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*Research article*

# When can local bird detection radars best complement broad-scale early-warning forecasts of risk potential for bird–aircraft strikes as part of an integrated approach to strike mitigation?

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Worldwide, wildlife–aircraft strikes cost more than US$1.2 billion in aircraft damage and downtime and jeopardize the safety of aircrews, passengers, and animals. Radar has long been used to monitor flying animal movements and can be a useful tool for strike mitigation. In the USA, the Avian Hazard Advisory System (AHAS) is an early-warning system that integrates data from next-generation weather radar (NEXRAD) weather surveillance radars (WSRs) with historic bird occurrence data to quantify avian activity and forecast the relative bird risk within a ~9.3-km radius of military and civilian airfields. Bird detection radars (BDRs) with both horizontal-surveillance and vertical-scanning components are also available for monitoring local avian activity at airports, but we have little information regarding the congruence of broad-scale warnings and local avian activity where WSRs and BDRs overlap. We quantified trends in biological activity recorded at hourly intervals by a BDR at an airfield in Texas, USA, and in the most frequently assigned AHAS risk forecasts for that site during the same intervals. We then examined the strength of association between these datasets by season and time of day to determine when information from BDRs might best complement forecasts from the broad-scale AHAS system. We found a strong overall association between the datasets but weak or moderate agreement during daylight periods, when most strikes occur. NEXRAD WSRs see only limited bird activity near the Earth's surface, where the majority of damaging strikes take place and, not surprisingly, AHAS warnings during our study were best predicted by the BDR at higher altitudes. Our results suggest BDRs might best complement early-warning systems, like AHAS, as part of integrated strike mitigation plans at airfields with large numbers of hazardous birds flying at low altitudes during daylight hours, especially in late afternoon.

Keywords: Avian Hazard Advisory System (AHAS), bird–aircraft strike, bird detection radar (BDR), NEXRAD, Randolph Air Force Base

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## Introduction

Worldwide, wildlife–aircraft strikes (hereafter strikes) cost more than US$1.2 billion each year in aircraft damage and downtime (Allan 2000, Allan and Orosz 2001, El-Sayed 2019). Given the high speeds of aircraft operation, mortality is nearly certain for the wildlife involved (DeVault et al. 2015), but human safety can also be compromised, with over 250 casualties reported globally since 1988 (Richardson and West 2000, Cleary et al. 2006, Thorpe 2012, Dolbeer and Begier 2019). Birds are the most frequently struck taxa, and experts at the US Federal Aviation Administration and other government agencies expect the number of strikes to grow with the frequency of air travel and improvements to aircraft efficiency that make planes faster and quieter (Sodhi 2002, Dolbeer and Begier 2019). Additionally, many airports are located in urban and suburban environments where increasing numbers of hazardous, synanthropic birds (e.g. vultures, geese, gulls, pigeons, doves; DeVault et al. 2011, 2018) further contribute to the likelihood of collisions (Dolbeer and Eschenfelder 2003, Novaes and Cintra 2015, Bradbeer et al. 2017, Colón and Long 2018).

Understanding bird movements can help minimize the potential for strikes, and radar has long been recognized as a tool that can be used to quantify the movements of birds and other volant animals (Eastwood 1967, Gauthreaux 1970, Chapman et al. 2011, McCracken et al. 2021). Radars emit pulses of electromagnetic energy that travel away from a transmitter until the energy encounters aerial objects and an echo of the energy is reflected back to a receiver, providing information about the bearing, altitude, and speed of objects within a volume of space (Eastwood 1967, Kingsley and Quegan 1999, Stepanian et al. 2016). When tracking flying organisms (birds, bats, insects), radars may fail to recognize all individual targets, especially those that are small, low-flying, or far from the radar location (Beason et al. 2010, 2013, Dokter et al. 2013, Gauthreaux and Schmidt 2013, Gerringer et al. 2015, May et al. 2017). Ground clutter (e.g. buildings, trees, hills, and vehicles) and volume clutter (e.g. precipitation) can also confound detection when not accounted for (Beason et al. 2013). In addition, radar data rarely allow for species-level inference, which may be important in assessing the potential for damaging strikes. Nonetheless, radars can generally detect wildlife at greater altitudes and across larger distances than human observers, and they are relatively unaffected by time of day or weather conditions (Cooper et al. 1991, Burger 1997, Harmata et al. 1999, Gerringer et al. 2015), potentially allowing for a more comprehensive picture of animal movements than may otherwise be available for use in strike mitigation.

Weather surveillance radars (hereafter WSRs), though not specifically designed to detect biological targets, are regularly used to study animal movements (Shamoun-Baranes et al. 2014, Stepanian et al. 2016, Bauer et al. 2017, Chilson et al. 2017), and early-warning systems that take advantage of broad-scale WSR networks have been developed in the USA, Europe, and the Middle East to help flight planners, pilots, and aircrews minimize exposure to birds (Kelly et al. 1999, 2000, Dekker et al. 2008, van Gasteren et al. 2019). One such system, the US Avian Hazard Advisory System (AHAS), integrates information on avian activity extracted from near-real time next-generation radar (NEXRAD) data with models that include landscape characteristics, atmospheric conditions, and historic locations of hazardous birds (i.e. large-bodied and flocking species typically associated with the most damaging strikes; Zakrajsek and Bissonette 2005, DeVault et al. 2011, 2018) to identify the relative bird risk (i.e. probability multiplied by severity) within an approximately 9.3-km radius of airfields as low, moderate, or severe (Kelly et al. 1999, 2000, AHAS 2017). The degree to which AHAS has been successful in reducing bird strikes in the USA is unclear. In fact, the US Air Force Safety Center reports a steady increase in the number of damaging strikes from 2000 to 2019 (USAF 2022). However, Nilsson et al. (2021) recently found that the variation in bird strikes at three major US airports was highly correlated with the level of bird movements recorded by NEXRAD WSRs, and air forces operating in parts of northwestern Europe with similar early-warning systems (e.g. FlySafe) experienced an average of 45% fewer damaging bird strikes per 10 000 h over a 10-year period compared to those operating in areas without such systems (van Gasteren et al. 2019).

An increasing number of airports are installing bird detection radars (hereafter BDRs) to help identify bird movements and reduce the potential for strikes (Brand et al. 2011, Ehasz 2012, Shamoun-Baranes et al. 2017, Phillips et al. 2018). These small, mobile radars are specifically designed to detect bird-like targets and can track both individuals and flocks at lower altitudes than WSRs, allowing for improved situational awareness at local scales by identifying hazards within the airport environment (Gauthreaux and Belser 2003, Kelly 2005, Nohara et al. 2005, Beason et al. 2013, Gauthreaux et al. 2018). Most BDRs can provide horizontal coverage extending several kilometers from an airfield and vertical coverage to at least 1000 m above ground level (AGL) (Beason et al. 2013). BDRs operate within the much larger coverage patterns of WSRs, and research suggests good levels of agreement among BDRs and WSRs in tracking avian migration (Dokter et al. 2011, Nilsson et al. 2018, Liechti et al. 2019). However, we have limited data as to how avian activity recorded by BDRs corresponds to warnings issued by AHAS or other early-warning systems that integrate WSR data with other sources. This information could be useful in assessing periods when BDRs might be best utilized for bird avoidance alongside broad-scale warnings as part of an integrated approach to mitigating strike potential.

