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Nilsson, C.; La Sorte, F.A.; Dokter, A.; Horton, K.; Van Doren, B.M.; Kolodzinski, J.J.; Shamoun-Baranes, J.; Farnsworth, A.

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Bird strikes at commercial airports explained by citizen science and weather radar data

Cecilia Nilsson[1,2] | Frank A. La Sorte[1] | Adriaan Dokter[1] | Kyle Horton[3] | Benjamin M. Van Doren[4] | Jeffrey J. Kolodzinski[5] | Judy Shamoun-Baranes[6] | Andrew Farnsworth[1]

[1]Cornell Lab of Ornithology, Cornell University, Ithaca, NY, USA; [2]CMEC, Copenhagen University, Copenhagen, Denmark; [3]Fish, Wildlife, and Conservation Biology, Colorado State University, Fort Collins, CO, USA; [4]Department of Zoology, Edward Grey Institute, University of Oxford, Oxford, UK; [5]The Port Authority of NY & NJ, New York, NY, USA and [6]Theoretical and Computational Ecology, IBED, University of Amsterdam, Amsterdam, The Netherlands

Correspondence
Cecilia Nilsson
Email: cecilia.nilsson@biol.lu.se

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Abstract

1. Aircraft collisions with birds span the entire history of human aviation, including fatal collisions during some of the first powered human flights. Much effort has been expended to reduce such collisions, but increased knowledge about bird movements and species occurrence could dramatically improve decision support and proactive measures to reduce them. Migratory movements of birds pose a unique, often overlooked, threat to aviation that is particularly difficult for individual airports to monitor and predict the occurrence of birds vary extensively in space and time at the local scales of airport responses.
2. We use two publicly available datasets, radar data from the US NEXRAD network characterizing migration movements and eBird data collected by citizen scientists to map bird movements and species composition with low human effort expenditures but high temporal and spatial resolution relative to other large-scale bird survey methods. As a test case, we compare results from weather radar distributions and eBird species composition with detailed bird strike records from three major New York airports.
3. We show that weather radar-based estimates of migration intensity can accurately predict the probability of bird strikes, with 80% of the variation in bird strikes across the year explained by the average amount of migratory movements captured on weather radar. We also show that eBird-based estimates of species occurrence can, using species' body mass and flocking propensity, accurately predict when most damaging strikes occur.
4. *Synthesis and applications*. By better understanding when and where different bird species occur, airports across the world can predict seasonal periods of collision risks with greater temporal and spatial resolution; such predictions include potential to predict when the most severe and damaging strikes may occur. Our results highlight the power of federating datasets with bird movement and distribution

data for developing better and more taxonomically and ecologically tuned models of likelihood of strikes occurring and severity of strikes.

KEYWORDS
bird migration, bird strikes, citizen science, eBird, flight safety, weather surveillance radar, wildlife management

1 | INTRODUCTION

The lengthy historical record of collisions between birds and aircraft ('bird strikes') begins with a bird strike during one of the first powered human flights by the Wright brothers in 1905 (Mckee et al., 2016). Primary concerns for aviation and aviators focus on human safety, but collisions also incur significant financial cost directly through physical damage of equipment and indirectly through delays in operations. World-wide, the annual costs of bird strikes have been estimated at $1.2 billion (Allan, 2000). Due to the high speeds involved, collisions are also almost always fatal to the birds involved (DeVault et al., 2015).

A wide diversity of bird species are known to collide with aircraft (DeVault et al., 2016, 2018). Many strikes occur at low altitudes (Dolbeer, 2006), indicating that mainly local movements are involved (e.g. to and from roosts, breeding sites and foraging locations). However, large-scale movements, such as seasonal migrations, pose a threat to aviation (Dolbeer, 2006; Shamoun-Baranes et al., 2018) that can be particularly difficult for individual airports to monitor and predict. During spring and fall migration, billions of birds move across broad geographic regions, greatly increasing the numbers of birds in aviation airspace (Dokter et al., 2018; Hahn et al., 2009; Horton, Van Doren, et al., 2019). In the continental United States, large movements take place around September–October, when migratory birds leave their breeding grounds to spend winter further south. In spring, they return to the breeding grounds, leading to another, slightly more condensed, pulse of large-scale movements taking place around May (Horton et al., 2020).

Most migrants fly at night, but many larger bodied species, such as raptors, migrate by day and some, such as waterfowl, migrate both day and night (Newton, 2008). However, pulses of migrating birds can pose risks both during migratory flight and during (daytime) stopover movements in unfamiliar territory, so strikes associated with migratory movements can occur at any time of the day. An example of the risks posed by migratory species is the 2009 emergency landing of US Airways Flight 1549 in the Hudson River, New York, caused by an in-flight collision with a flock of Canada geese *Branta canadensis*. The strike occurred outside the airport environment (approx. 8 km) and it was determined that the geese came from a migrant population, and occurred outside the population's breeding range (Marra et al., 2009).

Military aviation is particularly vulnerable to bird strikes, as flights are often conducted at high speeds, low altitudes and with single engine planes (e.g. Dolbeer, 2006; van Gasteren et al., 2019). The threat to commercial aviation is primarily during take-off and landing, as cruising altitudes are usually higher than bird flight altitudes (Shamoun-Baranes et al., 2018). Damage caused by bird strikes is highly variable, dependent on the body mass of the bird struck and the speed of the aircraft, as well as other factors such as the location on the aircraft (e.g. ingestion into an engine, impact with a critical sensor and aircraft composition; Pfeiffer et al., 2018; Shamoun-Baranes et al., 2018). Since the impact energy of a collision scales with mass, heavier birds are more likely to cause damage than lighter birds (DeVault et al., 2018; Dolbeer & Begier, 2019). Species' flight behaviours can also affect the hazard they present. Flocking increases the likelihood of an aircraft striking several birds at once, which increases the probability of damage (DeVault et al., 2018) and even multi-engine malfunction (e.g. the case for US Airways 1549, Marra et al., 2009).

