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RESEARCH ARTICLE

Towards a better understanding of avian collision in wind energy facilities using automatic detection systems

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Abstract

1. The rapid expansion of wind power energy has direct negative impacts on biodiversity, notably on avifauna through collisions with turbines. A better understanding of the collision causes is key to improving mitigation efforts. Collisions are the result of a combination of environmental factors that increase bird sensitivity and/or exposure to collisions. To date, potential risk factors have mostly been assessed individually, in few species of interest and/or at small spatiotemporal scales, despite the multifaceted nature of collision risk.
2. To fill this gap, we used for the first time data from automatic detection systems (optic systems that automatically detect and monitor birds in the vicinity of wind turbines) to simultaneously assess the effects of behavioural and environmental factors on bird sensitivity (here, estimated as the bird presence in the risk zone) and exposure (here, estimated as the frequency with which birds use the zone). We analysed 205,867 bird trajectories recorded between 2018 and 2023 in 11 French wind energy facilities.
3. We obtained results similar to previous studies relying on other methods (GPS, direct observations). Results suggest that bird sensitivity was higher during periods of high bird activity (first hours of daylight and migrations). They also suggest that sensitivity and exposure may increase in conditions that reduce the birds' visual perception of turbines (high nebulosity, low visibility and low rotor speeds) and in conditions that may influence birds' flight height (high temperatures and high wind speeds). We found a nonsynchronicity of exposure and sensitivity peaks, highlighting the importance of considering both drivers of risk when investigating the collision risk. However, our results show a high variability between species, flight behaviours and sites that should be addressed in the future to clarify the relationships between collision risk, birds' visual perception and behaviour.
4. *Policy implications*. Data from automatic detection systems are a promising non-invasive approach that requires few human and logistical resources to develop a more comprehensive bird collision risk mitigation strategy. They can be valuable to biodiversity stakeholders to highlight environmental factors that locally increase

bird exposure and sensitivity, to avoid installing turbines in sensitive areas or to adjust detection system settings.

KEYWORDS
bird collision, detection system, flight behaviour, wind turbines, wind energy facilities

1 | INTRODUCTION

In Europe, the European Commission aims at becoming the world's first climate neutral continent by 2050, notably by developing sustainable energies such as wind energy (2021). Despite the environmental benefits, the rapid transition to wind energy raises concerns about its consequences on wildlife. When poorly planned, wind energy facilities have a negative impact on biodiversity, especially birds (Schuster et al., 2015), indirectly through loss of natural habitat and behavioural changes (Loss et al., 2013; Marques et al., 2021) and directly through collisions with turbines (Drewitt & Langston, 2008; Thaxter et al., 2019). Collision-induced fatalities have dramatic consequences on bird population dynamics, especially for long-lived species with a slow pace of life (Duriez et al., 2023). A better understanding of collision risk is key to improving mitigation efforts, as mandated by public policies in most European countries (European Commission, 2021).

Vulnerability to collision risk varies with bird phenology (Barrios & Rodriguez, 2004; Balmori-de la Puente & Balmori, 2023; but see Aschwanden et al., 2018; de Lucas et al., 2008) and weather conditions (temperature, wind speed, visibility: Barrios & Rodriguez, 2004; Drewitt & Langston, 2008). Collision risk also varies between sites, notably because of environmental characteristics (topography: Barrios & Rodriguez, 2004; Péron et al., 2017; habitat and food availability: Morant et al., 2024) and technical characteristics (turbine dimensions: Loss et al., 2013; Schaub, 2024; turbine number: Morant et al., 2024; spatial arrangement: Huso et al., 2021; Schuster et al., 2015). In addition, collision risk depends on intrinsic characteristics of the species (migratory strategy: Barrios & Rodriguez, 2004; but see Drewitt & Langston, 2008; Fielding et al., 2023; Schuster et al., 2015; wing morphology: Barrios & Rodriguez, 2004; de Lucas et al., 2008; flight height: Rolek et al., 2022; flight behaviour: Balmori-de la Puente & Balmori, 2023) and individuals (age: Drewitt & Langston, 2008 but see Fielding et al., 2023; Santos et al., 2021; sex: Heuck et al., 2020 but see Santos et al., 2021).

Vulnerability to collision is the combination of two drivers: sensitivity and exposure (Thaxter et al., 2019). In the context of bird collision, sensitivity has previously been assessed as birds' presence in zones where collision risk is the highest (i.e., close to the turbine rotor) by measuring bird flight height (Morant et al., 2024), distance travelled by birds at rotor height (Thaxter et al., 2019) and proportion of flight time at rotor height (Schaub, 2024). Exposure has been measured as the frequency with which birds are present in the wind energy facilities (Morant et al., 2024) or as turbine density (Assandri et al., 2024; Thaxter et al., 2019). Based on these definitions, the most vulnerable birds are those who frequently use the wind energy facilities and fly close to the rotor. Sensitivity and exposure vary across temporal and spatial scales due to environmental factors that influence either one (Morant et al., 2024) or both of them (Aschwanden et al., 2018; de Lucas et al., 2008).

