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Using avian radar to examine relationships among avian activity, bird strikes, and meteorological factors

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***Abstract*:** Radar systems designed to detect avian activity at airfields are useful in understanding factors that influence the risk of bird and aircraft collisions (bird strikes). We used an avian radar system to measure avian activity at Beale Air Force Base, California, USA, during 2008 and 2009. We conducted a 2-part analysis to examine relationships among avian activity, bird strikes, and meteorological and time-dependent factors. We found that avian activity around the airfield was greater at times when bird strikes occurred than on average using a permutation resampling technique. Second, we developed generalized linear mixed models of an avian activity index (AAI). Variation in AAI was first explained by seasons that were based on average migration dates of birds at the study area. We then modeled AAI by those seasons to further explain variation by meteorological factors and daily light levels within a 24-hour period. In general, avian activity increased with decreased temperature, wind, visibility, precipitation, and increased humidity and cloud cover. These effects differed by season. For example, during the spring bird migration period, most avian activity occurred before sunrise at twilight hours on clear days with low winds, whereas during fall migration, substantial activity occurred after sunrise, and birds generally were more active at lower temperatures. We report parameter estimates (i.e., constants and coefficients) averaged across models and a relatively simple calculation for safety officers and wildlife managers to predict AAI and the relative risk of bird strike based on time, date, and meteorological values. We validated model predictability and assessed model fit. These analyses will be useful for general inference of avian activity and risk assessment efforts. Further investigation and ongoing data collection will refine these inference models and improve our understanding of factors that influence avian activity, which is necessary to inform management decisions aimed at reducing risk of bird strikes.

***Key words*:** airfield, avian activity, Beale Air Force Base, bird strikes, collision, human–wildlife conflicts, meteorology, migration, radar, weather

AN IMPORTANT GOAL of airfield resource managers is to take actions that avoid collision between birds and aircraft (bird strikes), while using practices that minimize the loss of avian species diversity. Airfields often are located in areas with high avian activity (e.g., suburbs, near wetlands). Bird strikes are a major concern in California because the entire region, and especially the Central Valley, is a major breeding, migration, and wintering area for Pacific Flyway birds (Gilmer et al. 1982, Shuford et al. 1998). The aviation industry suffers an annual loss of $1.2 billion due to bird–aircraft collisions. These accidents have resulted in 194 human deaths (Dale 2009) with more than 60% of collisions occurring within the vicinity of the airfield (Dolbeer and Wright 2009). A full understanding of links among bird-strike risk, bird activity, and environmental factors are needed to design actions that reduce monetary loss and human fatality or injury caused by bird strikes. Statistical inference models of avian activity based on time-dependent effects and meteorological factors at airports would be useful in aviation risk management plans, especially with regard to flight scheduling aimed at reducing the probability of bird strikes.

Quantifying the risk of bird strikes is a challenging task (Allan 2006, Soldatini et al. 2010), in large part because of the difficulties associated with accurately measuring avian activity and also the scarcity of bird-strike data. As a result, mechanistic studies that clearly define links between bird strikes and avian activity are lacking. Data from portable avian radar systems can be relatively more effective than other techniques used to quantify avian activity and identify relationships with environmental factors and bird strikes. One major advantage of using avian radar over conventional visual surveys is the ability to gather information continuously, including surveying both in nocturnal hours and conditions during daylight when visual observation is not practical (Cooper et al. 1991). This information is useful because bird strikes have been reported at pre-dawn hours (Burger 1985), and many birds migrate during those hours. Another advantage is that avian radar systems can provide information about origin, volume, and direction of bird flights (Russell and Gauthreaux 1998). Other types of radar technologies have been useful but have limitations. For example, weather radar, such as the NEXRAD Doppler system (Kelly et al. 2000), has been used as a tool for monitoring avian flight patterns for nearly 5 decades (van Belle et al. 2007). However, such technologies do not offer full coverage in all areas and have limited abilities in precision to detect individual birds at local scales. Thus, while useful for large-scale analyses that identify bird migration and flight patterns, weather radar lacks local precision and is not always available or useful for managing local bird populations at individual airfields.