Randolph Air Force Base (hereafter Randolph) is located along the North American Central Flyway, which is subject to some of the highest avian migration traffic in the USA (La Sorte et al. 2019, Lin et al. 2019). Randolph is also near (~19 km) Bracken Cave – the largest maternity roost of Mexican free-tailed bats *Tadarida brasiliensis mexicana* in the world (McCracken 2003) – and close to San Antonio, where the largest US population of white-winged doves (*Zenaida* *asiatica*; George et al. 1994, Waggerman 2001) presents a considerable hazard to aircraft (Colón and Long 2018). In 2015, Randolph installed a BDR to aid in strike mitigation. Herein, we quantified temporal variability in hourly aerial vertebrate activity recorded by that BDR over two years and in the most frequently assigned AHAS risk levels issued for Randolph during those intervals. We then examined the level of agreement between these datasets by time of year (i.e. season) and time of day, and discussed our findings in the context of long-term strike patterns at the base. We expected a high level of congruence between the two datasets; however, we predicted the strength of association would be greatest during periods of intense activity when birds and bats fly at higher altitudes (e.g. nocturnal avian migration in spring and fall and bat foraging activity in summer).

### Study area

Randolph (29.53°N, 98.27°W) is a 1168-ha military training facility in Universal City, Texas (232 m a.s.l.), located approximately 30 km southwest of NEXRAD station KEWX (29.70°N, 98.03°W; Fig. 1). To facilitate high-volume pilot training at the base, two parallel runways flank an improved area (e.g. buildings, landscaping) to the east and west (Fig. 1). There is an oak–grass savanna with water catchments to the north of the improved area and an 18-hole turfgrass golf course and ephemeral ponds to the south. Along with anthropogenic and hydrologic landscape features beyond the base perimeter (i.e. suburban areas to the north and west, agricultural fields to the south and east, and three nearby creeks), these areas provide foraging and roosting opportunities that may encourage bird or bat movements across the base (Fig. 1). The climate is humid and subtropical with an average of ~73 cm of precipitation annually and an average annual temperature of ~21°C (NOAA 2018). Over a 25-year period (1990–2014), aircraft collisions with wildlife (mostly birds) at Randolph resulted in > US$10 million in damages (Colón and Long 2018). White-winged doves and other columbids accounted for 25% and 73% of strikes and strike costs, respectively, for which species identification was possible (Colón and Long 2018).

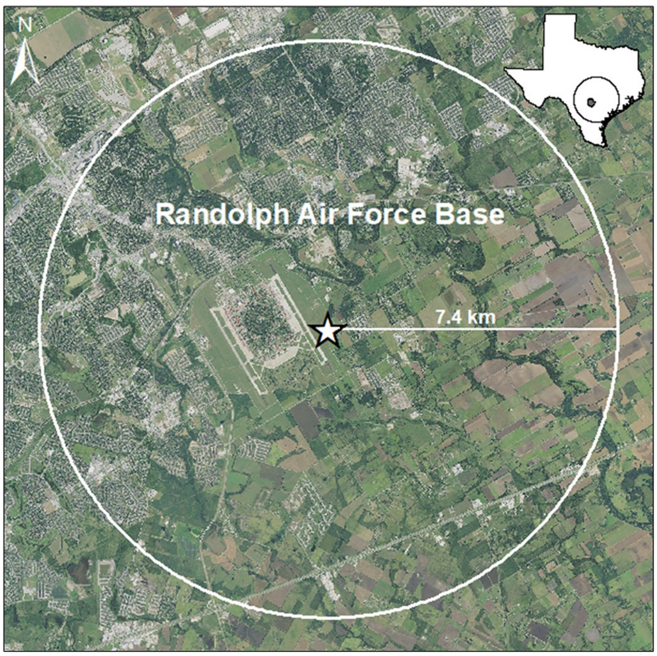


Figure 1. Bird detection radar (BDR; star) at Randolph Air Force Base in Bexar County, Texas, USA, with white circle depicting the detection area of the horizontal-surveillance radar (HSR) (7.4-km radius) located near the eastern runway. Background imagery (NAIP 2016) shows suburban development to the north and west of the base and agriculture to the south and east. Inset shows Bexar County (gray) within the 230-km detection radius (black circle) of the KEWX weather surveillance radar (WSR) located at New Braunfels Regional Airport in Guadalupe County, Texas.

## Material and methods

### Bird detection radar (BDR)

DeTect, Inc. (Panama City, FL) installed a Merlin™ Aircraft Birdstrike Avoidance Radar system near the eastern runway at Randolph in November 2015 (Fig. 1). The self-contained system uses simultaneously operating horizontal-surveillance (HSR) and vertical-scanning radars (VSR) to detect biological targets, and accompanying software enables users to track targets in near-real time.

The HSR was a solid-state Doppler radar that emitted a 30-kW, fan-shaped, S-band beam (10 cm wavelength, 26° beam width) at a 7° tilt angle during 360° rotations at a speed of 24 revolutions/min, and the VSR emitted a 25-kW, fan-shaped, X-band beam (3-cm wavelength). Algorithms within the software identified and tracked targets across sequential radar scans and quantified track frequency as well as direction (HSR) and altitude (VSR). The HSR beam at Randolph recorded tracks in the X–Y plane up to a maximum altitude of 2570 m AGL within a 7.4-km radius surrounding the radar unit (Fig. 2). The VSR scanned a vertical slice of the atmosphere providing altitude information from 91 m below the unit (where topography permitted) up to 1554 m AGL. The probability of detection likely declined with increasing distance to the unit, especially for small targets, so the maximum detection ranges for the HSR and VSR likely only applied to large birds (e.g. ducks, wading birds, raptors) or flocks (Dokter et al. 2013, May et al. 2017, Phillips et al. 2018). Operational settings (e.g. clutter mapping and suppression algorithms) minimized the characterization of insects, ground clutter, and other interference as targets, though these factors may still have interfered with detection to a limited extent, especially for the X-band radar, which is more sensitive to contamination by insects and precipitation (Bruderer 1997).