Factors that increase bird sensitivity or exposure have been mainly studied independently, despite their strong interrelationships (Marques et al., 2014). Similarly, very few studies have considered sensitivity and exposure simultaneously. A better understanding of collision risk needs to account for its multifaceted nature by assessing how environmental factors drive both sensitivity and exposure over large temporal and spatial scales. A common approach to study collision risk in birds is to rely on traditional bird census techniques with direct observations of bird fatalities, occurrences and trajectories by ornithologists during periods of interest such as the breeding season (Marques et al., 2021). However, sample sizes and spatial or temporal replication are typically low with this time-consuming, labour-intensive method. The use of location-based tracking, such as GPS telemetry, offers an attractive alternative for assessing bird flight behaviour in wind energy facilities. It provides detailed data that allow scientists to characterise both bird sensitivity (bird position, flight height and direction) and exposure (frequency with which they fly within the facility). However, tagging individuals with GPS devices is often limited to a few species/taxa of interest such as diurnal raptors (Assandri et al., 2024; Morant et al., 2024; Santos et al., 2022; Schaub et al., 2020) and is subject to ethical considerations, especially for endangered species.

An alternative to traditional bird census techniques or tracking devices would be automatic technologies, such as automatic detection systems used to mitigate bird fatalities in wind energy facilities. These systems installed on or near operating turbines detect, identify and track flying birds using cameras, and trigger turbines to slow down when birds approach (Gradolewski et al., 2021; May et al., 2012; McClure et al., 2018). Data recorded by detection systems are used primarily to evaluate system performance or efficiency (Duerr et al., 2023; May et al., 2012; McClure et al., 2018, 2021, 2022). To our knowledge, they have been used only once to assess bird occurrence and behaviour at wind energy facilities (Linder et al., 2022), despite their potential: they automatically record a wide range of information in various weather conditions throughout days, over years, in many facilities worldwide. Therefore, detection systems seem a promising lead to automatically collect a large amount of data to perform a global study examining how bird sensitivity and exposure are influenced by multiple environmental factors, providing the robust and generalizable results needed to go further in our understanding of bird collision risk.

As proof-of-concept, this study leverages automatic detection system data to examine the relationships between exposure, sensitivity and environmental factors known or suspected to enhance bird collision risk (e.g. weather, turbines' technical characteristics and rotor speed). Using data from 11 wind energy facilities, we expect results with this new data source to be consistent with previous studies relying on other methods. We hypothesize that sensitivity would be mainly driven by factors affecting birds' flight behaviour, turbine perception and/or detection system efficiency, notably temperature, wind speed and visibility (Marques et al., 2014); while exposure would vary seasonally (Schuster et al., 2015).

2 | MATERIALS AND METHODS

2.1 | Study sites

We gathered data shared by 11 wind energy facilities equipped with automatic detection systems in France. The vast majority of data originated from facilities in eastern France (Figure 1), in temperate continental agricultural plains (see Table S1 for site details). Their exact location is kept confidential to protect the identities of the operators and the industrial secrets of the detection system manufacturers.

2.2 | Data collection

2.2.1 | Data from automatic detection systems

We gathered data from two brands of automatic detection systems that rely on 2D optics and two brands that rely on 3D optics (hereafter, 2D- and 3D-systems). When a bird was detected near a turbine, 2D-systems recorded videos and/or pictures until the bird left the detection zone. When detected by 3D-systems, birds were tracked in a three-dimensional space and their positions were recorded at regular intervals depending on the technical characteristics of detection systems (one position per second for the first system and 6 ± 6 positions per second for the second; Table S1). In addition, most detection systems recorded contextual information about the bird detection (e.g. bird taxa or size class, bird-turbine distance, turbine reaction