Airport operators employ a variety of methods to reduce the probability and severity of bird strikes caused by wildlife in the local airport environment, such as bird surveys, habitat management, harassment and lethal control (Cleary & Dolbeer, 2005). In the United States, wildlife monitoring and mitigation is required in an area that extends 3,048 m (10,000 feet) around most airports (Federal Aviation Administration, 2018). Some airports use dedicated avian radars for identifying individual birds locally at the airport (Mckee et al., 2016). However, these measures are less efficient for identifying risks posed by changes in species composition as populations move through the area, as well as for avoiding strikes that take place en-route and outside the immediate airport environment (see Dolbeer, 2011). The hazard level at any given place and time is not constant, but varies over the year, and requires information on the presence of both transient and resident species in the region, as well as each species' hazard level.

Information on bird distributions (e.g. from breeding bird surveys) and bird movements (from observations, expert knowledge and radar observations) has been used to create warning systems, including forecast models for aviation in several countries, with the most successful implementations developed for military aviation (Shamoun-Baranes et al., 2008; Van Belle et al., 2007; van Gasteren et al., 2019). For example, the US military Bird Avoidance Model (BAM) uses yearly point counts to estimate species composition (Shamoun-Baranes et al., 2008), and hazard level has been estimated using historical strike data (DeVault et al., 2018).

Information on bird movements extracted from weather radar and other radar types has also been critical for supplying real-time

information for military flight planning, developing forecast models (Van Belle et al., 2007; van Gasteren et al., 2019) and modelling bird strike risks (Metz et al., 2018). Weather surveillance radar is used in a similar capacity for US military aviation safety via the Avian Hazard Advisory System (AHAS; Kelly et al., 2000).

Here, we investigate two complementary approaches to estimate dynamic bird strike risk (probability and hazard) levels throughout the year. We use two free and publicly available datasets. Data from US network of weather surveillance radars are used to identify large pulses of migratory birds, and eBird data (Sullivan et al., 2009) collected by citizen scientists are used to estimate species composition. Weather radar data provide information on the timing of movements, and eBird provide bird occurrence information across the full annual cycle, allowing us to estimate the occurrence of resident, migratory and transient species in a region. We combine this with two estimates of species' individual hazard levels. The first is based on species mean body mass and flocking propensity, and the second on the record of previous strikes caused by the species. We then compare these metrics to bird strike records at three airports, testing if they can provide useful information and potentially complement local wildlife surveys and inform other mitigation actions conducted at airports.

2 | MATERIALS AND METHODS

2.1 | Bird strikes

We analysed bird strike incidents at three airports in the New York City (NYC)/New Jersey (NJ) area: John F. Kennedy International Airport (JFK), Newark Liberty International Airport (EWR) and LaGuardia Airport (LGA) (Figure 1). We selected these three airports as a test case because the airport operator, Port Authority of NY & NJ (PANYNJ), keeps very detailed records of wildlife interactions occurring on or around the airports. The PANYNJ database is maintained separately from the national FAA Wildlife Strike Database, however all strikes are also reported to the national database. We included data from 2013 through 2018, as preliminary analysis indicated that this period had the highest reporting frequency. The entire dataset includes reports dating from 1979, but early data are heavily skewed towards large-bodied bird species, as strikes with smaller birds were less likely to be reported, see Figure 2. A clear demonstration of this can be seen in how the number of reported strikes within 'passerines, perching birds, etc', increased after the 2009 Hudson River incident (Figure 2), especially compared to the more stable reporting frequency of 'Waterfowl and Waterbirds' (Figure 2). The number of reported strikes of smaller bodied species increased while the reporting of larger bodied species did not to the same extent, probably due to both increased diligence in reporting and ability to identify remains via DNA analysis (see e.g. Dove et al., 2008). The same pattern can be seen in the number of reported strikes for two common species, Canada goose *Branta canadensis* and American robin *Turdus migratorius* (Figure 2), even though American robin populations were largely stable within the United States between 1970 and 2017 (5.5% increase, Rosenberg et al., 2019) and Canada goose populations increased substantially during the same period (101% increase, Rosenberg et al., 2019).

The bird strike dataset includes all types of interactions between aircraft and wildlife, even if no carcass was recovered or no species identification was made, including carcass encounters and near misses. Strikes were reported by airport staff, flight crews or maintenance workers. Wildlife remains were identified by trained staff or sent to the Smithsonian Institute's Feather Identification Laboratory,

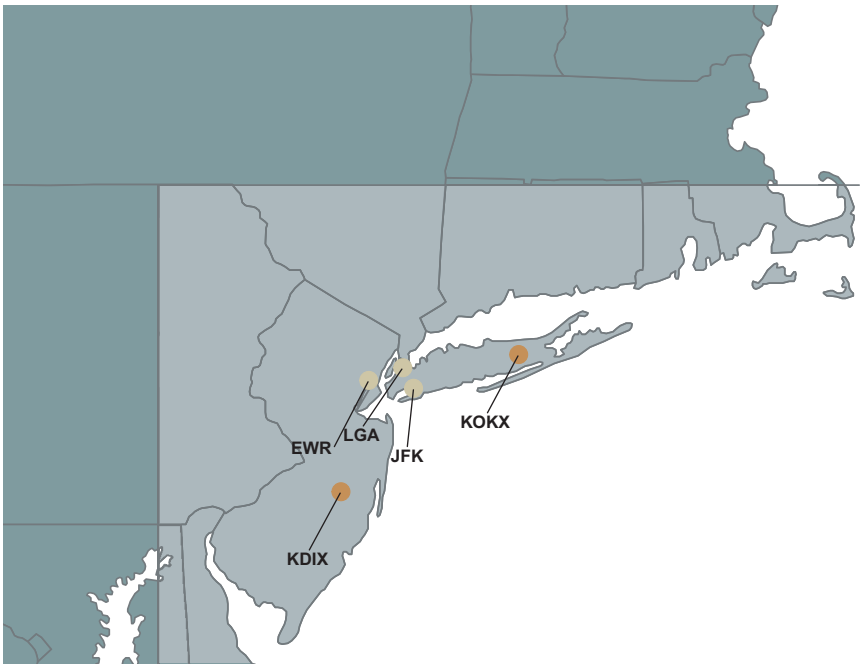

FIGURE 1 Map of the Northeastern United States showing the three airports considered in the analysis in beige; LGA (LaGuardia), JFK (John F Kennedy International) and EWR (Newark Liberty International). Shown in orange is the locations of the two NEXRAD WSR-88D weather surveillance radar stations considered in the analysis—KOKX (New York City) and KDIX (Philadelphia). Bird occurrence information from eBird was compiled within the light-grey region