We obtained archived target data (i.e. track counts) recorded at hourly intervals by the HSR and VSR at Randolph over a two-year period from 1 December 2015

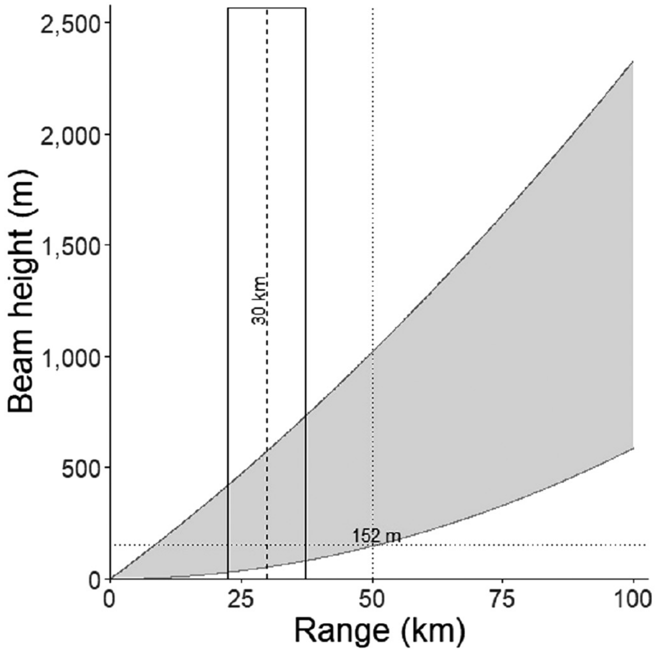


Figure 2. Idealized coverage areas of the horizontal-surveillance radar (HSR) and weather surveillance radar (WSR) described in this study assuming standard atmosphere. The WSR beam coverage (gray) is shown as a function of distance from the radar (i.e. range; calculated using Dokter et al. 2019). The bird detection radar (BDR) was located 30 km (dashed line) from the WSR with a maximum detection radius of 7.4 km, as indicated by the solid rectangle. The dotted lines identify a beam height of 152 m, below which most damaging bird–aircraft strikes occur (Dolbeer 2006), and the distance from the WSR at which there is little to no coverage at those altitudes.

through 30 November 2017 from the 12th Flying Training Wing Safety Office. The VSR data were provided as track counts within ~30-m altitude bins that were standardized by volume coverage, allowing for comparison among bins. We excluded intervals from each dataset in which rain occurred for > 30 min or there were no tracks recorded. It is possible in the latter case for there to have been intervals during which no targets passed through the radar beam, but long-term patterns suggested that scenario was unlikely. As such, we assumed the data gaps reflected periods of radar error or maintenance. Among the remaining intervals were those during which the radar recorded for < 60 min. We included these intervals in analyses if the total recording time was ≥ 30 min, but we used interpolated track counts for the entire interval (60 min) assuming a homogenous distribution of tracks throughout the interval. Mean recording time during such intervals was 58 min for both the HSR (± 1.5 SD, range 31–59 min) and VSR (± 1.9 SD, range 30–59 min). We retained 15 871 and 16 231 intervals from the HSR and VSR datasets, respectively, within which track interpolation accounted for ~1% (7756 min of 952 260) and < 1% (4635 min of 973 860) of the total minutes possible. Given our large sample sizes, we assumed interval exclusion and limited interpolation would have minimal effects on our analyses.

A single bird or bat passing through a radar beam more than once can register as multiple targets, and multiple tightly grouped individuals can present a single signature (Richardson 1978), such that the number of tracks recorded per interval represents an index of activity that reflects both target abundance and movement (Coates et al. 2011). Because the system cannot distinguish birds from bats, we referred to the number of tracks included in each interval as the biological activity index (BAI), similar to the avian activity index referred to by Coates et al. (2011).

### Avian Hazard Advisory System (AHAS)

The NEXRAD network comprises 160 continuously operated, high-resolution S-band Doppler WSRs (i.e. model WSR-88D; 10-cm wavelength) distributed across the USA and a few overseas locations. The system has two basic modes: the clear air mode, which operates when there is little to no precipitation, and the precipitation mode, which scans at a faster rate to track active weather. The two modes sample the atmosphere using various volume coverage patterns (VCPs) wherein the WSR performs 360° rotational scans at predetermined tilt angles (0.5–19.5°) and pulse repetition frequencies (318–1300 Hz) every 4.5–10 min, depending on the VCP selected (https://weather.gov/jetstreatm/vcp_max). During scans, the WSRs detect both biological (i.e. flying animals) and non-biological (e.g. weather, smoke, chaff) targets within a 230-km radius (Gauthreaux and Belser 1998, Weber et al. 2005, Kunz et al. 2007).

For near-real time bird activity alerts, the AHAS uses a suppression algorithm to automatically filter out non-biological targets from NEXRAD Level II data products, which include base meteorological data (i.e. reflectivity, mean radial velocity, spectrum width) and dual polarization variables (i.e. differential reflectivity, correlation coefficient, differential phase). The suppression model uses the first four tilt angles for the reflectivity data and the lowest tilt angle for all other measures (R. White, DeTect, Inc., unpubl.). AHAS interprets the filtered data using the US Bird Avoidance Model (BAM) (Lovell 1997, Lovell and Dolbeer 1999) and neural networks to forecast the bird risk as low, moderate, or severe within each sampling frame (Kelly et al. 2000, AHAS 2017). When NEXRAD data are unavailable, AHAS bases risk on whichever is greater between the soaring bird model and the BAM (Kelly 2005, Szafrański et al. 2022). Beyond 24 h from the last soaring bird model update, AHAS assigns risk solely based on the BAM (R. White, unpubl.). The soaring bird model updates output every 12 h given the latest upper air weather data and known spatiotemporal information regarding turkey vultures *Cathartes aura*, black vultures *Caragyps atratus*, red-tailed hawks *Buteo jamaicensis*, bald eagles *Haliaeetus leucocephalus*, and golden eagles *Aquila chrysaetos* (R. White, DeTect, Inc., unpubl.).

When using NEXRAD inputs, AHAS multiplies severity, according to the level of energy reflected back to the receiver, by the probability of a strike, estimated as the percentage of area filled with biological activity (AHAS 2017, Szafrański et al. 2022). AHAS classifies risk as low, moderate, or severe given products of ≤ 300, 301–4000, and > 4000, respectively, such that moderate- and severe-risk assignments are up to 708 and 38 647 times riskier than low-risk assignments (AHAS 2017). The suppression algorithm used by AHAS to filter out non-biological targets does not account for insects. However, insect returns rarely, if ever, contribute to moderate or severe warnings (R. White, DeTect, Inc., unpubl.).

