure 8: (a) Number of bat species found to occur in each grid cell (species richness, for the 22 species considered). (b)(c)(d) Summary statistics of estimated collision–mortality rates across all bat species occurring in a grid cell (sum, mean, and standard deviation).

3.4.2 Summary maps across all considered bird species



In birds, cumulative mortality rate also mirrored spatial patterns of species richness overall (Figure 9).

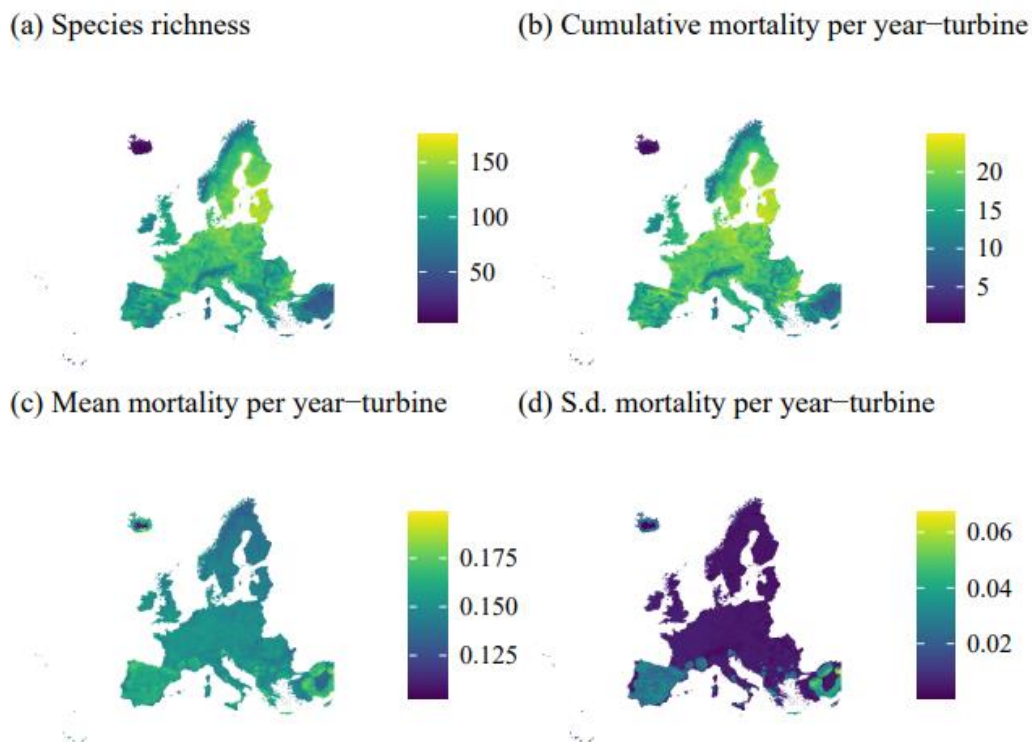


Figure 9: (a) Number of bird species found to occur in each grid cell (species richness, for the 320 species considered). (b)(c)(d) Summary statistics of estimated collision–mortality rates across all bird species occurring in a grid cell (sum, mean, and standard deviation).

3.4.3 Species richness by collision vulnerability groups

Mapping species richness within collision vulnerability classes (Figure 10) highlighted contrasting spatial patterns in the occurrence of highly vulnerable species across Europe. Several highly vulnerable species were notably concentrated in Spain and in Southern France, as well as in Baltic and Nordic countries. Such areas also harbored higher numbers of species at high latent risk. Areas with multiple highly vulnerable species or concentrating species at high latent risk were not necessarily the areas of highest cumulative collision mortality (Figure 10). This highlights that vulnerability to collision mortality at any given location depends on the local specific composition of the ecological assemblage, rather than solely on species richness.