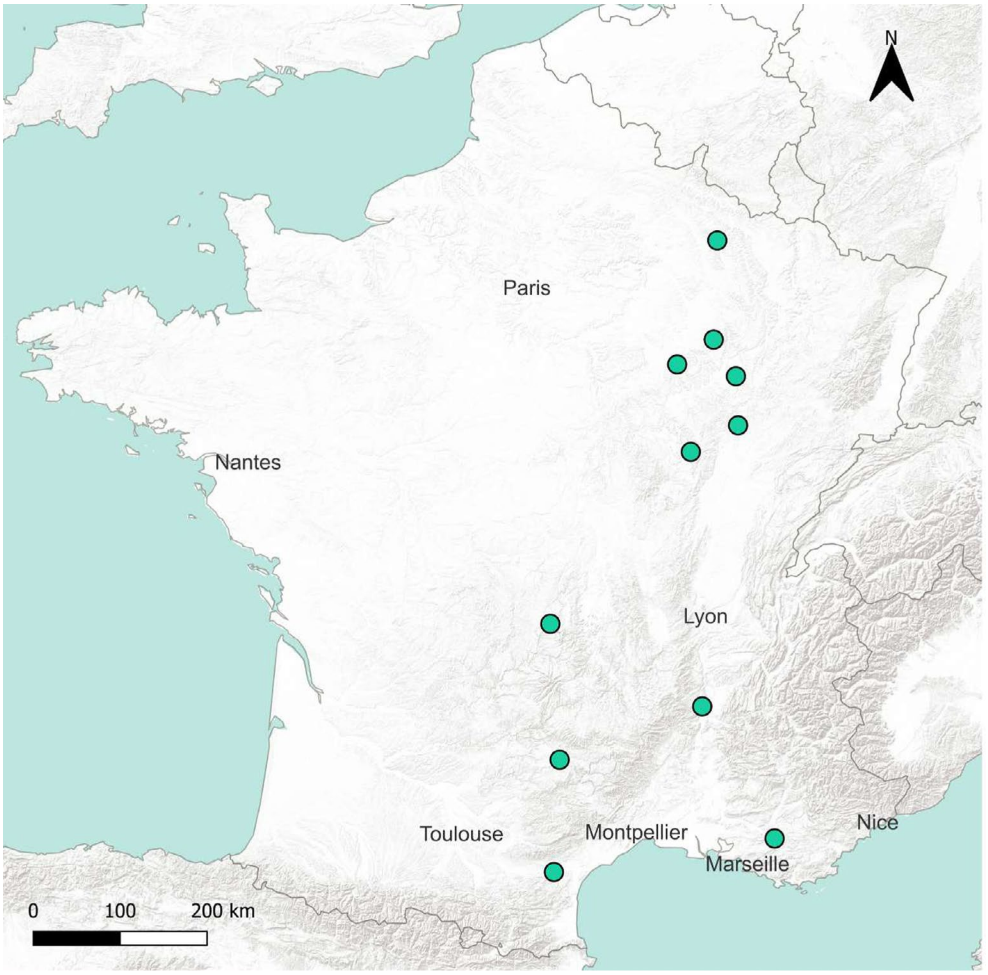

FIGURE 1 Location of the wind energy facilities that provided data from automatic detection systems.

such as curtailment, emission of acoustic and/or visual repelling signal). Data ranged from April 2018 to September 2023, but the study period and duration vary between the 11 sampled wind energy facilities (Table S1). Detection systems work during the day and have a better detection rate with birds with a wingspan >0.75 m (Gradolewski et al., 2021). Therefore, nocturnal species and small birds were excluded from the analyses. No ethical approval is required for the use of such monitoring data, collected automatically and non-invasively.

2.2.2 | Location and technical characteristics of wind energy facilities

We collected four variables related to turbines that may influence collision risk: number of turbines, height of the turbine hub (i.e. ground-hub distance), diameter of the rotor and construction year (see Table S2 for a reference list and Table S3 for the variable list), from operators and publicly available databases (The Wind Power, 2024). We calculated the age of the facilities as the number of years between their construction and the time of bird detections. We defined the risk zone around each turbine as a vertical cylinder with a 350-m radius centered on the turbine, whose height equals the maximum height of the turbine, from ground level to the tip of a vertical blade (New et al., 2015). These dimensions are based on the technical characteristics used by most detection systems to design the curtailment order zone (zone in which the detection system curtails the turbine if a bird is detected inside; Duerr et al., 2023). By including the space from the ground to the lowest point of the rotor (ground clearance), we included the likelihood of collisions with the mat and accounted for sudden altitude changes in the bird's flight behaviour (New et al., 2015).

2.2.3 | Weather data

We collected five weather variables that may influence the detection system efficiency and/or collision risk (Table S2): temperature, wind speed, nebulosity, humidity and visibility. Data were downloaded from the publicly available database of Météo France, the French national meteorological service. We chose weather stations at distances <30 km from the focal facility and at a similar altitude (<60 m) when possible.

2.2.4 | Landscape data

We described land cover and relief heterogeneity at each facility using two geographic layers derived from satellite imagery: Corine Land Cover (CLC) and European Digital Elevation Model (EU-DEM), respectively. We used CLC with a 100-m resolution from 2018 and EU-DEM with a 25-m resolution from 2010 (Copernicus Land Monitoring Service, n.d.). We created a 600-m radius from the centre of each facility using QGIS 3.28.3-Firenze. We then calculated the proportion of forest and the Terrain Ruggedness Index (TRI) within the buffer. TRI is a measure of elevation changes across a given area, relying on an elevation model (here EU-DEM; Riley et al., 1999).

2.3 | Pre-processing data from automatic detection systems

Automatic detection systems provided heterogeneous data depending on their characteristics and settings. A cleaning phase was necessary to find equivalence between systems, notably between bird classification (Gradolewski et al., 2021). Some systems classified a few species (kites, buzzards), while others used classes based on the target size (e.g. small, medium and large for birds with wingspan <0.75, 1.2 and >1.2 m). We applied the broadest classification available consisting of two classes (large vs. medium-sized) to data from each detection system.

Videos from 2D-systems were analysed to extract bird position in flight in 2D in each video frame using BirdTracker software, developed by WIPSEA (available under an end-user licence agreement; wipsea.com). This application detects any moving element (here birds) whose size is in a defined range, in each video frame and returns a list of 2D positions in pixels. The two 2D-systems recorded videos at 12 and 25 frames per second, respectively. We subsampled to keep one position per second to reconstruct bird trajectories in 2D (N=21,792). Trajectories were described by calculating five metrics with the R package *trajr* (McLean & Skowron Volponi, 2018): flight duration (in s), flight total length (in pixels), displacement (distance between the beginning and end of the flight trajectory, in pixels), average speed (pixels/s) and straightness (tortuosity index, from 0 to 1, with 1 being a straight line). Similarly, we reconstructed 3D-system flight trajectories (N=261,809) and described them with the same five metrics using the R package *trajr*, with distance in meters.