We acquired AHAS risk assignments for Randolph from DeTect Inc. for the period corresponding to that recorded by the BDR. AHAS determined 95% of the near-real time risk assignments for our study area during the survey period using NEXRAD data, 3% according to the soaring bird model, and < 2% with the BAM alone. Because AHAS updates risk assignments every 6–10 min with new NEXRAD inputs, the data were not directly comparable with the hourly BAIs in the archived BDR datasets. As such, we classified AHAS risk for each hourly interval using the most frequently assigned (i.e. mode) AHAS risk level for that hour. When there was a tie for the most frequently assigned level, we classified the interval by the most severe of the tied levels. Collapsing AHAS data in this way resulted in 17 099 intervals with risk assignments for use in analyses.

### Statistical analyses

We classified each hourly interval according to temporal factors thought to influence bird and bat activity. We first grouped intervals according to meteorological seasons (i.e. spring: March–May, summer: June–August, fall: September–November, winter: December–February), which relate to the annual temperature cycle (Trenberth 1983), then classified each interval by light period based on daily sunrise and sunset times. We characterized intervals as diurnal if they occurred between sunrise and sunset and nocturnal if they occurred between sunset and sunrise. Following Coates et al. (2011), we further divided each diurnal and nocturnal period into three equal parts and classified each interval as occurring during the early, middle (mid), or late portions of the day or night. We assigned hourly intervals to light periods according to the class that best reflected the entire interval (i.e. greatest total minutes). For example, we considered the 6:00 to 6:59 interval to be an early diurnal period if sunrise occurred during the first half of the hour and a late nocturnal period if sunrise occurred in the second half of the hour. The BDR recorded, and we analyzed and presented, all information according to Central Standard Time without adjusting for daylight savings.

We calculated mean (± SD, range) BAI in the HSR dataset and the total number of intervals identified in each AHAS risk class by season and time of day. We then used analysis of variance (ANOVA) and multinomial logistic regression models to examine temporal patterns (i.e. season, time of day, and their interaction) in BAI and AHAS risk, respectively. We chose multinomial over ordinal logistic regression because our data violated the assumption of proportional odds (Brant 1990). Given our large sample sizes, we considered tests significant at $p \leq 0.001$ (Huberty 1987). We followed significant models with Tukey's tests as appropriate and reported p-values for non-significant pairwise comparisons where relevant. We calculated partial eta-squared to estimate the effect sizes of each predictor in our ANOVA model and used a random forest approach with unbiased classification trees based on conditional inference to determine variable importance (VI) in our regression model (Hothorn et al. 2006, Janitza et al. 2016). The former considers the effects of each predictor on the dependent variable while statistically controlling for the effects of other predictors in the model (Cohen 1973). The latter accounts for bias resulting from differences in the number of levels among categorical variables (van der Laan 2006, Strobl et al. 2007, Boulesteix et al. 2012); it does not assign an importance value to interaction terms. To simplify interpretation, we standardized VI values, assigning the most important variable a relative importance of 100% (Oppel et al. 2009). We calculated McFadden's pseudo-$R^2$ (McFadden 1973) as a measure of overall fit for our regression model and predicted the probability of each AHAS risk class according to season and time of day.

We then used ANOVA models with eta-squared to examine the strength of association between HSR-derived BAI and AHAS risk level overall and within each season by time-of-day combination (e.g. winter × early day). When assessing model significance, we applied a Holm–Bonferroni correction with $\alpha = 0.001$ to account for potential growth in the familywise error rate due to multiple comparisons ($n = 24$; Holm 1979, Olejnik et al. 1997). We considered eta-squared equal to 0.01 to represent a weak association, 0.10 a moderate association, and 0.25 a strong association (Vacha-Haase and Thompson 2004). To account for positive skewness in the data, we used the square root of BAI as the dependent variable in all ANOVA models.

Excluding BAIs from altitudes below the radar unit, we found total BAI across altitude bins in the VSR dataset to be moderately correlated with BAI in the HSR dataset ($r = 0.45$, $p \leq 0.001$, $n = 15\,394$; Fig. 3). Given this relationship, we did not combine data from the altitudinal bins to statistically examine overall temporal trends in the VSR dataset. However, we summarized mean BAI by altitude and explored at which altitudes BAI best predicted AHAS risk assignments. For these analyses, we combined track counts from the 30-m altitude bins ≥ 0 m AGL in the VSR dataset to create 152-m bins. To capture as much variation as possible, we combined bins using a moving window approach across the 30-m bins such that the aggregated bins had overlapping coverage areas (e.g. 0–152, 30–182, 60–212 m AGL, and so on). We created separate multinomial regression models for each aggregated altitudinal bin, then ranked models for each period (season × time of day) according to Akaike's information criterion ($AIC_c$; Burnham and Anderson 2002). We considered all models with $\Delta AIC_c < 2.0$ to be equally plausible and presented all plausible models in a comparative season by time-of-day graph. We calculated classification accuracy for all altitude models.

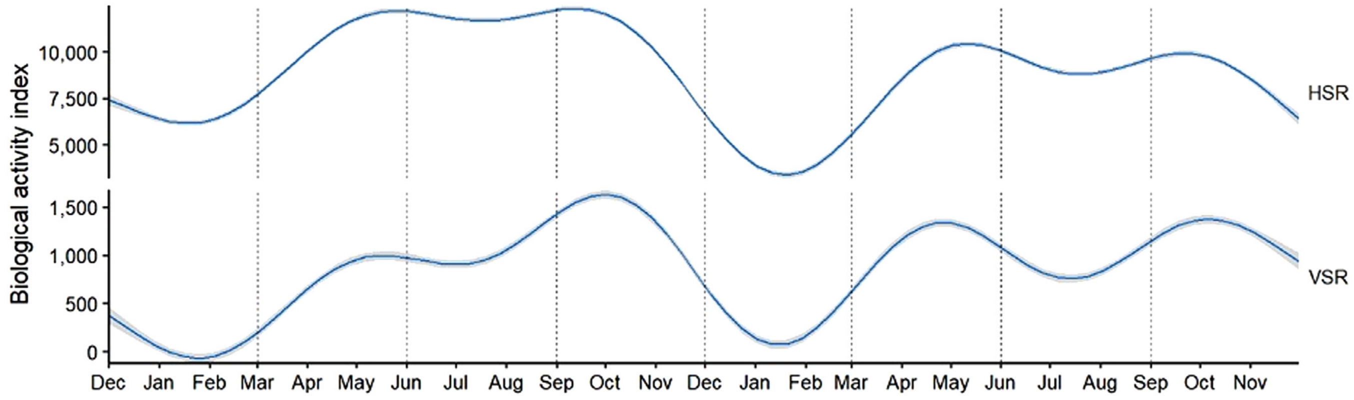


Figure 3. Trends in biological activity (i.e. track counts) as measured by the horizontal-surveillance (HSR) and vertical-scanning (VSR) radars at Randolph Air Force Base in Bexar County, Texas, USA, from 1 December 2015 to 30 November 2017. Dashed lines represent seasonal breaks.