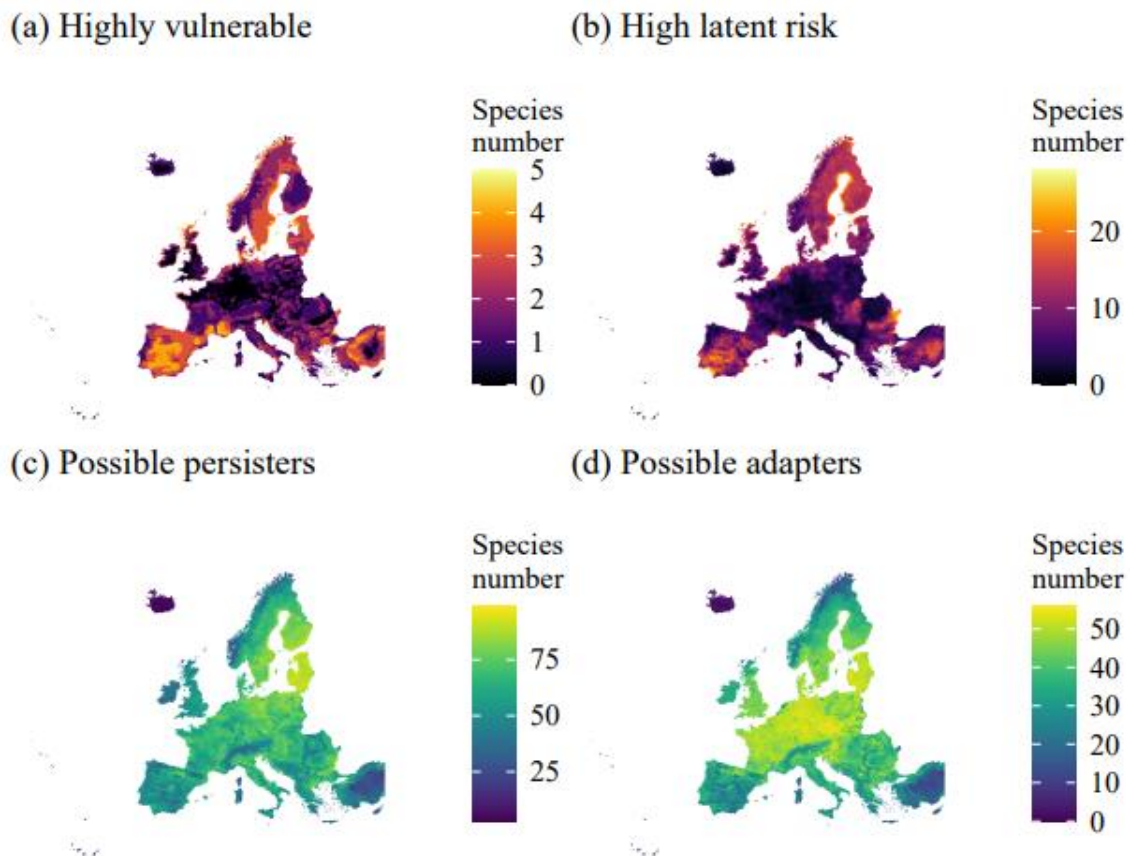


Figure 10: Species richness across Europe in each collision vulnerability group. Overall, we found that 8 species were classified as highly vulnerable, 71 were at high latent risk, 74 were classified as possible persisters, and 163 were classified as possible adapters.

3.5 Outputs

Some outputs described in Table 5 are accessible on the project's Yoda platform. The files and metadata are accessible under: <research-wimby-data/wimby_results/D1.6_birds_bats_collision_mortality_rates>.

Table 5: Description of the outputs and results of the task (Task 1.3).

Result	Format and access
<p>Dataset: Estimated collision-mortality rate at the species level, i.e., predicted number of collision victims per turbine-year, mean and 95% credible intervals. Provided for birds and bats separately. For birds only, estimated vulnerability class.</p>	<p>2 datasets, .csv files, under <i>D1.6_birds_bats_collision_mortality/1.species_predictions_tables</i></p>
<p>Maps: Mean estimated collision-mortality rate projected onto each species suitability map. Cropped around Europe; resolution of 10 km by 10 km; Lambert azimuthal equal-area projection.</p>	<p>2 folders containing 320 .tif files for birds and 22 .tif files for bats, under <i>D1.6_birds_bats_collision_mortality/2.Individual_species_maps.</i> Code and original suitability maps to generate outputs accessible upon request.</p>
<p>Maps: species richness and summary statistics of collision-mortality rate across all species occurring in a grid cell; for all considered bats and birds.</p>	<p>2 folders containing .tif summary maps (cumulative mortality rate, mean & standard deviation of mortality rate, and species richness), under <i>D1.6_birds_bats_collision_mortality/3.summary_maps.</i> For birds, we also provide species richness for each vulnerability class. Code and original suitability maps to generate outputs accessible upon request.</p>