We did not verify the accuracy of the distance or species classification provided by the detection systems. Nonetheless, we removed outliers and potential detection errors. Since detection and tracking are most effective during daylight hours (Gradolewski et al., 2021), we excluded trajectories recorded before sunrise and after sunset using the R package *suncalc* (Thieurmel & Elmarhraoui, 2022). Detection efficiency decreases with increasing distance, leading to a higher likelihood of errors, false detections and trajectory interruptions (Ballester et al., 2024; McClure et al., 2018). Currently, the most advanced detection systems can detect large diurnal species such as eagles up to 1000 m (Gradolewski et al., 2021; McClure et al., 2018), with performances and effectiveness that may vary based on weather conditions, bird size, flight behaviour and speed (Ballester et al., 2024). Preliminary analyses showed a decrease of flight duration at 600 m from the turbine, suggesting detection interruptions (Figure S1). Hence, we excluded flight trajectories recorded at distances >600 m from the turbine. We also removed trajectories with fewer than five positions, considered too short for proper trajectory analysis, based on the k-means clustering detailed in the next paragraph. Obviously anomalous trajectories with speeds >60 m/s (most species have a horizontal flight speed between 8 and 25 m/s, although greater speeds can be reached during dives; Pennycuick, 1997), negative altitudes or a straightness score of 0 (extremely twisted) or 1 (perfect straight line) were deleted, as these are likely the result of detection errors. In total, we retained 18,913 flight trajectories from 2D systems and 186,954 from 3D systems, of which 32% and 84%, respectively, were within the risk zone.

Trajectories were classified into different flight types using the k-means clustering method described in Bergen et al. (2022). We separately analysed trajectories from 2D and 3D systems as the measurement units were not comparable (pixels/m). To describe each trajectory, we used a set of five variables previously calculated (total flight duration, travelled distance, distance between the beginning and end of the flight trajectory, average speed and straightness). We checked for skewed distributions by visualizing histograms and we centered and scaled all variables. We implemented the clustering using the R function *kmeans*. We chose the best number of clusters *K* using the average silhouette width that gives a bootstrapped average silhouette width ranging from −1 (potential incorrect cluster) to 1 (very confident cluster) for each cluster. Here, we obtained two clusters with both types of data (2D/3D systems). The behavioural interpretation was made by plotting the distribution of each variable among each cluster. Our two clusters corresponded to short-duration and short-distance straight flights, and to long-duration long-distance sinuous flights (Figure S2). They respectively indicate transit flights and foraging flights (Bergen et al., 2022).

2.4 | Indicator of bird exposure

We measured exposure as an encounter rate (Morant et al., 2024), calculated as the number of birds detected per hour for each date and at each wind energy facility.

2.5 | Indicators of bird sensitivity

We calculated two sensitivity indicators commonly used in collision risk models (CRM): minimal bird-turbine distance (in m) and the duration of the intrusion (time spent by the bird in the risk zone, in s) in cases where the bird penetrated the risk zone. When these indicators were not automatically provided by the detection systems, we calculated them. Using data from 3D systems, we used the birds' 3D positions to calculate the bird-turbine distance and to determine whether they were in the risk zone and, if so, the intrusion duration. Videos from 2D systems did not enable us to calculate the exact bird-turbine distance, but some 2D systems provided a distance estimate. This estimate is calculated by counting the number of pixels occupied by a detected bird and comparing it to the known number of pixels representing a 150-cm wingspan bird at a known distance. We used it to define whether the detected birds intruded the risk zone or not, and if so, the intrusion duration.

2.6 | Statistical analysis

We first checked collinearity (existence of correlation between covariates) among the chosen weather factors, technical characteristics and landscape features by calculating correlation coefficients. We excluded from our analyses the altitude of the wind energy facility, the number of turbines and the diameter of the rotor that were highly correlated (correlation coefficient >0.80) with TRI, soil occupation, age of the wind energy facility and hub height and that had the lowest inter-site variability (Figures S3 and S4). Because some facilities and detection systems contributed larger to the dataset than others, we checked that the system type (2D/3D) and the number of days of data did not bias the results by using a point-biserial correlation and a Pearson correlation, respectively (Figures S5 and S6).

To assess the statistical relationships between exposure, sensitivity and chosen factors, we applied generalized additive mixed models (GAMM). We fitted one model per sensitivity indicator (bird-turbine distance and intrusion duration) and one model for exposure using the R package *mgcv* (Wood & Wood, 2015). We used a Gaussian distribution for bird-turbine distance and intrusion duration models; a Poisson distribution with log link function for the exposure model. Because the dataset is unbalanced and consists of repeated measurements (i.e. multiple days of data and bird observations per site, not evenly distributed across sites), the identity of the wind energy facilities was used as a random intercept in each GAMM. The concurvity (approximation of smooth terms in a model by one or more other smooth terms) of each factor was checked using the *concurvity* function from the R package *mgcv*. Values close to 1 indicate a total lack of identifiability, which can lead to fitting problems and unstable estimates (Wood & Wood, 2015). Variables related to landscape (TRI, ground cover) and technical characteristics (hub height, number of years since construction) of the wind energy facilities had a concurvity index >0.8 and were therefore removed from the models (Table S4).

The final models included humidity, nebulosity, temperature, visibility, wind speed, rotor speed, date, number of hours after sunrise and age of the wind energy facility as continuous predictors and flight behaviour (transit/foraging flight), species class (large/medium) and detection system type (2D/3D) as categorical predictors, as follows:

$$
\begin{aligned}
Y \sim \beta_0 &+ \mathrm{s(humidity)} + \mathrm{s(nebulosity)} + \mathrm{s(temperature)} + \mathrm{s(visibility)} \\
&+ \mathrm{s(wind\ speed)} + \mathrm{s(rotor\ speed)} + \mathrm{s(date)} + \mathrm{s(number\ of\ hours\ after\ sunrise)} \\
&+ \mathrm{s(wind\ energy\ facility\ age)} + \mathrm{flight\ behaviour} + \mathrm{species\ class} \\
&+ \mathrm{detection\ system\ type} + \varepsilon.
\end{aligned}
$$

Model assumptions were verified by plotting residuals. Residual plots did not show signs of non-linearity or heteroscedasticity, indicating that the model assumptions were met. No model selection was performed, as the large sample size of over 200,000 flight trajectories allows for stable parameter estimation. In this case, curve interpretation provides more meaningful insights into bird behaviour than factor selection or statistical significance.