We conducted all analyses using the open-source statistical program R ver. 3.6.1 (www.r-project.org). We used the 'sjstats' package (Lüdecke 2019) in R to calculate eta-squared and partial eta-squared and the 'MBESS' package to calculate 95% confidence intervals for eta-squared (Kelley 2017). We used the 'nnet' package to perform multinomial logistic regression (Ripley and Venables 2016) and the 'party' package to calculate variable importance (Hothorn et al. 2019).

## Results

### Temporal patterns in biological activity measured by the horizontal-surveillance radar (HSR)

The BAI recorded by the HSR varied strongly by season ($F_{3,15847}=2892.4$, $p \le 0.001$, $\eta_p^2=0.35$; Fig. 4) and, to a lesser extent, by time of day ($F_{5,15847}=126.1$, $p \le 0.001$, $\eta_p^2=0.04$, Fig. 4). Mean BAI was 10 to 11% greater in spring and summer ($p=0.19$) than in fall and 77 to 96% greater in all seasons compared to winter (Fig. 4). Mean BAI was significantly greater during early-night periods and significantly lower during mid-day periods compared to all others (Fig. 4). Mean BAI was similar during early-day, late-day, and mid-night periods ($p \ge 0.76$; Fig. 4). A significant interactive term in our ANOVA model indicated that, in addition to the main effects, BAI recorded during each light period varied according to season ($F_{15,15847}=212.2$, $p \le 0.001$, $\eta_p^2=0.17$; Fig. 4). BAI was greatest during early- and late-day periods in winter ($p=1.00$; Fig. 4), in mid-night periods in spring and fall, and from late day throughout the night in summer ($p \ge 0.47$; Fig. 4).

### Temporal patterns in broad-scale AHAS risk classifications

Based on AHAS risk assignments, we classified 21, 53, and 26% of intervals as low, moderate, and severe risk, respectively (Fig. 4). Both season ($\chi^2_6=919.9$, $p \le 0.001$, VI$=75\%$) and time of day ($\chi^2_{10}=1160.0$, $p \le 0.001$, VI$=100\%$) influenced the level of risk for each interval, with low-risk intervals occurring in winter 6 to 33 times more often than in other seasons and in early diurnal periods up to three times more often than during other light periods (Fig. 4). Severe-risk intervals were up to four times more frequent in fall compared to other seasons, and up to seven times more frequent during early nocturnal periods than other times of day (Fig. 4). Post hoc tests indicated that all pairwise seasonal and time of day contrasts were significantly different at $\alpha=0.001$. As with BAI derived from the HSR, we found a significant interactive effect of season and time of day on risk level in addition to the main effects ($\chi^2_{30}=844.36$, $p \le 0.001$, pseudo-$R^2=0.29$; Fig. 4). Regardless of time of day, the predicted probability of a low-risk assignment was greater, and the predicted probability of a severe-risk assignment lower, in winter relative to other seasons (Table 1). During the rest of the year, moderate risk was generally more likely during diurnal periods and severe risk more likely during nocturnal periods; though the probability of severe risk declined over time during nocturnal periods in spring and fall (Fig. 4, Table 1).

### Relationships of local biological activity to broad-scale risk classifications

We found a strong association overall between AHAS risk level and BAI recorded by the HSR ($F_{2,14727}=4789.0$, $p \le 0.001$, $\eta^2=0.39$). Congruence between the datasets was generally stronger at night than during the day and increased over time from early to late nocturnal periods, except in winter when association strength decreased with time at night (Fig. 5). Despite a similar nocturnal trend, agreement between AHAS risk potential level and BAI was lower on summer nights relative to spring and fall nights (Fig. 5). There was strong agreement during early diurnal periods in fall, but agreement was otherwise weak or moderate during daylight periods in all other seasons (Fig. 5).