4. DISCUSSION, LIMITATIONS, AND POSSIBLE DEVELOPMENTS

Using compiled data on recorded collision mortality for birds and bats, we investigated whether species traits, mean wind speed at the central location of wind farms, and turbine capacity, were associated with collision-mortality rates. From the models, we predicted collision-mortality rates (estimated number of collision victims per year-turbine) for 531 bird and 26 bat species known to occur in Europe. We mapped the outputs to visualise spatial patterns in collision mortality across Europe. For birds, we further assessed vulnerability by combining the estimated mortality rates with additional life-history and ecological traits, finding eight species to be highly vulnerable (including two European vultures and three eagles). Our work contributes to assess potential areas of higher risk from wind-power developments for flying animals at the European scale and can be employed in further tasks and work packages of the WIMBY project. Our outputs also help to assess which species could be more affected by wind-power developments.

We found that collision-mortality rates for birds were overall low (but see Nilsson et al. (2023)), but with significant variation around the mean attributed to fixed effects. We found turbine capacity to be significantly positively associated with collision-mortality rates. In past work, larger turbines with higher capacity have also been found to be associated with higher collision rates (Thaxter et al., 2017), but Thaxter et al. (2017) emphasized that deploying fewer turbines of higher capacity should result in lower mortality overall than deploying more turbines of lower capacity. We did not find significant associations between traits and mortality; we found a near-significant negative association of hand-wing index with collision mortality, and a near-significant positive effect for sedentary species, which might indicate that species tending to disperse less far may experience higher collision mortality. However, the fixed-effects structure of the model fitted on birds explained only a small part of the overall variation in collision-mortality rate (~0.1%). The random-effects structure explained a more important part of the variation (~96%). Interspecific variation in collision mortality were notably captured by the random effects of species identity, which highlighted significant differences in collision mortality



across species that we were unable to capture with our fixed effects. For instance, we found high collision mortality rates for the Griffon vulture (*Gyps fulvus*; estimated mean collision mortality rate: 1.6 victims per year-turbine) and the common murre (*Uria aalge*; estimated mean collision mortality rate: 0.64 victims per year-turbine). Given the amount of variation left unexplained by the fixed-effects structure of our model, our results highlight that patterns in collision mortality may not be generalisable, such that context specificity and local interactions between species and their direct environment may be most important in influencing collision mortality.

In bats, collision-mortality rates were overall higher than in birds, but we did not detect any significant differences in collision-mortality rates among the considered bat species, such that spatial patterns in collision mortality reflected patterns in bat species richness. However, the sample size for bats was lower than for birds, with fewer sampled species and sites, which might impede our ability to detect potential effects.

In both birds and bats, we fitted random effects of local site (wind farm) identity, to control for differences in collision-mortality rates among wind-farm locations. There were significant differences in estimated random effects of site identity, most notably for bats (Figure A4), which again highlights the importance of local, site-level characteristics for assessing collision-mortality risk. Local landscape characteristics are known to influence collision mortality (Kuvlesky Jr. et al., 2010; Moustakas et al., 2023), and context-specificity has been highlighted in past work (Marques et al., 2014). Our work therefore emphasizes the importance of local-scale assessments of collision-mortality risk for wind-power projects.

In bats, most of the variation in collision-mortality rates remained unexplained by our model's fixed- and random-effects structure, while in birds, part of the variation remained unexplained. Unexplained variation could be attributable to factors influencing collision mortality that we did not capture in our models. Some of these factors may relate to environmental characteristics such as landscape and terrain, as well as to variability in weather conditions, to wind-farm characteristics (e.g., lighting), or to



species characteristics that we did not include. It is also possible that different factors have interactive effects on collision–mortality rates.