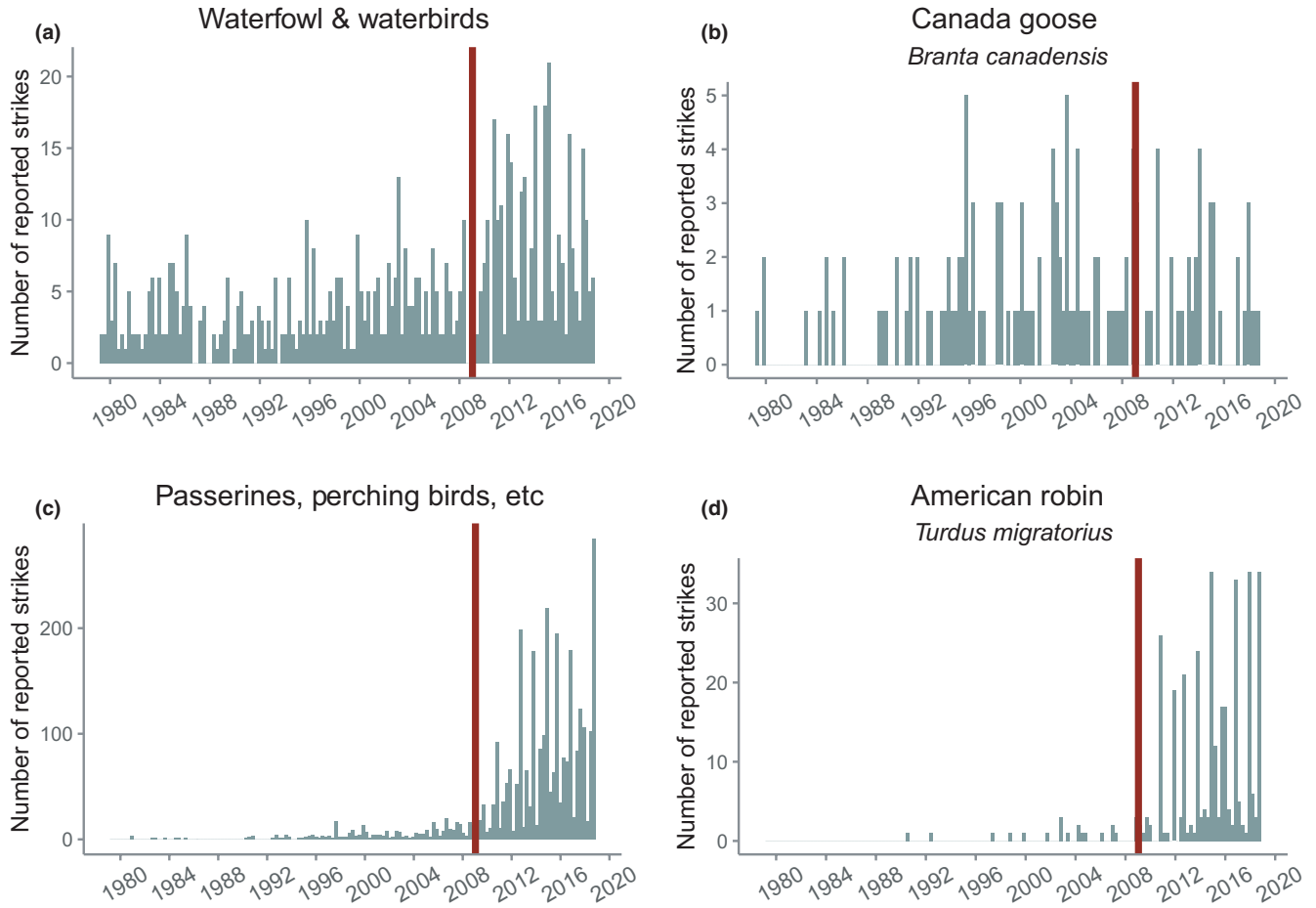

FIGURE 2 Number of bird strikes at three NYC commercial airports attributed to (a) waterfowl and waterbirds, (b) Canada goose *Branta canadensis*, (c) passerines and other perching birds and (d) American robin *Turdus migratorius*. The red vertical lines indicate the date of the Hudson River incident (January 2009). After this date, the reporting frequency of bird strikes at the three airports increased

Washington DC, for identification through DNA analyses or feather microstructure examination (see e.g. Dove et al., 2008). We only included strikes labelled as 'bird' in the database, thereby excluding strikes labelled as 'Unknown', bats or other wildlife, but did include bird encounters of unidentified bird species in the overall sums of bird strikes. We defined all strikes where damage was indicated (either 'minor', 'substantial' or 'destroyed', according to the International Civil Aviation Organization standards) as a 'damaging strike'. We included bird strikes from all locations and phases of flight (e.g. take-off, landing). We classified each bird species identified in the strike data as migratory or non-migratory (based on author assessment, see also supplement in Horton, Nilsson, et al. (2019) and Table S2). We divided the number of reported bird strikes by the number of aircraft movements (take-offs and landings) at the airports on the same day. Preliminary analysis showed no significant differences in regard to our analysis between the three nearby airports, so we summed the number of bird strikes per aircraft movement among the three airports and then averaged this total across each 5-day period of the year. We selected a time resolution of 5-day periods to match the time interval used to estimate species' probability of occurrence, described below.