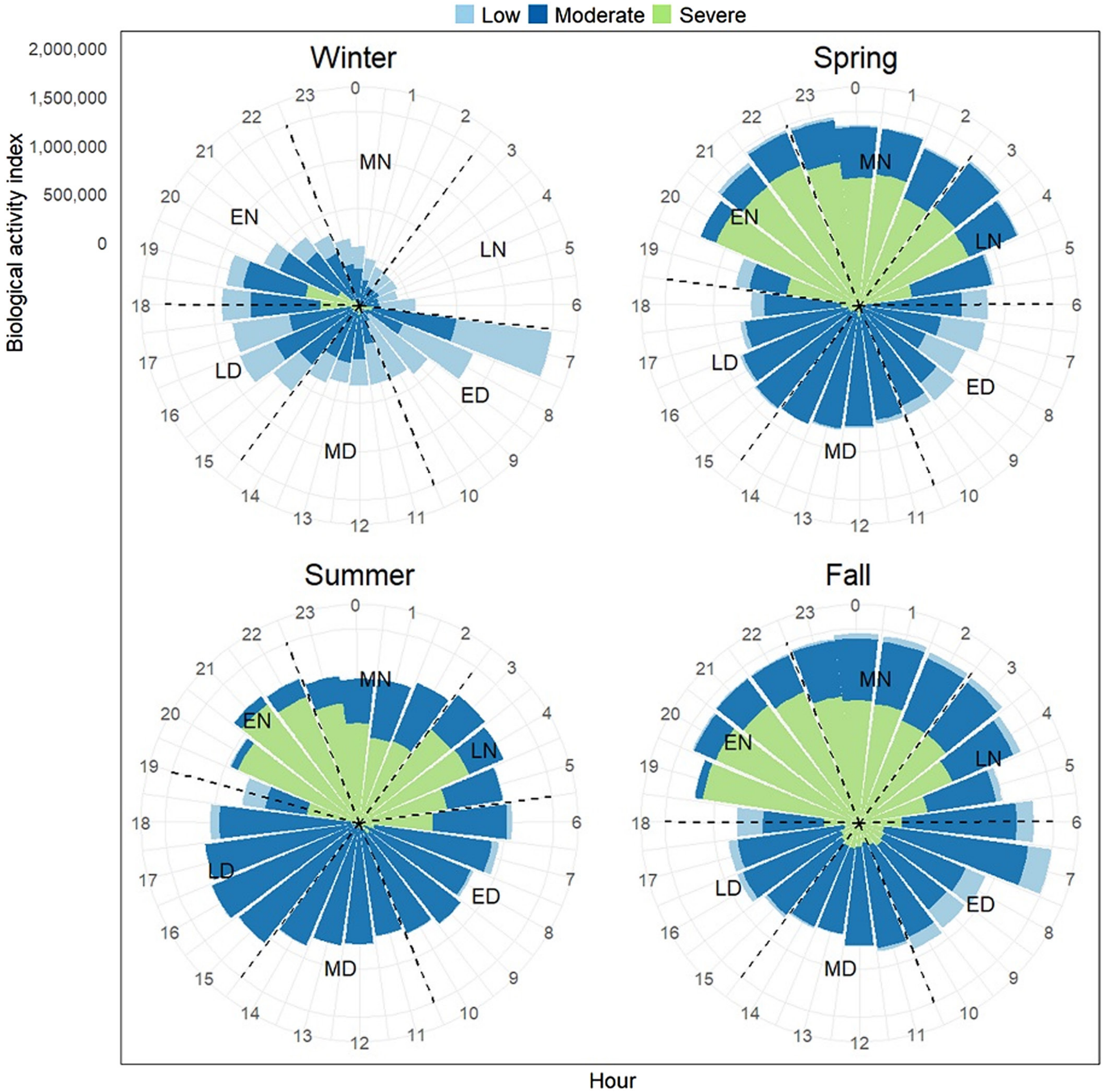


Figure 4. Biological activity index (BAI) (i.e. track counts/hour) recorded by the at Randolph Air Force Base by season and hour from 1 December 2015 to 30 November 2017 and most frequently assigned Avian Hazard Advisory System (AHAS) risk class per hour for the same location. Dashed lines separate light phases indicated as early, mid-, and late day (ED, MD, and LD) and early, mid-, and late night (EN, MN, and LN). Dashed lines bisect bars for intervals represented by multiple light phases, depending on day of year.

### Temporal patterns in biological activity measured by the vertical-scanning radar (VSR) and relationship to broad-scale risk classification by altitude

Overall, mean BAI in the VSR dataset was greatest within the altitude bin spanning 213 to 366 m AGL (Fig. 6), but there was considerable seasonal and diurnal variability. BAI within the 457 to 609 m AGL bin best predicted AHAS risk level overall during the study period (66% accuracy; Fig. 7). Within this altitude bin, the predicted probability of moderate risk was greater than that for low risk, and both declined with increasing BAI (Fig. 7). The predicted probability of severe risk increased with BAI and reached 100% at ~1000 tracks (Fig. 7). When accounting for season and time of day, with the exception of mid-day periods, lower altitudes generally characterized AHAS risk assignments in winter better

Table 1. Predicted probabilities (%) of Avian Hazard Advisory System (AHAS) risk class per hour based on an interactive multinomial logistic regression model examining the most frequently assigned risk class per hour as a function of season and time of day at Randolph Air Force Base, Texas, USA, from 1 December 2015 to 30 November 2017.

| | Winter | | | Spring | | | Summer | | | Fall | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Period | Low | Moderate | Severe | Low | Moderate | Severe | Low | Moderate | Severe | Low | Moderate | Severe |
| Early-day | 67 | 26 | 7 | 27 | 64 | 9 | 3 | 84 | 13 | 20 | 66 | 14 |
| Mid-day | 39 | 52 | 9 | 3 | 90 | 7 | 1 | 94 | 5 | 2 | 81 | 17 |
| Late-day | 38 | 55 | 7 | 7 | 84 | 9 | 6 | 88 | 6 | 7 | 79 | 14 |
| Early-night | 40 | 45 | 14 | 5 | 26 | 69 | 2 | 11 | 87 | 6 | 22 | 72 |
| Mid-night | 66 | 32 | 2 | 1 | 40 | 54 | <1 | 36 | 64 | <1 | 39 | 56 |
| Late-night | 75 | 24 | 2 | 12 | 46 | 41 | 1 | 33 | 66 | 13 | 50 | 37 |

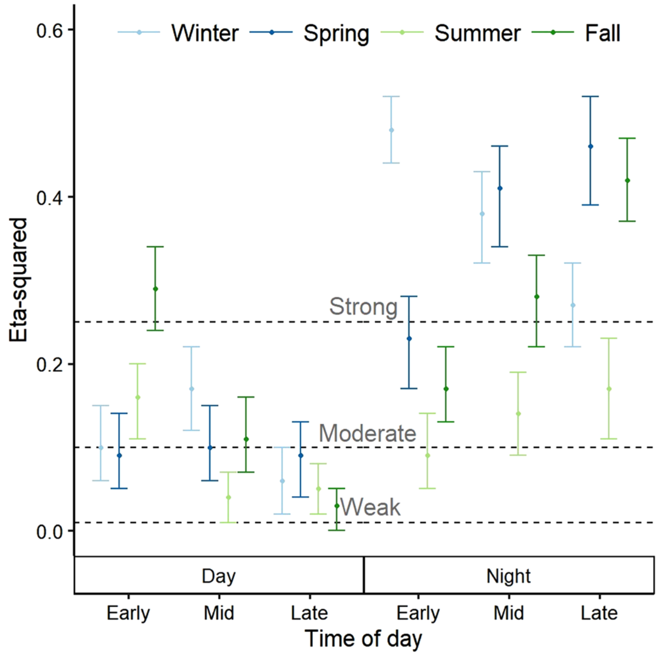


Figure 5. Strength of association ($\eta^2$ with 95% confidence intervals) for analysis of variance models examining the relationship of the most frequently assigned Avian Hazard Advisory System (AHAS) risk class per hour and biological activity index (BAI) (i.e. track counts/hour) recorded by the horizontal-surveillance component of a bird detection radar (BDR). Dashed lines ($\eta^2 = 0.01$, 0.10, 0.25) and gray text indicate strength of association thresholds.

relative to other seasons, and higher altitudes were typically more characteristic of AHAS assignments in summer (Fig. 8). However, there was considerable temporal variation in the classification accuracy of the best-fit models, with the lowest accuracy during mid-night periods in fall (55%) and the highest accuracy during mid-day periods in summer (95%; Fig. 8).

## Discussion

Several researchers have evaluated the performance of mobile radars (e.g. BDRs) to track birds near airports (Gerringer et al. 2015, Phillips et al. 2018). Few, however, have examined the relationship between avian activity recorded by a BDR and the probability of strikes. Notably, Coates et al. (2011) quantified avian activity using the horizontal-surveillance component (HSR) of a BDR at Beale Air Force Base and found that the probability of strikes increased with avian activity near the airfield. Similarly, Nilsson et al. (2021) demonstrated that estimates of migration intensity derived from weather surveillance radar (WSR) data could be used to reliably predict the likelihood of strikes at three airports in the northeastern USA (but see Dipilla 2021). Though some have examined the correspondence between BDRs and WSRs in tracking animals in flight (particularly the vertical-scanning component [VSR]; Buhler and Diehl 2009, Nilsson et al. 2018, Liechti et al. 2019), this is the first paper to explore relationships between early-warning