A limitation of our work is that we did not account for intraspecific variation in collision–mortality rates. Collision–mortality rates may vary within a species, for instance with the age of individuals (Dahl et al., 2013). However, capturing intraspecific variation in trait values was infeasible in our work. Further, among the different factors that influence collision mortality, some may be capturable at the species- and landscape-level, but other factors (such as weather, or species behavioural plasticity) are difficult to capture in a quantitative synthesis such as ours. Ultimately, collision mortality is influenced by complex interactions among a wide range of factors (Drewitt & Langston, 2008; Marques et al., 2014), some of which possibly difficult to account for. Another limitation of our work is that the estimated collision–mortality rates are yearly averages; however, collision mortality can vary seasonally (Balmori-de la Puente & Balmori, 2023; Cabrera-Cruz & Villegas-Patraca, 2016; Lloyd et al., 2023), but we did not account for such temporal variations here.

Our work nevertheless provides species-level estimates of collision–mortality rates and vulnerability which can help assess which species and areas could be most affected by wind-power developments at the continental scale. An important question is how collision mortality impacts species populations and demography on the long term and over large spatial scales (Arnett & May, 2016; Chambert & Besnard, 2021; Desholm, 2009; Duriez et al., 2023; May et al., 2019). Long-term impacts of collision mortality depend on species' demography and population density. Here, we employed a comparative assessment to assess vulnerability for birds, factoring in additional life-history and ecological traits. Further developments of our work could consider investigating population-level impacts of collision mortality using demographic models.

Finally, while wind-power farms can negatively affect flying animals through collision mortality, the effectiveness of different mitigation measures for reducing collision mortality has been assessed in some past works (Marques et al., 2014), which show that mitigation measures can



successfully reduce collision mortality at wind-power farms (Arnett et al., 2011; de Lucas et al., 2012; Ferrer et al., 2022). As anthropogenic pressures on biodiversity act in combination (Harfoot et al., 2021; Maxwell et al., 2016), it is notably important to ensure that wind farms do not increase the risk for species that are already threatened by multiple other anthropogenic pressures, by putting into place appropriate mitigation strategies (Arnett & May, 2016; Voigt et al., 2022). We would like to further highlight that it is essential to also mitigate the risk posed to birds by power lines. Indeed, in a recent study of mortality causes for birds over the Eurasian–African flyway, Serratos et al. (2024) showed that mortality events related to energy infrastructure represented 49% of human-induced mortality events, but only a small proportion of these mortality events were attributed to wind-farm collisions; electrocutions and collisions with power lines represented the majority of these mortality events. Thus, as more and more wind-power farms are deployed in the coming decades, it is essential not only to mitigate the risk they pose directly to flying animals, but also to mitigate the risk posed by the necessary expansion of related energy infrastructure.