2.2 | eBird

We estimated the probability of occurrence of 184 species identified in the bird strike data using spatiotemporal exploratory models (STEMs; Fink et al., 2010, 2014; Johnston et al., 2015) and crowd-sourced bird observations from eBird (Sullivan et al., 2014), www.ebird.org. Observations in eBird are compiled in checklist format in which the observer determines sampling protocol and survey effort. We only considered eBird checklists marked as 'complete' that employed 'travelling count' and 'stationary count' protocols from 1 January 2004 to 31 December 2016 within a rectangular region centred on the three airports (76° to 72°W, 39° to 43°N; Figure 1). Data after 2016 were not yet available at the time of this analysis, and we included data from the start of 2004 (before the 2013 cut-off for the other datasets) to get an accurate representation of species composition throughout the year. We included checklists with a maximum duration of 3 hr and a maximum distance of 5 km for the travelling count protocol. We only considered confirmed observations that were identified as such by eBird's quality control procedure (Sullivan et al., 2014), which represents a combination of human and machine intelligence (Kelling et al., 2013). A total of 23,211 checklists were

available for analysis within the study area (see Figure 1). We rendered STEM estimates of probability of occurrence for each species at a 0.05° spatial resolution and a 5-day temporal resolution. We define the probability of occurrence as the probability that a species is reported on a checklist standardized to 1 km and 1 hr of observation starting at 7 a.m. To get an accurate estimate of birds present in the region, we averaged the estimates of probability of occurrence across the 0.05° pixels within the study area for each species and 5-day period. We excluded ten 5-day periods from our analysis that were poorly sampled by eBird (see Figure S1).

2.3 | Hazard level

To estimate the hazard present at a given time, it is important to know the local species composition at that time, as well as the relative danger posed by each species. We used eBird estimates of probability of occurrence to determine which species were present at a given time, and we explored two different ways of estimating strike severity for each species. The first approach was based on body mass and flight behaviour of each species, and the second was based on previous strike data. We defined the occurrence of birds present in the region of the three airports at 5-day intervals across the year to ensure sufficient eBird coverage. We compiled body mass information for each species from Dunning (2008), which we averaged between sexes. We categorized species into three groups based on their propensity to flock: 'rarely', 'sometimes' and 'usually' (Table S2). The mean percentage of strikes that caused damage was 3.6% for the species that rarely flock, 5.5% for the species that sometimes flock and 7.3% for the species that usually flock. We calculated a body mass-based hazard index (BMHI) by taking for each species the eBird estimates of probability of occurrence multiplied by average body mass, doubled for 'usually flocking' species and multiplied by 1.5 for 'sometimes flocking' species (based on the mean percentage damaging strikes in each group). Other aspects of flight behaviour, such as manoeuvrability, were not taken into account. To generate the combined hazard index in the region, we summed these values for all species during each 5-day period of the year. For 5-day periods with missing eBird estimates (see Section 2.2), we used the average BMHI from the period before and after, however, for identifying the species with the top individual body mass hazard indices this was not done and these periods are left empty (see Figure 3 and Figure S1).

$$\mathrm{BMHI}_{\mathrm{fiveday}} = \sum_{s=1}^{n} O_s \times m_s \times F_s,$$

where O_s is the eBird-based estimate of probability of occurrence for a species, m_s is the average body mass for a species, F_s is a multiplier based on flocking behaviour—1.5 for 'sometimes flocking' and 2 for 'usually flocking'—and n the number of species present in that 5 days.

The relative hazard score (RHS) is a commonly used measure of species-specific damage rates based on previous bird strikes involving that species (DeVault et al., 2018). RHS was calculated for each species that had more than 10 strikes recorded in the strike dataset, using the entire bird strike data set from 1979 to 2018. For each species (s), we summed the percentage of strikes that resulted in damage (%D), percentage of strikes that resulted in substantial damage (%SD), and the percentage of strikes that caused an effect on the flight (%EF; see DeVault et al. (2018) and Dolbeer et al. (2000)). Substantial damage is defined as damage or structural failure that adversely affects an aircraft's structural integrity, performance or flight characteristics. Substantial damage normally requires major repairs or replacement of the entire affected component. The RHS is then standardized between 1 and 100 by dividing by the maximum value for a species in the dataset and multiplying by 100. We then multiplied the RHS by the eBird estimates of probability of occurrence (O) for that species in each 5-day period to create an index with both relative hazard and occurrence taken into account. The sum of this for all species present in the area on each 5-day period