We explored the statistical relationships between exposure and sensitivity, both components of vulnerability to collision. We fitted a generalized additive mixed model (GAMM) with a Poisson distribution, bird-turbine distance and intrusion duration as covariates and the identity of the wind energy facilities as a random intercept, using the *mgcv* package in R (Wood & Wood, 2015) (Figure S7).

Statistical analyses were implemented in the R environment 2024.12.0 (R Core Team, 2023).

3 | RESULTS

3.1 | Exposure

Automatic detection systems detected more flying birds when humidity, nebulosity and temperature were moderate (approx. 40%–50%, 3-6 oktas and 10°C–25°C, respectively), although unique values of nebulosity were scarce (Figure 2). More bird detections also occurred when visibility and wind speed were low (<20 km and <5 m/s, respectively), when the rotor speed was about 10 rpm, in the morning and in April and October (Figure 2). Automatic detection systems detected more large species than medium species and more individuals foraging than individuals transiting. 3D systems detected more birds than 2D systems (Table S5). We observed a significant site effect on exposure ($\chi^2 = 5920.0$; edf = 8.64; $p < 0.001$) with a random intercept estimated at 0.91 (95% CI = 0.56–1.48). Wind energy facilities installed 3–5 years earlier seemed more frequented than new facilities (Figure 2).

3.2 | Sensitivity

Birds seemed to approach closer to turbines when humidity, nebulosity and temperature were high and when rotor speed and wind speed were low (Figure 2). Birds flew closer to turbines in the late morning (approx. 5 h after sunrise) and in April and October (Figure 2). Birds may have approached closer to turbines when visibility was high, although the large confidence interval indicates a lack of extreme values (Figure 2). Medium-sized species, individuals in transit flight and individuals detected by 3D systems approached significantly closer to turbines than large species, individuals foraging and birds detected by 2D systems, respectively (Table S5). We observed a significant site effect ($F = 12.06$; edf = 3.86; $p < 0.001$) with a random intercept estimated at 0.12 (95% CI = 0.05–0.28), but the curve interpretation is difficult due to the width of the confidence interval.

Birds spent more time within the risk zone when humidity was high (>75%), visibility low (<10 km), wind speed and temperature moderate (approx. 5–7 m/s, 15°C–25°C) and rotor speed low (<5 rpm; Figure 2). The duration of the intrusion was also longer at the end of the day and between March and June (Figure 2). Individuals of medium species and/or with foraging flights spent more time within the risk zone than individuals of large species and/or in transit. We observed no significant differences between the detection system types (Table S5) and a significant site effect ($F = 711.94$; edf = 3.71; $p < 0.001$) with a random intercept estimated at 0.63 (95% CI = 0.29–1.35), but the curve interpretation is difficult due to the width of the confidence interval.

4 | DISCUSSION

The aim of this study was to propose, as proof-of-concept, a novel utilization of data from automatic detection systems to investigate environmental factors that may enhance the risk of bird-turbine collisions. Our results are largely consistent with results obtained with other methods, confirming that detection system data have a great potential to improve our understanding of bird collision causes in wind energy facilities. Our results suggest a phenological response of exposure and sensitivity, both the highest during migration periods. Weather conditions that influence the visual perception of turbines by birds (low visibility and high nebulosity) and flight behaviour (temperature, wind speed) might increase bird sensitivity to collision. However, data from detection systems have certain limitations that may have affected our results, notably the diversity of flight heights and behaviours of the species studied, as discussed hereafter.

As expected, exposure and sensitivity to collision varied with bird phenology (Balmori-de la Puente & Balmori, 2023; Barrios & Rodriguez, 2004). Exposure peaks were observed in spring (March to May) and autumn (October). These well-documented periods of high activity, which correspond to pre- and post-nuptial migration peaks in central Europe (Newton, 2023), also correspond to peaks of abundance and fatalities in wind energy facilities (Schuster et al., 2015). However, the intrusion duration peak suggests that sensitivity in our study was still high after the first exposure peak. It may represent the frequent use of the wind energy facilities by resident birds for their daily activities, such as foraging. Contrary to residents, migrant birds flying through are more numerous but do not intensely use this area (Marques et al., 2014). Consequently, their area use is reflected in exposure rather than sensitivity. This nonsynchronicity of exposure and sensitivity peaks is consistent with previous studies that examined the lack of relationship between bird abundances (exposure) and fatality rates (Aschwanden et al., 2018; de Lucas et al., 2008). This result highlights the importance of examining both exposure and sensitivity, and how they vary, when assessing a risk.