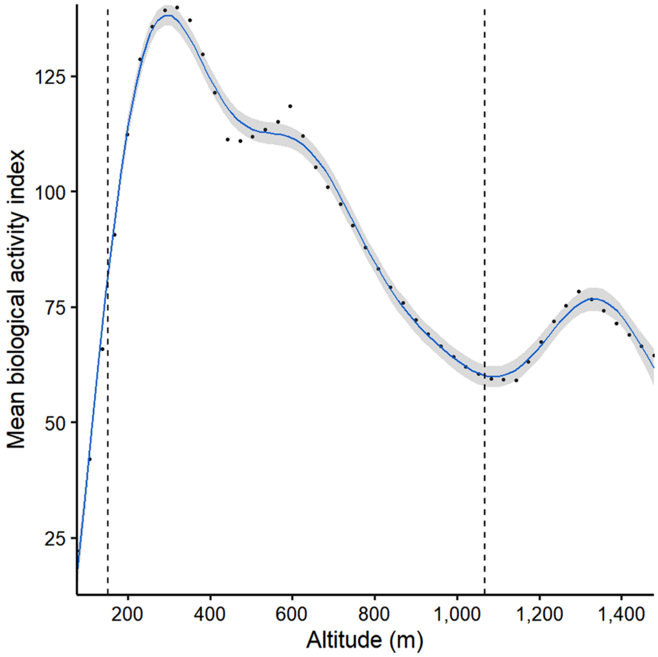


Figure 6. Distribution of mean biological activity (i.e. track counts/hour) as a function of 152-m altitude bins (depicted by midpoints) recorded by the vertical-scanning radar. Dashed lines identify the altitudes below which most wildlife–aircraft strikes (i.e. 1067 m above ground level (AGL) and the majority of strikes resulting in substantial damage (i.e. 152 m AGL) occur according to Dolbeer (2006).

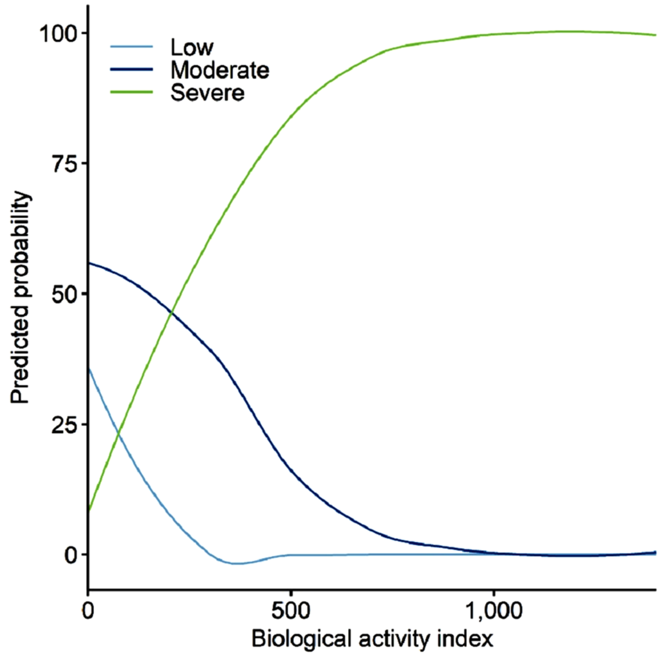


Figure 7. Predicted probability of the most frequently assigned Avian Hazard Advisory System (AHAS) risk class per hour given biological activity index (BAI) within the altitude bin spanning 457 to 610 m above ground level recorded by the vertical-scanning radar.

forecasts of bird risk, derived from WSR data and other sources, and biological activity recorded by both components of a BDR, and to relate this information to strike patterns.

Like Coates et al. (2011), we found temporal variability in biological activity recorded by the HSR at Randolph, with diel patterns dependent on season. Activity at Randolph was greatest during the mid-night periods in spring and fall, and there was strong agreement between avian activity and AHAS bird risk warnings during these periods, with the probability of a severe warning considerably greater than that of low or moderate warnings. These results were expected and correspond well with known nocturnal bird migration activity, which typically begins within the first few hours after sunset and reaches peak intensity during the mid-night hours before trailing off until shortly after sunrise (Lowery 1951, Hassler et al. 1963, Gauthreaux 1971, Fortin et al. 1999, Dinevich et al. 2003). During migration, the number of strikes per aircraft movement is greater at night than during the day, especially at higher altitudes (i.e. > 152 m AGL; Dolbeer 2006). At Randolph, most flight operations (99%) take place between 7:00 and 18:00 (JLUS 2015), and nocturnal strikes are rare (8%; Colón and Long 2018). In the 1960s, however, Randolph operated many nighttime flying missions that exposed pilots and aircraft to migratory birds, with peaks in strike frequency from August to October and then again in April (Pruess 2002).

Randolph is located in close proximity to Bracken Cave, where historic Mexican free-tailed bat populations have been estimated in the tens of millions (Davis et al. 1962, Wahl 1993, Betke et al. 2008). Of the nocturnal strikes observed at Randolph in the 1960s, many were later identified as bat strikes, especially in summer (Pruess 2002). Mexican free-tailed bats are most active during the early night period in summer (Lee and McCracken 2001, Reichard et al. 2009), when they emerge from caves in densely packed streams until reaching several hundreds of meters above the ground and dispersing into smaller groups (Horn and Kunz 2008). During our study period, biological activity recorded by the HSR on summer nights likely corresponded with bat activity.

The WSRs informing the AHAS are regularly used in bat research (Horn and Kunz 2008, Frick et al. 2012, Stepanian and Wainwright 2018, Stepanian et al. 2019), and evidence suggests bat presence can affect NEXRAD-derived AHAS risk assignments (AHAS 2022). The predicted probability of a severe AHAS warning was high on summer nights, particularly during the early-night period. Yet, the strength of association between the AHAS and HSR datasets was weak to moderate on summer nights. The weaker association during the early night period in summer likely reflects the distance between Randolph and Bracken Cave (19 km), which is beyond the detection radius of the HSR but within the coverage of the WSR. Increasing nocturnal agreement between the datasets over time at night may indicate greater detection by the HSR of bats foraging closer to the base after dispersal. However, bats are not included in the US BAM (Lovell 1997, Lovell and Dolbeer 1999) or the soaring bird model, and WSRs are likely to miss low-flying bats, where most damaging bat strikes at Randolph have occurred (i.e. < 300 m