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ANNEX

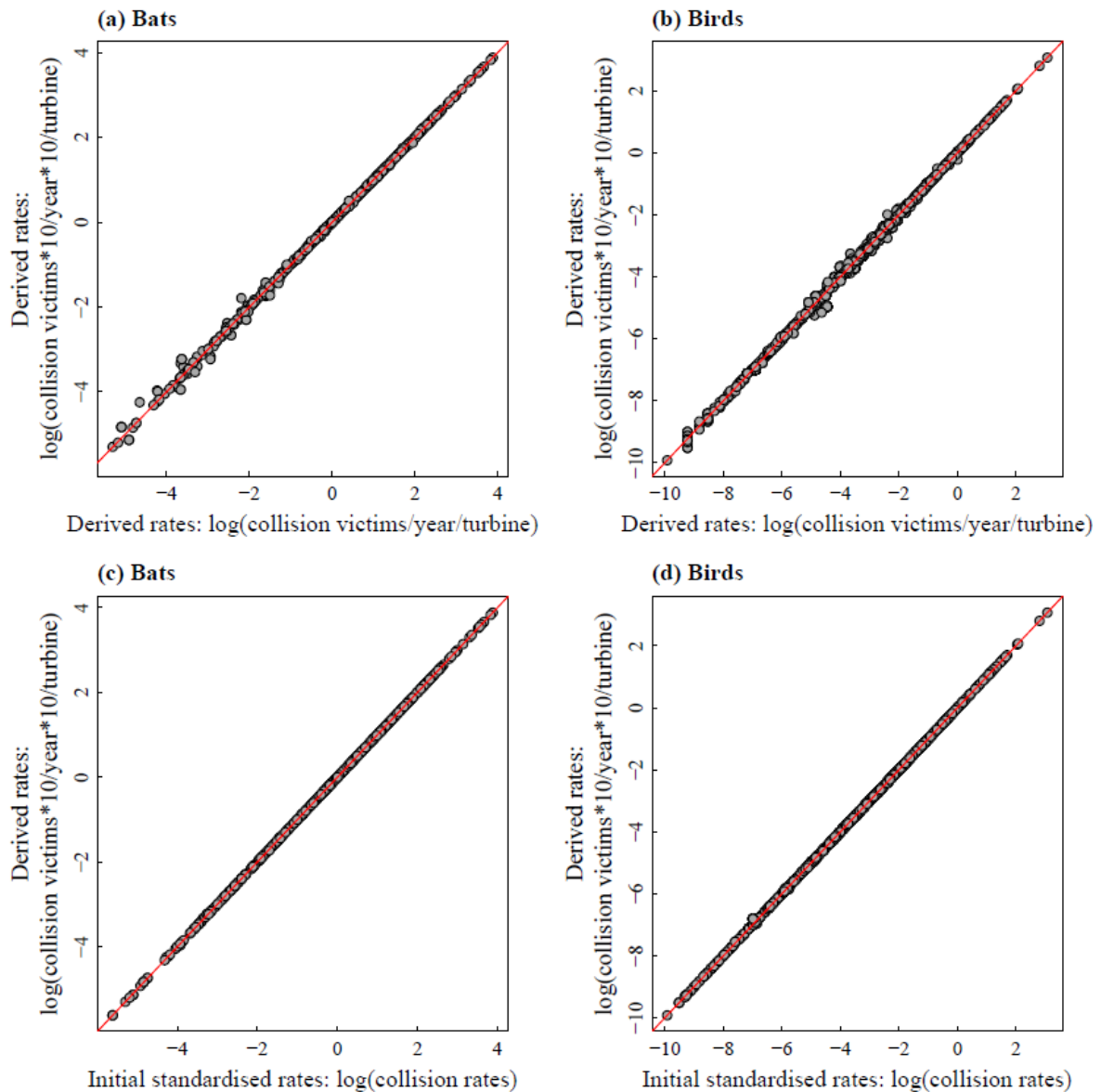


Figure A1: (a) and (b): Collision-mortality rates derived from the original compiled data, calculated after converting the original rates to counts of collision victims, either after multiplying original rates and study duration by 10 before rounding (y-axis), or rounding values directly without multiplying by 10 (x-axis). (c) and (d): Derived collision-mortality rates we used (from counts and study duration multiplied by 10; y-axis) against the original collision-mortality rates in the data.