Our results suggest that exposure and sensitivity were low in winter and at temperatures below 10°C, while we would have expected the opposite, based on bird use of thermal updrafts. Thermal updrafts generated by high temperatures are weak in winter, constraining raptors to fly at lower heights by using orographic uplifts (updraft airflows due to ground relief), increasing the proportion of flight at rotor height (de Lucas et al., 2008; Péron et al., 2017), and thus bird sensitivity. However, results from de Lucas et al. (2008), reporting that raptor fatalities were more frequent in winter, may not be comparable to ours. They focused on two wind energy facilities located in mountainous areas, with different avifauna than ours

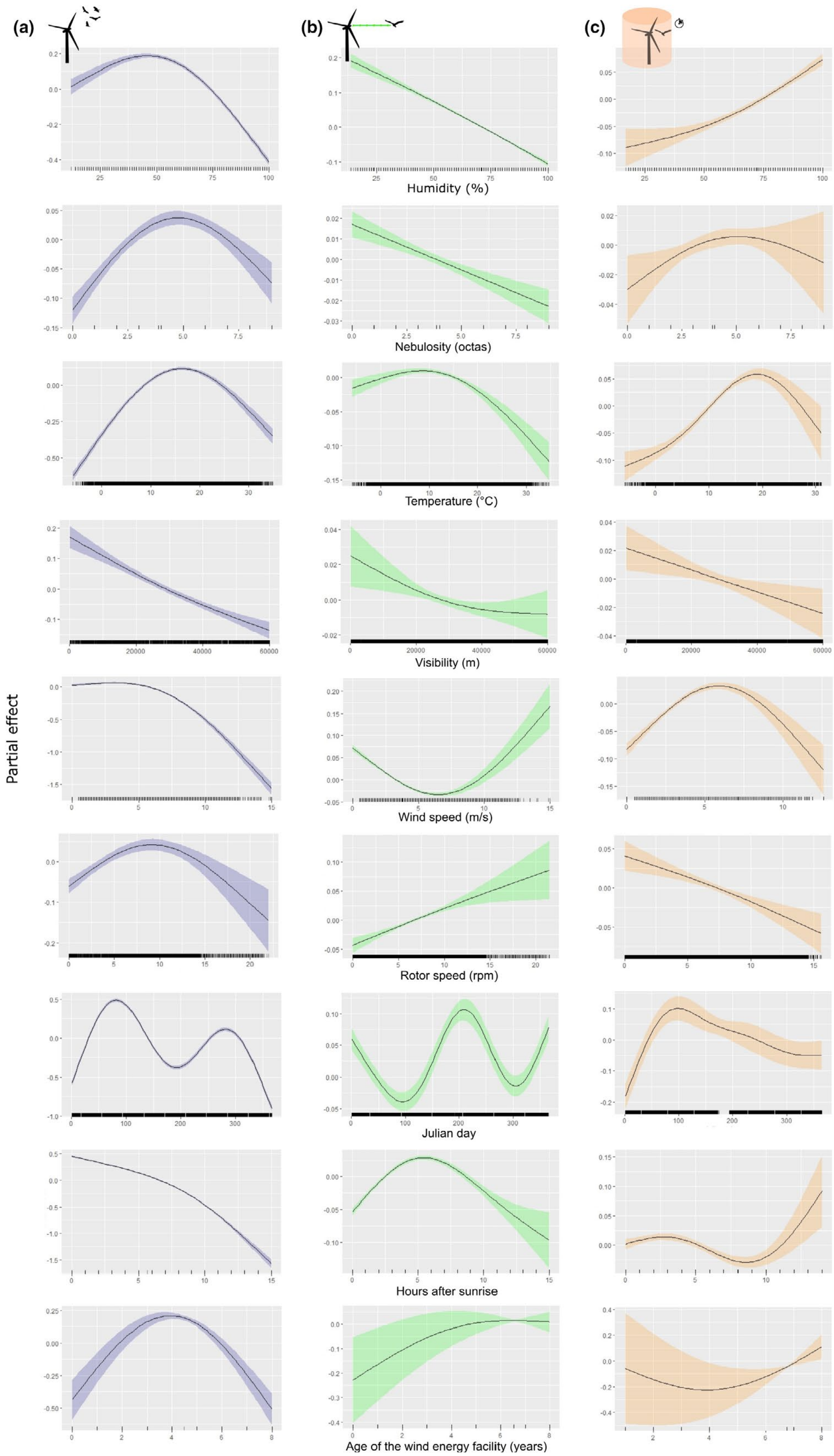

FIGURE 2 GAMM predictions of bird exposure and sensitivity to collision (expressed as (a): number of detected birds per hour, (b): bird-turbine distance, (c): intrusion duration), to weather, rotor speed and phenology. Lines indicate predicted average values and ribbons indicate 95% confidence intervals.

and with landscape characteristics more conducive to generating orographic lifts than open lands that made up the majority of our study sites.

Results may indicate that birds came closer to turbines at moderate wind speed (5–10 m/s), which is consistent with Linder et al. (2022). However, other studies reported an increased sensitivity in raptors at high wind speeds (Lanzone et al., 2012) and conversely, at low wind speeds (de Lucas et al., 2008). The lack of consensus on the effect of wind speed and temperature on bird sensitivity may be explained by species effects, as each species has its own specific behaviour and flight height depending on its use of thermals and orographic lift to minimize energy expenditure. For example, raptors that typically fly low (e.g. harriers *Circus* sp. and buzzards *Buteo buteo*) may fly higher (in the risk zone) at high temperature, whereas species that typically fly high (e.g. short-toed eagles *Circaetus gallicus* and golden eagles *Aquila chrysaetos*) would fly at relatively lower heights (in the risk zone) at high temperature (Lanzone et al., 2012; Schaub, 2024). Here, we used two large species classes based on bird wingspan (medium/large) and two flight types (transit/foraging) to address the detection systems' technical characteristics. Using such large classes can lead to oversimplification and mixing of species with completely different ecologies and behaviours, resulting in opposite trends for certain factors (here, wind speed and temperature). In addition, wind direction influences birds' flight behaviour nearby turbines (Santos et al., 2022) but is scarcely included in collision risk assessment.