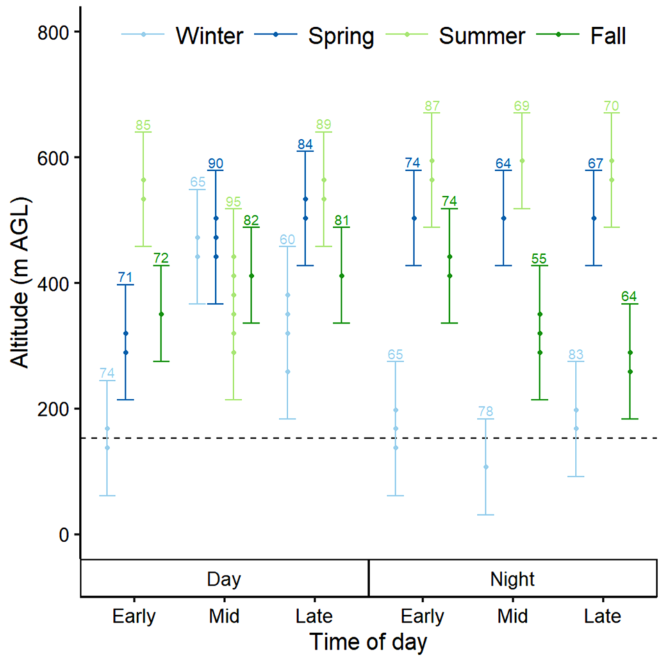


Figure 8. Altitude bins at which biological activity indices recorded by the vertical-scanning component of a bird detection radar (BDR) best predicted the most frequently assigned Avian Hazard Advisory System (AHAS) risk class. Solid points indicate midpoints of the 152-m bins identified by the best-fit models, and lines extend to minimum and maximum altitudes of those bins. Multiple points for a given period indicate more than one best-fit model and values above each line identify the mean percent classification accuracy of best-fit models. The dashed line identifies the altitudes below which the majority of strikes resulting in substantial damage (i.e. 152 m above ground level) occur according to Dolbeer (2006).

AGL; Pruess 2002), potentially contributing to the disconnect between the datasets we observed on summer nights.

Because most aircraft activity occurs during the day, the total number of strikes is greater during daylight hours, with the most damaging strikes occurring at altitudes < 152 m AGL (Dolbeer 2006, Dolbeer et al. 2022). At Randolph, the correlation of AHAS risk with biological activity recorded by the HSR was weak to moderate during the day, except on early fall mornings. Though most migratory birds travel at night (Newton 2008, Horton et al. 2019), many of the most hazardous species to aircraft (Dolbeer et al. 2000, Zakrajsek and Bissonette 2005, DeVault et al. 2018, Pfeiffer et al. 2018) migrate during daylight hours (e.g. turkey vulture [Eisenmann 1963, Mandel et al. 2008], red-tailed hawk [Mathisen and Mathisen 1968]). From 1990 to 2021, diurnal raptors, including vultures, accounted for 12% of all strikes with civilian aircraft in the USA and 24% of damaging strikes, resulting in 16 casualties, 91 injuries, 14 destroyed aircraft, and > US$186M in damage (Dolbeer et al. 2022). Kerlinger and Gauthreaux (1985) used a BDR to observe raptors during spring migration along the Texas coast. They noted birds flying at low altitudes (< 100 m) early in the morning before thermals developed (~900–1000), with the majority (76%) flying at altitudes from 300 to 600 m AGL for the remainder of the day, during periods when most raptor strikes occur (Blackwell and Wright 2006).

Despite large numbers of raptors and other diurnal migrants traveling through Texas and the Central Flyway (La Sorte et al. 2019, Lin et al. 2019, Córdoba et al. 2020), the probability of a moderate AHAS risk warning was considerably higher than that for other warning levels in all diurnal periods in all seasons, except winter. The US BAM and the AHAS were developed to inform military aircraft operating at low altitudes, but moderate risk warnings issued during most periods may not be especially helpful for flight planners, pilots, or ground crews in mitigating the potential for daytime strikes. Kerlinger and Gauthreaux (1985) suggested that an HSR may be particularly effective for monitoring raptors during the early morning hours when migration altitudes are lower. The same is also likely true for monitoring local movements of most birds, which primarily occur within a few hundred meters above the ground (Shamoun-Baranes et al. 2006, Larsen and Guillemette 2007, Avery et al. 2011). At Randolph, raptor strikes comprise a small percentage of the total number of strikes and the number of damaging strikes relative to other taxa, and the HSR may be helpful in monitoring species like white-winged doves, which represent a more substantial hazard to aircraft at the base (Colón and Long 2018).

Most damaging strikes take place within the airport environment (< 152 m AGL), often on takeoff or landing (Dolbeer 2006), but the low-altitude bins of our VSR dataset were rarely the best predictors of AHAS warnings. There was overlap in the low-altitude coverage of the BDR at Randolph and the nearest WSR but, because of tilt angles and distance, WSRs cannot detect wildlife at the lowest altitudes, and the weaker agreement we observed between the HSR and AHAS datasets during the day likely resulted, at least in part, from risk assignments that did not incorporate the diurnal activity of birds flying between foraging, roosting, and nesting locations at altitudes below the WSR beam (Shamoun-Baranes et al. 2006, 2017). Outside the airport environment (i.e. > 152 m AGL), the rate of damaging strikes may be increasing with numbers of hazardous birds (e.g. Canada geese *Branta canadiensis*; Dolbeer and Eschenfelder 2003, Dolbeer 2011, Dolbeer et al. 2014), especially in spring and fall (Dolbeer et al. 2016). To mitigate strike potential at these higher altitudes, Dolbeer (2006) recommended using radar to monitor bird movement activity from 152 to 1067 m AGL. At Randolph, the VSR indicated that most local biological activity occurred within the altitude bin spanning 213 to 366 m AGL, and AHAS risk classifications were best predicted by biological activity recorded within the altitude bin from 457 to 609 m AGL, with limited predictability above that range.

In the early tests, AHAS accurately predicted large migratory movements of waterfowl, allowing the US Air Force to adjust their flying activities to minimize the risk of strike (Kelly et al. 1999). Similarly, our findings suggest that AHAS likely predicts the risk of encountering nocturnally migrating birds in spring and summer accurately, particularly outside the airport environment. However, as most strikes occur during daylight hours, with most damaging strikes occurring below 152 m AGL, AHAS warnings may offer little guidance during the times and in the locations that are of greatest concern, and BDR data may offer a useful tool to complement AHAS in mitigating strikes. BDRs may be especially valuable at airfields located more than 90 km from a WSR or in parts of central and western USA, where distance to or elevation of WSR sites greatly limits low-altitude coverage (Westrick et al. 1999, Maddox et al. 2002, Chilson et al. 2012). The ability of BDRs to track flying animals in real time may also provide added value to airfields operating nighttime flights, where large numbers of bats and migratory birds occupy low-level airspace (Kelly et al. 2007).

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## Author contributions

**Melanie R. Colón**: Conceptualization (equal); Formal analysis (lead); Methodology (lead); Project administration (supporting); Writing – original draft (lead); Writing – review and editing (equal). **Ashley M. Long**: Conceptualization (equal); Formal analysis (supporting); Funding acquisition (lead); Methodology (supporting); Project administration (lead); Writing – original draft (supporting); Writing – review and editing (equal).

## Data availability statement

AHAS are available to the public on request from DeTect, Inc. (ahas@detect-inc.com). Data recorded by the bird detection radar at Randolph Air Force Base are also held by DeTect, Inc., but access requires permission from the Air Force.

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