More recently, radar systems designed for local-scale use allow for relatively small but highly detailed zones of coverage. For example, the Merlin™ avian radar system (DeTect Inc., Panama City, Fla.) uses horizontal (S-band) and vertical (X-band) radar beams at relatively short distances (4 to 12 km) to obtain high resolution, which allows estimation of avian activity at individual airfields. Further, these systems target and track individual birds and have limited ability to separate targets into different size classes, allowing some types of organisms to be discriminated (Kelly et al. 2007). However, well-designed studies are needed to fully evaluate the performance of this technology to estimate population abundance or density. Nevertheless, this radar technology serves as a valuable tool to develop indices of avian activity.

We carried out a study with 2 major objectives at Beale Air Force Base (AFB) in California using data collected from 3 sources. We obtained avian activity data from the avian radar system. We then acquired data of bird strikes that were reported at Beale AFB during the same time period as radar data from strike reports managed by the Bird–Wildlife Aircraft Strike Hazard (BASH) team. Lastly, we acquired meteorological data from the National Weather Service (NWS) during the same time period. Our first objective was to develop a statistical model that evaluated the relationship between avian activity and the occurrence of bird strikes. Our second objective was to develop a set of *a priori* models to examine the effects of meteorological and time-dependent factors on avian activity. We used an information theoretic approach and cross-validation technique to evaluate model support from the data, and we reported the estimated averaged model parameters (e.g., coefficients). These parameters will be valuable to local planning authorities for strategies that are aimed at improving flight safety and reducing costs associated with bird strikes. This study provides a baseline for further refinement in estimated parameters and examination of additional hypothesized variables as ongoing data collection from radar systems becomes available.

Study site

Beale AFB in eastern Yuba County, California, in the northeastern portion of the Sacramento Valley (UTM 635139 E, 4333045 N, Zone 10) consists of 9,308 ha of rolling hills at the base of the Sierra Nevada mountain range. The natural resources on these lands are managed by the U.S. Department of Defense in cooperation with the U.S. Department of Agriculture, Wildlife Services (WS) and the U.S. Fish and Wildlife Service. The area is primarily composed of grasslands interspersed with small areas of riparian vegetation, oak (*Quercus* spp.) woodlands, and seasonal and permanent wetlands. Grazing (approximately 1,500 cows) is carried out in the grasslands on approximately 4,450 ha (48% of the total land area) during the wet months of the year (i.e., November to May). Non-native grasses (e.g., *Taeniatherum caput-medusae*) and forbs (e.g., *Centaurea solstitialis*) dominate portions of the study site. The elevation ranges from 26 to 213 m, with higher areas near the eastern boundary. The average annual temperature is 17°C (average minimum = 10, average maximum = 24). The average annual precipitation is 56 cm, with most falling during November through March. The climate is characterized by cool, wet winters and hot, dry summers.

Beale AFB is an active airfield where the Ninth Reconnaissance Wing operates the nation's U-2 reconnaissance aircraft. Multiple landscape features within or adjacent to the base likely contribute to bird flight activity. For example, Beale AFB abuts the western boundary of Spenceville Wildlife Management Recreation Area (WMRA), which is a 4,850-ha area managed by California Department of Fish and Game. The base also consists of a riparian preserve (298 ha), open water sites (84 ha), and vernal pool conservation areas (405 ha; U.S. Army Corps of Engineers 1999), which attract numerous species of waterfowl for roosting, feeding, and loafing activities (Cain et al. 2004). Adjacent south and west of Beale AFB are expansive agricultural areas, primarily rice fields where waterfowl and other waterbirds are common throughout the year, especially during fall and winter (Elphick 2000, Miller et al. 2010) when food is abundant. A municipal and commercial solid waste landfill (103 ha) is located within 500 m of the southeastern boundary of Beale AFB. This landfill affects a variety of scavenging bird species.