Our results may indicate that large species and foraging individuals detected by detection systems exhibited higher exposure compared to medium-sized species and individuals in transit. We would have expected the medium species to be more numerous and more abundant and consequently more exposed than large species. This result may be an artefact of the detection system characteristics, as some systems are unable to detect species below a certain wingspan threshold and/or are configured to focus on large species of interest, such as raptors with conservation issues only (Gradolewski et al., 2021). Here, 3D systems detected more birds than 2D systems, suggesting that their detection abilities might be superior, which supports the bias hypothesis. However, we cannot exclude a potential confounding effect of local abundance due to the small number of wind energy facilities equipped with each type of detection system in our study. Improving the detection capabilities of detection systems would allow us to study species that we currently excluded from our analysis, such as nocturnal and small species, despite the nonnegligible number of fatalities they represent in wind energy facilities (Aschwanden et al., 2018; Erickson et al., 2014; Nilsson et al., 2023). Because Passerines have a low wing aspect ratio, they alternate flapping and gliding phases in a bounding flight. These types of flights are less impacted by weather conditions than soaring flights that rely on weather-induced thermals and orographic lifts (Shamoun-Baranes et al., 2006), suggesting that the weather-dependent response of sensitivity would be different in these species. Therefore, including small and/or nocturnal species in the assessment of collision risk should be a priority to provide relevant recommendations for a wide range of bird species.

Results suggest that sensitivity was higher in large species than in medium-sized species. This disparity may be related to the behavioural tendencies of large species to have lower manoeuvrability when soaring and to use sinuous flights, which usually imply longer flight durations and less vigilance (Linder et al., 2022; Sassi et al., 2024). Moreover, large raptors, as ground predators using the wind energy facilities studied here to hunt terrestrial prey, tend to focus on the ground rather than ahead or above them when foraging, due to their visual field shape (Potier et al., 2018).

The results suggest enhanced exposure and sensitivity in low visibility, high humidity and high nebulosity, which may be related to the birds' visual perception of turbines. Most species have a poor perception of achromatic contrasts (Blary et al., 2024), even lower under conditions that reduce the contrast between the turbines and their background. Although our study has few unique observations of nebulosity, Aschwanden et al. (2018) found similar results and attributed two thirds of observed fatalities to poor visibility and high nebulosity. In addition, some species are not able to discriminate rotary motion at curtailment speed (2–3 rpm) and may perceive turbines as stationary (Blary et al., 2023), which may explain the increased sensitivity we observed at very low rotor speeds. This result is unlikely to be an artefact of curtailment triggered by bird intrusion, as curtailment is typically triggered for certain species of interest only, usually raptors (Gradolewski et al., 2021), whereas we considered all detected species. To reduce bird sensitivity to collision, the two recommendations based on bird visual perception and our results are an increased contrast between turbines and their environmental background and/or a full turbine shutdown (Blary et al., 2023; May et al., 2020).

Our results suggest that sensitivity was high at medium wind speeds and at low rotor speeds. It may seem contradictory, but we suggest two explanations. First, turbines must be stopped regularly, regardless of wind speed, for current mitigation measures including automated and passive curtailments (complete shutdown for several days, for instance, during sensitive periods of the annual cycle of birds or agriculture operations) and for scheduled shutdowns for maintenance. Furthermore, wind speed alone is not sufficient to achieve high rotor speed; wind direction must also be considered. Second, our results are not contradictory but complementary, as wind speed may influence bird flight behaviour, whereas rotor speed may influence the bird's visual perception of turbines.

This comprehensive study reveals phenological and meteorological effects on bird exposure and sensitivity to collision in wind energy facilities, yet also contains numerous results that are challenging to explain with no clear biological mechanisms, probably due to the considerable heterogeneity of the data sources and the ecology and behaviour of the pooled monitored bird species. Some aspects remain unexplored, notably the site effect, due to a lack of data from a sufficient number of wind energy facilities with heterogeneous landscape contexts. Here, exposure may have been higher in wind energy facilities installed a few years ago, but sensitivity might be higher in recent facilities, although no conclusions can be confidently drawn from these results. Land cover and topography have not been included in the analyses in spite of their known influence on bird phenology and flight behaviour by shaping resource availability, orographic lifts and thermals. They are also related to weather conditions and land cover and consequently to the visual perception of turbines in their background (Marques et al., 2014). Site effect and interspecific variability should be the focus of future research to obtain a more detailed understanding of bird collision risk in wind energy facilities, with the endgame of identifying high-risk situations in which mitigation measures must be increased.

Using data from automatic detection systems has the potential to provide management recommendations to reduce the risk of bird collisions at wind energy facilities. At a local scale, analysing data collected over one or more years at a facility—similar to the approach proposed here—would highlight specific periods and situations of high (or low) risk within the focal area that may allow for the improvement of detection system settings or curtailment strategies. At a global scale, analysing data from multiple facilities worldwide, across different landscape contexts, would highlight environmental factors that influence bird exposure and sensitivity. Hence, current mitigation strategies could be improved, for example, by avoiding the installation of new facilities in particularly sensitive areas or by adapting detection system settings based on proven effectiveness in similar environments, pending further refinement from local data. Ultimately, the combination of local and global data would create a more comprehensive bird collision risk mitigation strategy, ensuring that both immediate and long-term solutions are in place to bridge bird conservation and turbine productivity.