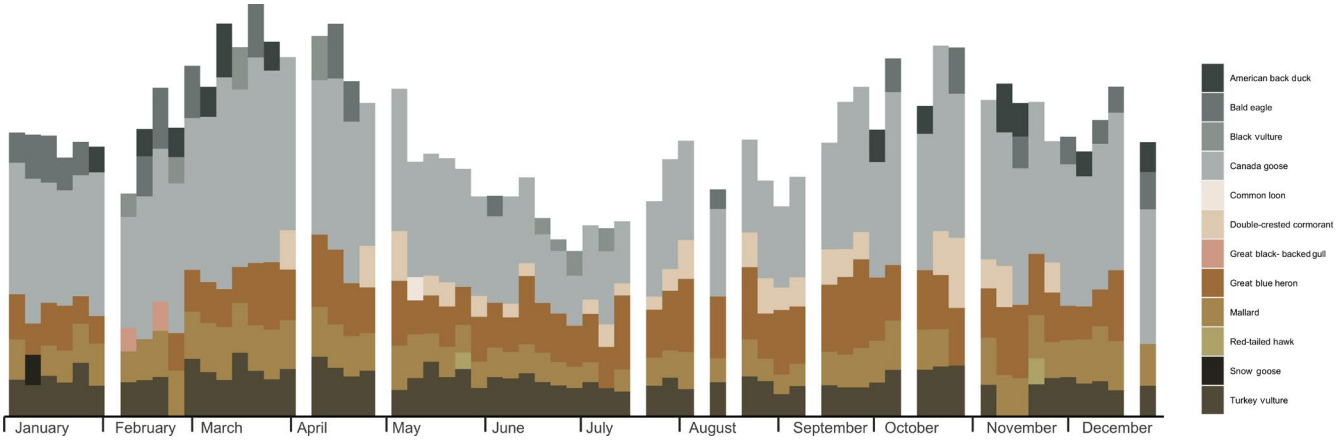

FIGURE 3 The top five species with the highest individual BMHI during 5-day periods for the yeas 2013–2018 combined at three NYC commercial airports. The index is calculated using species' mean body mass, flocking propensity and probability of occurrence. The index for each species varies over the year as occurrence in the area changes, leading to a total of 12 species being top 5 at some point of the year. Empty columns show 5-day periods when not enough occurrence data were available to calculate indices (see also Figure S1)

(*n*) gives us a dynamic index, RHSI, showing how the RHS and occurrence changes over the year.

$$\mathrm{RHSI}_{5\mathrm{days}} = \sum_{s=1}^{n} \frac{\%D_s + \%\mathrm{SD}_s + \%\mathrm{EF}_s}{max_s\left(\%D_s + \%\mathrm{SD}_s + \%\mathrm{EF}_s\right)} \times 100 \times O_s.$$

2.4 | Weather surveillance radar

The US weather radar network (NEXRAD) consists of 143 radar stations across the contiguous United States, each station scanning the atmosphere every 5–10 min, registering information on hydrometeors and other 'small' objects in the airspace, and archiving these data in near real time in a curated and public database (Ansari et al., 2018). The potential value of this dataset for biological study and recent advances in the field of radar ornithology (Shamoun-Baranes et al., 2019), including machine learning methods (Lin et al., 2019) and increased computational power, facilitated mining this large and unique resource to extract information on bird movements at large spatial (Dokter et al., 2018) and long temporal scales (Horton, Van Doren, et al., 2019). We sample nocturnal migration periods because most migratory species fly during the night (Horton, Nilsson, et al., 2019; Newton, 2008) and the algorithms for automated extraction of bird movement from weather radar have been optimized for nocturnal migration (Dokter et al., 2011, 2019).

We extracted the amount of nocturnal bird movements registered at two NEXRAD WSR-88D stations (KDIX and KOKX, Figure 1) in the NYC/NJ area from 2013 to 2018, 1 January to 31 December each year. We extracted vertically integrated reflectivity (VIR) profiles attributed to biological targets for a 35-km radius centred at each radar station, using the vol2bird algorithm in the R package BIORAD (Dokter et al., 2019). The lowest 200-m bin was excluded to avoid influence of ground clutter. Flight altitude is of course important for bird strike risk; however, since we in this case are using the radar data to indicate when large pulses of movements occur rather than exactly where birds are, we integrate movements across all altitudes (200–5,000 m). We calculated profiles of VIR for every half hour between sunset and sunrise and then averaged these values for each night (see Dokter et al., 2019 for additional details). We then averaged the VIR first per night between the two radar stations, and then over each 5-day period (to match eBird, see above). Lastly, for use in Figure 4, we standardized the average nocturnal bird movement overall years to the interval [0, 1].

2.5 | Analysis

We performed all comparisons as averages over non-overlapping, 5-day periods of the year to match the temporal resolution of eBird estimates of probability of occurrence.