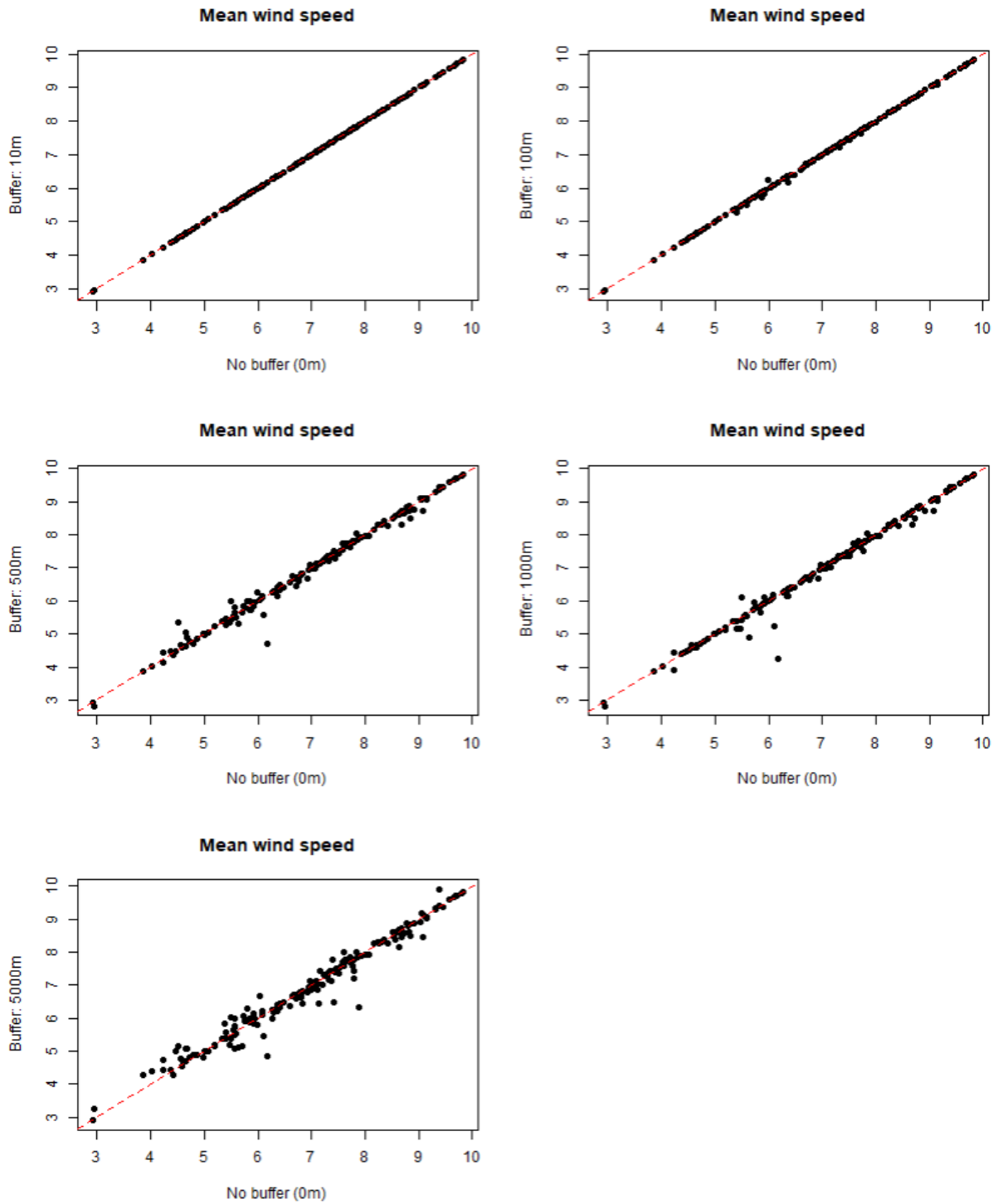


Figure A2: Mean wind speed (m/s) at 100 metres at the central wind farms' locations calculated using various buffer sizes around the locations: 0m (no buffer), 10m, 100m, 500m, 1000m, and 5000m.



Table A1: Summary of the model fitted for birds, investigating associations of collision–mortality rates with species–level characteristics, mean wind speed at the wind farms’ central locations, and turbine capacity.

Collision fatality counts		
Predictors	Log-Mean	95% CI (lower; upper)
Intercept	-3.74	-5.69; -1.77
Migration: partial migrant	-0.04	-0.32; 0.23
Migration: sedentary	0.30	-0.02; 0.61
Flight mode: soaring	0.13	-0.27; 0.54
Habitat density: open	-0.02	-0.33; 0.29
Habitat density: semi open	-0.16	-0.48; 0.15
Hand-wing index (log)	-0.29	-0.62; 0.05
Mean wind speed	0.11	-0.09; 0.33
Turbine capacity	1.04	0.71; 1.38
Quality: Medium	0.00	-0.49; -0.53
Quality: Low	-0.83	-1.14; -0.53
Random effects		
σ^2	13048746.62	
N _{Study ID}	80	
N _{Site ID}	68	
N _{Species}	330	
Observations	2204	
Marginal R ² / Conditional R ² 0.064 / 0.964		

Table A2: Summary of the model fitted for bats, investigating associations of collision–mortality rates with species–level characteristics, mean wind speed at the wind farms’ central locations, and turbine capacity.