5 | CURRENT LIMITS TO USING AUTOMATIC DETECTION SYSTEMS IN COLLISION RISK ASSESSMENT

Our results call for a greater use of camera-based detection systems, in conjunction with field observations and tracking devices, to assess collision risks in anthropogenic facilities. Despite their novelty and the possibilities they offer, data from detection systems are subject to management decisions, technological limits and legal constraints that should be addressed to improve our understanding of collision risk.

(i) *Bird distance* and *flight height*, which are indicators of birds' sensitivity to collision (Morant et al., 2024; Schaub, 2024; Thaxter et al., 2019). However, some detection systems do not yet provide an accurate estimation of these indicators. The wider use of stereovision cameras and/or more accurate species identification to calculate the size of detected birds would significantly improve distance and height estimation, ultimately improving the intrusion probability models and real-time curtailment decisions (Rolek et al., 2022).

(ii) Reliable *identification and classification of detected bird species*. Some detection systems are able to correctly classify some species of interest (e.g. kites, eagles and buzzards) using artificial intelligence (Duerr et al., 2023; McClure et al., 2018). However, this classification is not always available while collision risk is species dependent (Schuster et al., 2015). One solution to improve the current classification is to combine different technologies, such as marine radar, infrared and acoustics (Mirzaei et al., 2015).

(iii) *Detection and identification of small and nocturnal species*, which represent a nonnegligible portion of avifauna and observed fatalities (Aschwanden et al., 2018; Nilsson et al., 2023). Nocturnal birds can be monitored by thermography and radar-based systems. Although radar-based systems have a better detection and a wider detection range than optic systems, weather, landscape characteristics and anthropogenic structures can affect their detection. Improving detection and classification algorithms and combining different technologies (e.g. radar for detection and optics with AI for identification) would help to suggest effective mitigation measures applicable to a wider range of species.

(iv) *Data availability*. accessing data from detection systems is challenging due to legal and confidentiality constraints. Mutualising efforts to improve data availability, for example by creating national or international databases, would greatly benefit future research that addresses the current challenge of reconciling wind energy development with wildlife conservation. In addition, having access to data from underrepresented countries to cover the full range of bird species, weather conditions and landscapes would help the development of effective mitigation strategies across a diverse range of species and environmental contexts.

(v) *Data homogeneity*. The heterogeneity of data from detection systems results from different management decisions and technologies. Establishing independent, standardized guidelines for the collection and storage of detection system data would allow a more robust comparison between sites (Ballester et al., 2024), leading to a better understanding of collision risk at large spatial scales.

AUTHOR CONTRIBUTIONS

Charlène Gémard conducted the research, analysed the data and led the writing of the manuscript. Aurélien Besnard, Olivier Duriez and Gwénaël Duclos participated in funding applications, conceptualised and supervised the research. Gwénaël Duclos and Olivier Chappe developed BirdTracker. All co-authors contributed substantially to the drafts and gave their final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing financial interests or personal relationships that could have influenced the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data collected for the need of this study are anonymous as stated in the confidentiality agreements made between operators of wind energy facilities, developers of automatic detection systems and researchers in the MAPE research programme. The dataset is available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.sj3tx96fx (Gémard et al., 2025).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1: Landscape context and technical characteristics of the wind energy facilities.

Table S2: Non-exhaustive list of environmental factors known from scientific literature to increase birds' risk of collision with turbines (sensitivity and/or exposure) in wind energy facilities (WEF) by influencing birds' flight behaviour and/or visual perception of the turbines.

Table S3: Variables and their sources used to investigate the effect of bird-related, seasonal, technical, site-related factors on bird sensitivity and exposure to collision in wind energy facilities.

Table S4: Concurvity scores between each term of the models and the other covariates using the *concurvity* function from the R package *mgcv*.

Table S5: Summary of the parametric coefficients from the GAMMs to compare exposure and sensitivity of different species class (medium/large), flight behaviors (transit/foraging flights), and automatic detection systems (2D/3D-optic) in wind energy facilities.

Figure S1: Relationships between the flight duration of birds detected by automatic detection systems and the minimal distance to the turbine.

Figure S2: Flight characteristics used to discriminate transit (green) and foraging (yellow) flights using 2D-ADS (A) and 3D-ADS (B) data, following the k-mean method by Bergen et al., 2022.

Figure S3: Data distribution for eight variables describing the landscape context and technical characteristics of the 11 wind energy facilities sampled.

Figure S4: Correlation plot between landscape features, technical characteristics of the wind energy facilities, weather conditions, bird flight behaviour and phenology (see Table S3 for details).

Figure S5: Boxplots of exposure (A), bird-turbine distance (B) and intrusion duration (C) according to the detection system types (2D/3D optics).

Figure S6: Boxplots of exposure (A), bird-turbine distance (B) and intrusion duration (C) according to the number of days of data.

Figure S7: Relationship between exposure (here, number of birds detected per hour) and two sensitivity indicators (A: intrusion duration in the risk zone and B: bird–turbine distance) modelled with a Generalized Additive Mixed Model including bird-turbine distance and intrusion duration as covariates, and the identity of the wind energy facilities as a random intercept.

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