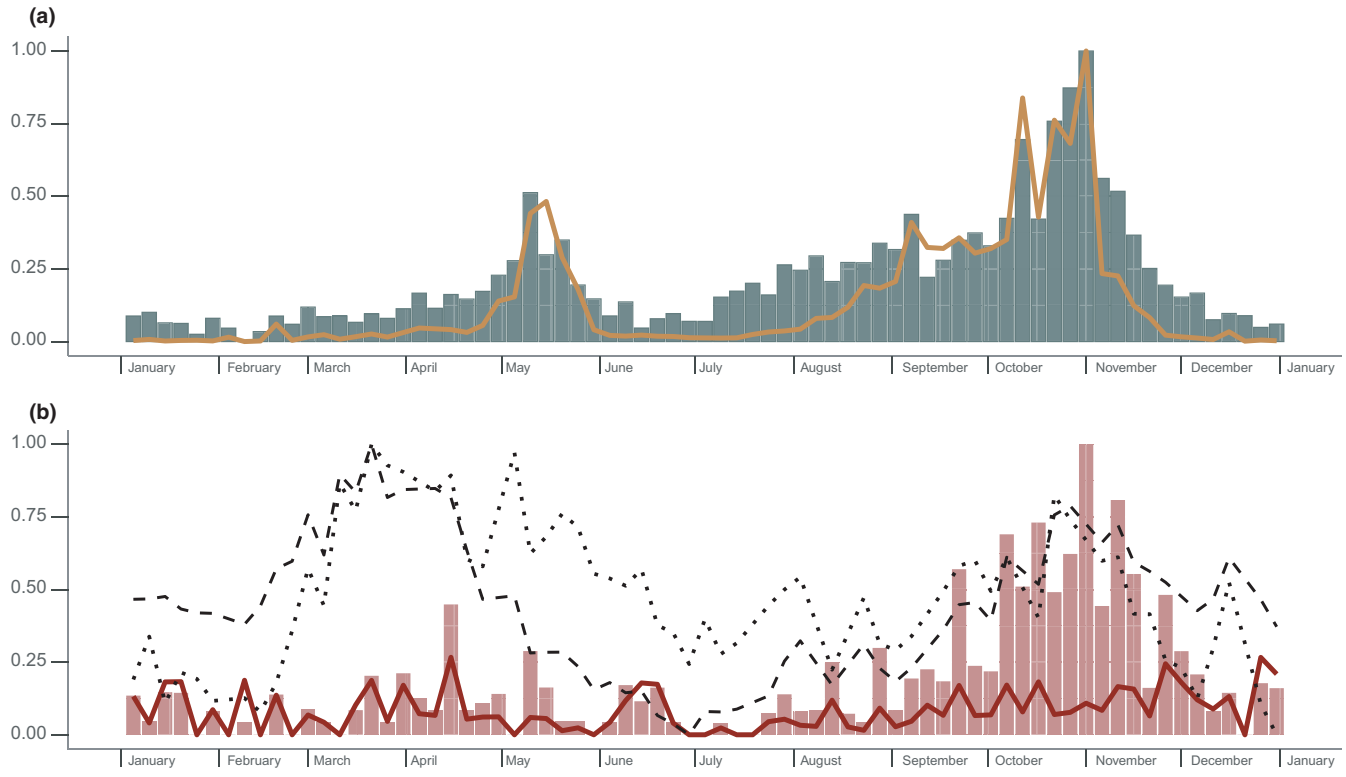

FIGURE 4 (a) Number of bird strikes per aircraft movement (bars) and amount of bird movements (line), averaged for each 5-day period for the years 2013–2018 combined at three NYC commercial airports standardized to the interval 0 to 1. (b) The number of damaging strikes per aircraft movement (bars) averaged for each 5-day period standardized to the interval 0 and 1. Also shown is BMHI (dashed line) and RHSI (dotted line) here standardized to the interval 0 and 1, and proportion of strikes that caused damage (full line) for each 5-day period

We investigated whether increases in nocturnal bird flight activity within the region, as measured by weather radars, corresponded to increased bird strikes at the three airports. To test this, we correlated the mean number of bird strikes with the mean migration intensity (VIR) for each 5-day period of the year in a linear regression. We also tested how well RHSI, BMHI and VIR predict the number of damaging bird strikes at the airports with GLMs using a Poisson distribution. We included data for every 5-day period between 2013 and 2018 and specified an offset with the number of aircraft movements taking place, to account for varying numbers of flights. We included year as a random effect to allow for inter-annual variation in the average number of strikes. We scaled fixed effects to unit variance and centred them to a mean of zero in order to directly compare effect sizes. We did not test RHSI and BMHI in the same models, as these variables were closely correlated ($r^2 = 0.77$). We compared modules using Akaike information criterion (AIC) and performed tests in R 3.6.0 (R Core Team, 2019), using packages LME4 (Bates et al., 2015), MuMIn (Bartoń, 2019) and plots made with GGPLOT (Wickham, 2016) and GGEFFECTS (Lüdecke, 2018).

3 | RESULTS

3.1 | Bird strikes

Of the 3,610 bird strikes reported to PANYNJ from the three airports (2013–2018), 3,239 (90%) were identified as a species that we classified as migratory, indicating that it is unlikely to be present in the area year-round. This is consistent with the high proportion of migratory species in this region. Only 3%, 120 strikes, belonged to typically resident species. In 291 cases (8%), the remains were not identified to species level. Forty-seven per cent of the total number of strikes occurred during the three peak migration months (May, September and October). Five per cent of all strikes resulted in damage (3% in substantial damage and 3% in an effect on flight) and 87% of all damaging strikes were caused by species classified as migratory. In total, 173 aircraft were damaged in some way by birds from the migratory group between 2013 and 2018. In 99 instances (3%), an effect on the flight, such as a delay or cancellation, was reported. Of the 2,111 strikes classified as belonging to the guild 'passerines, perching birds, etc', 58 caused damage to the aircraft (3%), while in the guild 'Waterfowl and Waterbirds', 26% caused damage (48 damaging strikes).

3.2 | Bird movements aloft

The VIR, attributed to birds aloft, measured by the two weather radar stations showed the expected pattern of two main migration periods per year, with a shorter period of high aerial densities in the spring, mainly in May, and a longer period with more birds aloft during fall migration (peaking in September and October), see gold line, Figure 4a. Bird strikes showed 2 yearly peaks, co-occurring with these migration periods in spring and fall (grey bars Figure 4a). We found a high correlation in a regression between aerial bird movement (VIR) and bird strike occurrence, averaged across all years (2013–2018). Approximately 80% of the variation in average bird strikes in each 5-day period was captured by the average amount of biological VIR registered by the weather radars (linear regression $R^2 = 0.8$, $p < 0.001$, $df = 72$, Figure 5). When examining 5-day periods directly (pooling all data but not averaging across years), the correlation was still high, $R^2 = 0.61$ (linear regression, $p < 0.001$, $df = 437$, data not shown).

3.3 | Hazard level

We observed a correspondence between the number of damaging strikes and BMHI, as shown in Figure 4b. Most of the damaging strikes occur during late fall (October and November, red bars Figure 4b), although the proportion damaging strikes is not particularly high, especially during October and early November (red line Figure 4b). In spring, most strikes occur during May, when movements also peak (Figure 4a). However, the highest proportions of damaging strikes occur outside of this period, in late March, April and during June (Figure 4b).

The hazard-level indices varied over the year as different species were present in the region. The BMHI matched reasonably well when there were high proportions of damage (compare dashed line and red bars Figure 4). The match was best in periods with high levels of damage during autumn, while the match was not as close during spring migration. March and April (just before the main migration movements), and October and November are identified by the BMHI