Collision fatality counts		
Predictors	Log-Mean	95% CI (lower; upper)
Intercept	0.54	-3.60; 4.58
Home range (log)	0.07	-0.29; 0.41
Body mass (log)	-0.72	-1.74; 0.39
Recorded movement (log)	0.03	-0.33; 0.37
Mean wind speed	0.18	-0.15; 0.52
Turbine capacity	-0.26	-1.16; 0.57
Quality: Medium	-0.08	-1.45; 1.30
Quality: Low	0.28	-0.94; 1.51
Random effects		
σ^2	69126.43	
N _{Study ID}	11	
N _{Site ID}	42	
N _{Species}	12	
Observations	356	
Marginal R ² / Conditional R ² 0.057 / 0.203		

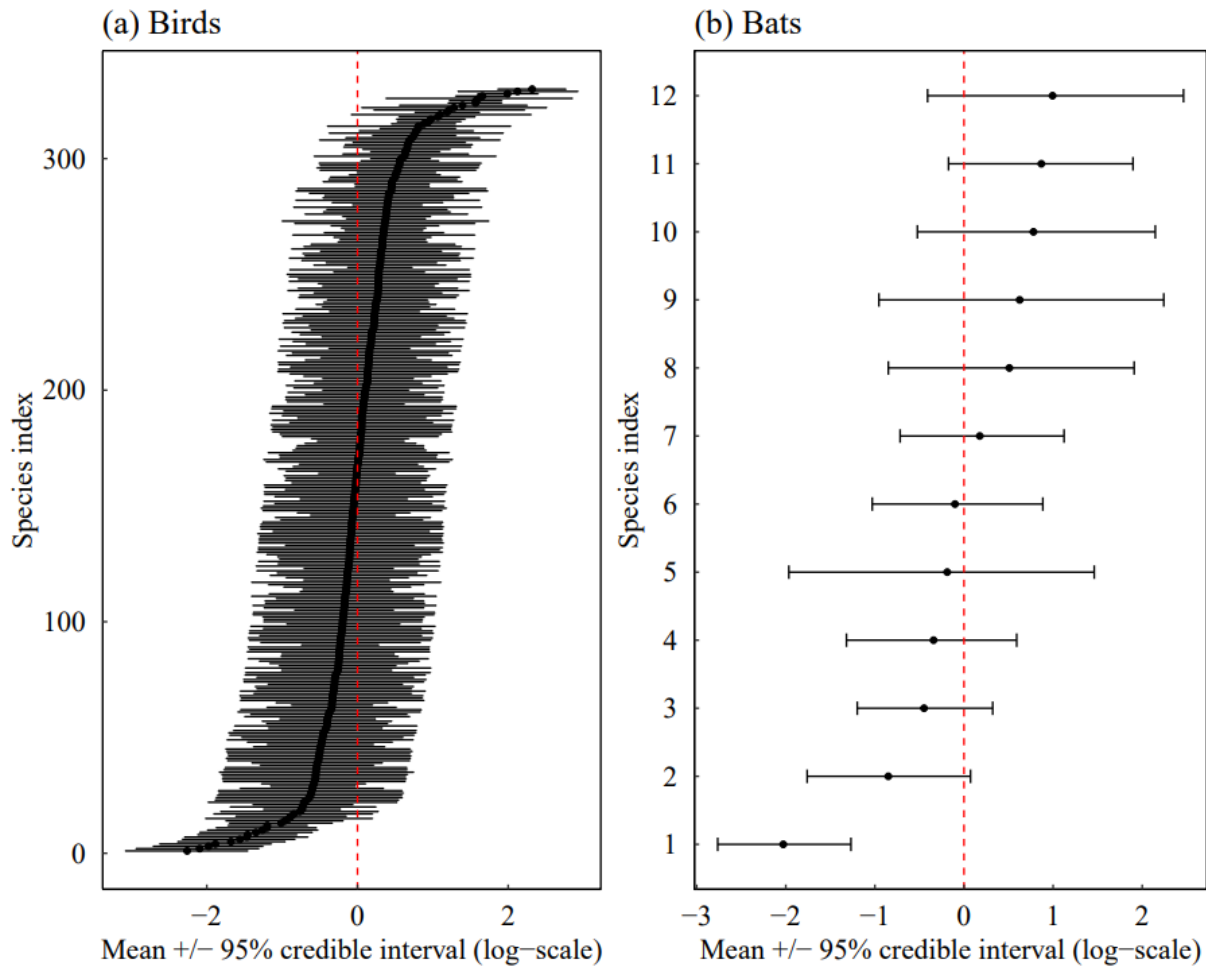


Figure A3: Random-effects estimates of species identity for the model fitted on (a) birds and (b) bats, investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms' central locations, and turbine capacity.