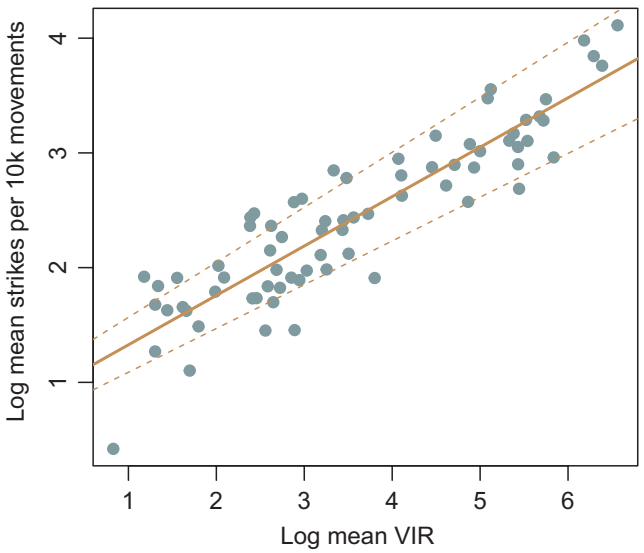

FIGURE 5 The mean number of bird strikes per 10,000 movements (landings and take-offs) by migration intensity (VIR), means over 5-day periods of the year for the years 2013–2018 combined. Both variables are on a natural logarithm scale. The solid line shows a linear regression ($R^2 = 0.8$, $p < 0.001$, $df = 72$) with the dashed lines showing the 95% confidence bands

as periods when many large species with high flocking likelihood are present in the area (Figure 3). March and April do not have a correspondingly high number of damaging strikes; however, as this is a period with very little strikes overall, the proportion of strikes causing damage (red line in Figure 4b) is comparable to the high-risk period in autumn. As the hazard index then decreases in late April–May, the proportion of damage also decreases as strikes increase. The largest contributors to the BMHI in March and April were Canada geese, great blue herons *Ardea herodias*, mallards *Anas platyrhynchos* and turkey vultures *Cathartes aura*, with Canada geese having by far the largest contribution (Figure 3). In September and October, the patterns are similar: Canada geese, great blue herons, turkey vultures and double-crested cormorants *Phalacrocorax auritus* contribute the most (Figure 3). Late May through to end of August had low hazard levels.

The RHSI also identified a period in March/early April, just before the start of the main spring migration period, as the highest risk period (Figure 4b). In autumn, the RHSI and BMHI were more similar to each other than during the rest of the year (Figure 4b).

Model selection indicated strong support for the model using bird migration (VIR) and body mass (BMHI) to predict damaging strikes across all years (Table 1 and Table S1, Figure 6). Models including only one of these predictors, or the RHSI index, had virtually no support (Table 1). The best model showed that a 1-standard deviation increase in BMHI is associated with an 27% increase in the likelihood of a damaging collision (Table S1). A 1-standard deviation increase in VIR is associated with an increased likelihood of a damaging collision by 39% (Table S1).

4 | DISCUSSION

In 2017, over 14,000 bird strikes were reported only in the United States, with a minimum price tag of 142 million for that year alone (Dolbeer & Begier, 2019). Actions to mitigate both direct (e.g. collision damage) and indirect (e.g. delays in operations) costs from bird strikes, especially in civil and commercial aviation, often rely on monitoring local risk factors, but such monitoring may not capture the presence of transient birds, creating a potentially dangerous loss of information that is impractical and costly to remedy. At the three airports, we looked at (situated along the Atlantic Coast flyway) approximately 50% of all bird strikes took place during three primary migration months, and 90% of all bird strikes, and 87% of damaging bird strikes, are attributable to bird species that are considered migratory and thereby not present in the region throughout the year. Across the United States, Devault et al., 2016 found 66% of all bird strikes occurred during migration periods, emphasizing the need for knowledge about migration as well as migratory movements in bird strike prevention.

Many sites lack the detailed historical record of strikes needed to understand how the likelihood of strikes changes over the year and during migration periods. Since strikes with small birds do not cause

TABLE 1 Model selection results for the number of damaging bird strikes in all 5-day periods between 2013 and 2018. We tested combinations of predictors RHSI, BMHI and migration intensity (VIR). RHSI and BMHI were not tested in the same models as they were highly correlated. All models include the total number of aircraft movements (take-offs and landings) as an offset and year as a random effect. Significance levels and estimates for the top model are given in Table S1

Intercept	BMHI	RHSI	VIR	*df*	logLik	AICc	Delta	Weight	Best model evidence ratio
−1.570	**0.241**	—	**0.330**	**4**	**−375.620**	**759.3**	**0.0**	**0.991**	1.0
−1.544	—	—	0.313	3	−381.767	769.6	10.3	0.006	168.8
−1.548	—	0.066	0.320	4	−381.253	770.6	11.3	0.004	279.5
−1.486	0.218	—	—	3	−394.328	794.7	35.4	0.000	4.8e+07
−1.465	—	—	—	2	−398.789	801.6	42.3	0.000	1.5e+09
−1.466	—	0.035	—	3	−398.667	803.4	44.1	0.000	3.7e+09

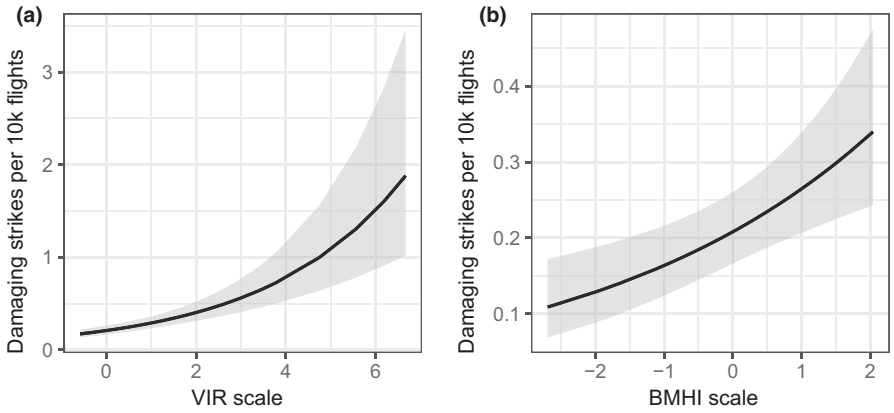

FIGURE 6 Mean model predictions of the number of damaging strikes by (a) scaled migration intensity (VIR) and (b) scaled body mass hazard index (BMHI). VIR and BMHI are standardized to make effect sizes comparable

as much damage and often are less conspicuous, they have been particularly overlooked and records can be incomplete. This is evident by the historically much lower reporting frequency of small bodied birds compared to that of larger species (Figure 2). However, a strike with a small bird can still cause delays, incur maintenance costs and, in rare cases, produce damage. In our example, strikes reported as belonging to 'passerines, perching birds, etc' caused damage to aircraft in 3% of the cases. This corresponds to 58 damaged aircraft at the three airports over 6 years. Most of this damage was light, but potentially incurred costs and caused delays. There is also the small but ever-present possibility of strikes from small birds causing severe damage.