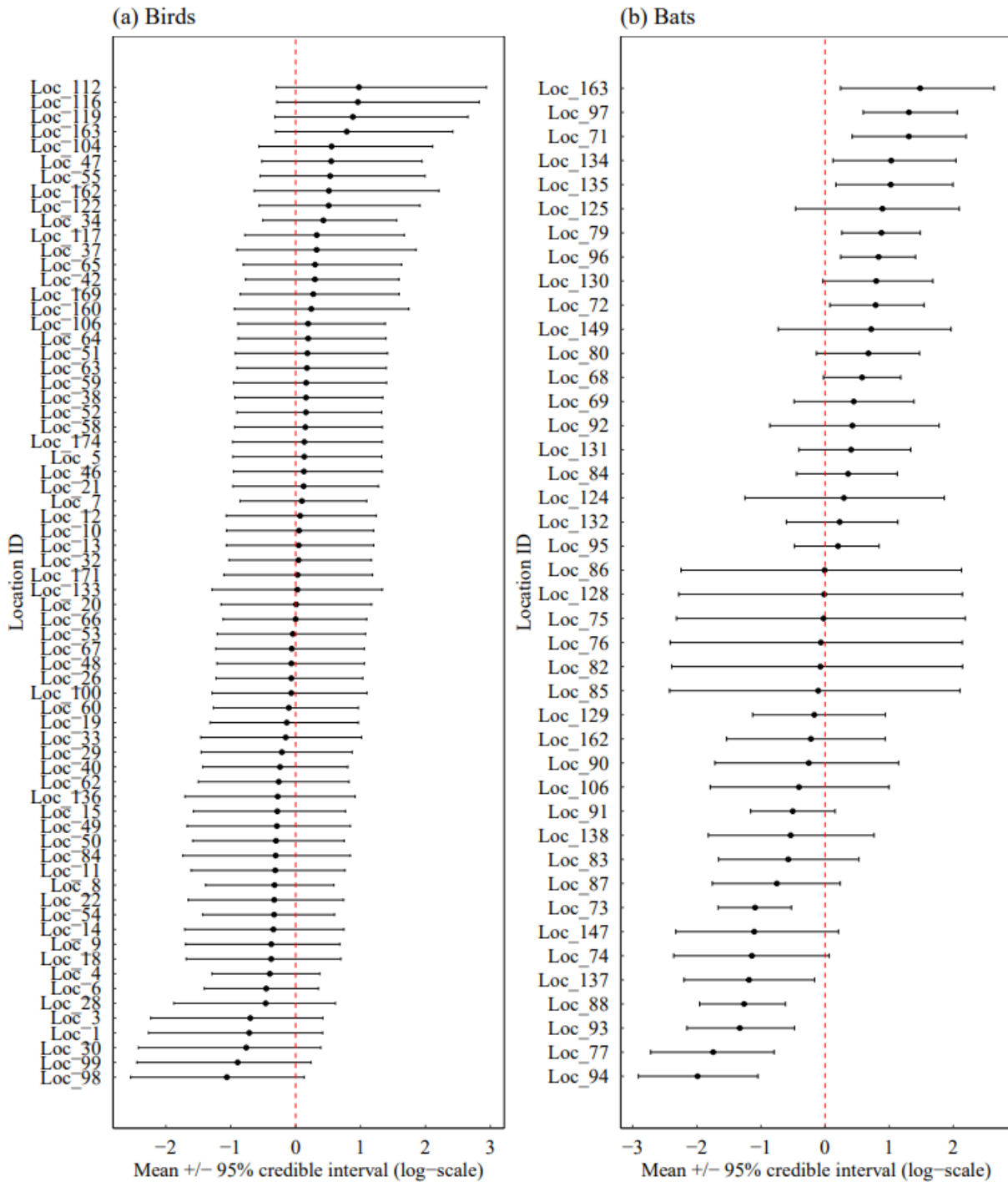


Figure A4: Random-effects estimates of site locations (central wind farms' locations) for the model fitted on (a) birds and (b) bats, investigating associations of collision-mortality rates with species-level characteristics, mean wind speed at the wind farms' central locations, and turbine capacity.