Numbers of bird strikes reported and amounts of bird movements registered by the weather surveillance radar system were highly correlated, with 80% of the total number of strikes explained. This when compared as annual means across years, showing the potential for using archived weather radar data to inform present strike risk, which would be especially valuable at sites with limited historical strike data. However, we also saw a high match when comparing migration activity and strikes in each 5-day period directly. Together, this shows that weather radar is a promising tool to accurately, and with high temporal resolution and low cost compared to other survey methods, identify periods with large movements of birds and thereby high likelihood of bird strikes, as is done for military aviation in several countries (van Gasteren et al., 2019). In the United States, the NEXRAD weather radar database spans nearly 2.5 decades and offers both near real-time data and access to historical data, and is already used to predict and show migratory pulses (birdcast.info, Van Doren & Horton, 2018).

The weather radar data used here characterized nocturnal movements; however, bird strikes are not limited to collisions with nocturnal migrants. Diurnal migrants may pose even greater risks, as many large-bodied species migrate during the day (e.g. raptors and some geese). Days with beneficial migration conditions may overlap for diurnal and nocturnal movements, which may also contribute to the strong relationships we found between bird strikes and nocturnal migration. Further methodological development to adapt algorithms for diurnal migration, and separate bird movements from other diurnal targets such as insects, would engender the inclusion of diurnal radar data and improve information on diurnal migratory movements and bird strike risk.

Our results indicate that changing species composition during the migration season has important implications for understanding strike risk, especially in regions with high migratory turnover of species. The species probability of occurrence in the region, derived from eBird, combined with body mass and flight behaviour, was a crucial predictor of damaging strikes. This highlights the potential to use eBird observations to identify the time periods when particularly hazardous species are present in a region. This could supply important information for bird strike advisory messages, bird strike avoidance models and inform timing of local mitigating actions as well as supplying an additional source of information to use in wildlife hazard assessments and management plans (Federal Aviation Administration, 2018). In contrast, the hazard index based on previous strike damage (RHSI) was not a useful predictor for damaging strikes in our dataset. This might be due to the RHS inherently assigning more weight to the severity of the damage, while we here tested against any reported damage, or it could be due to incomplete records of previous strikes. Bird migration often occurs in pulses of large movements, and our model predicts that the risk for damaging strikes during periods with very high migration intensity increases by as much as 400% to 700% (Figure 6). Unsurprisingly, predicting when damaging strikes occur requires both information on which species are present in the specific region and the amount of movement that is taking place. This further highlights the need for site-specific and dynamic ways to describe bird strike risk.

eBird is a global database (La Sorte & Somveille, 2020), with observations in eBird being skewed towards human population centres (Fink et al., 2020). The eBird species distribution models have been developed from local to global scales (Fink et al., 2020; https://ebird.org/science/status-and-trends/), and we therefore feel it is appropriate to suggest that the hazard-level index presented in this study can be replicated at other urban airports. The STEM modelling framework used to estimate the probability of occurrence does account for sampling biases in the data, but the effect of these biases may increase as sample sizes decrease. These estimates describe the likelihood of encountering a given species in a given area, not the number of individual birds in that area. The recent development of methods to estimate relative abundance using eBird data (Fink et al., 2019) may provide means to further enhance the quality of the metrics developed in this study.

By using data sources that take seasonal variation into account, pilots and flight support staff can access accurate information on variation in potential risks for collisions. General and less informative alerts can be avoided, as such alerts lose value and attention rapidly if they lack spatial and temporal specificity. Since eBird and weather radar data provide standardized measures of bird movements in any given area, using these datasets could also help increase the standardization of bird strike warnings between airports and different countries, enabling comparisons and evaluation of site-specific risk factors. The use of weather radar as a warning system for military aviation and standardization of bird warnings (BirdTAMs) has been successfully implemented in parts of Europe (see e.g. van Gasteren et al., 2019; Ginati et al., 2010). This method is in no way limited to the United States, as use of weather radar data to monitor bird movements is increasing world-wide (Nilsson et al., 2019; Shamoun-Baranes et al., 2019) and so is the use of eBird and other similar monitoring programs (such as www.eurobirdportal.org), further expanding the sites where similar data could easily, and with low cost, be obtained and used to inform bird strike mitigation.

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CONFLICT OF INTEREST

The authors have no conflict of interest to report.

AUTHORS' CONTRIBUTIONS

A.F. and J.J.K. planned the project and obtained the bird strike data; F.A.L.S. processed the eBird data; A.D. and K.H. processed the weather radar data; C.N. analysed the data with help from B.M.V.D; and C.N. wrote the paper with considerable input from J.S.-B. and all other co-authors. All authors contributed to drafts and approved the final version.

DATA AVAILABILITY STATEMENT

Data available via the Dryad Digital Repository https://doi.org/10.5061/dryad.gtht76hmr (Nilsson et al., 2021).

ORCID

Cecilia Nilsson https://orcid.org/0000-0001-8957-4411
Frank A. La Sorte https://orcid.org/0000-0001-8521-2501
Adriaan Dokter https://orcid.org/0000-0001-6573-066X
Kyle Horton https://orcid.org/0000-0003-3243-3081
Benjamin M. Van Doren https://orcid.org/0000-0002-7355-6005
Jeffrey J. Kolodzinski https://orcid.org/0000-0001-5300-5786
Judy Shamoun-Baranes https://orcid.org/0000-0002-1652-7646
Andrew Farnsworth https://orcid.org/0000-0002-9854-4449

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