Methods

Avian radar system

An avian radar system (Merlin™) was deployed in the approximated center of the airfield at Beale AFB California, USA, during 2008 and 2009 (Figure 1a) by personnel from DeTect Inc. (Panama City, Fla.). The system was fully self-contained and mounted on a trailer, developed specifically for the U.S. Air Force and NASA to continually detect and track birds within their airfields. The system used high-resolution industrial surveillance radar that emitted dual marine radar sensors: horizontal and vertical scanning beams. The horizontal wide array antenna transmits a 30-kW power, S-band (10-cm wavelength) radar beam covering a circular area with a radius of 2.0 Nm centered on the system. This beam was wedge-shaped (25°) and scanned the x-y plane. The vertical wide array antenna transmits a 25-kW, X-band (3-cm wavelength) radar beam with a transmission radius of 0.75 Nm. We used data from only the horizontal radar (S-band) for this study. The rationale for excluding data from the vertical radar was to reduce false positives that were often a result of increased signal attenuation associated with X-band wavelength. For example, precipitation increased occurrence of false positives in the X-band but not the S-band radar beams. Additionally, the larger wavelength of the S-band allowed us to achieve a greater detection range. The horizontal radar scanned at a rate of ~2.5 second (rotations) and offered the greatest spatial resolution with the lowest sidelobe returns.

The processing software developed by Merlin™ differentiated birds from ground characteristics and other flying objects. Parameters were specified for minimum and maximum reflectivity (measure of target

Figure 1. (**a**) Aerial photograph of Beale Air Force Base. Images from the avian radar system depicted (**b**) relatively low activity at late dark and (**c**) high activity at early light. Dots represent individual bird identification.

intensity), target size (based on pixel area), and target speed to correspond with bird detection and minimize false-positives. Other parameters that were less important were also specified. Raw radar analysis and ground truthing were carried out to identify signals of contamination. Specific areas that contribute to false positive objects or noise (e.g., roads with vehicle use) were masked from detection throughout the duration of the study. Those areas were identified before data collection for this study and were not changed throughout the study period. Insect contamination was removed based on size (i.e., area of 8 pixels), whereas very small bird species (approximately 7-cm in length) could still be detected. Moving aircraft were removed based on criteria of ground and flight speeds. Automated clutter (e.g., ground clutter from foliage) suppression was implemented to identify noise but still allowed detection of objects that met the size, speed, and reflectivity criteria. Additionally, a process known as constant false alarm rate (CFAR) was used to simplify clutter and make the reflectivity consistent with range, allowing targets to be detected while considering variation in ground cover.

Following the filtering process, flying objects that met the definitions were recorded. A unique track identification number (ID) was created for an object that had 4 subsequent detections. Each subsequent detection for that object was assigned a track ID and was calculated using a least squares regression technique. Specifically, the software identified detections that fit a linear track sequence through time by using specified parameters (e.g., size) and then assigned a unique ID. However, objects with fewer than 4 detections were not considered flying birds and were not assigned IDs. Thus, individual birds with multiple detections during flight were processed and recorded as separate track IDs. The radar system simultaneously tracked every bird (track ID) through time and stored the data in an onsite database. Although insect and other forms of contamination were considerably reduced through operational settings (specified parameters) and the use of S-band radar, additional post-processing steps were employed. For example, single track IDs consisting of only 4 sequential detections were eliminated from the database because those often represented additional ground clutter, insects, or other forms of interference instead of flying birds, which accounted for approximately 10% of the track IDs (Michael Bierman, DeTect Inc., personal communication).

This study consisted of 4 important assumptions regarding detection of birds. First, although contamination by false positives was unknown within the quality-filtered database, the rate was negligible based on extensive false positive removal from operational and post-processing steps. The second assumption was that any existing false positive errors were spatially and temporally random. Although probability of detection slightly decreased with increased distance from the radar system, the third assumption was that the probability of detection at a given distance was constant through time. The last assumption was that meteorological factors did not affect probability of detection using horizontal (S-band) radar. With these assumptions, avian radar can provide a useful index of avian activity. Personnel from DeTect Inc. carried out the avian radar system set-up, ground operations, database development and maintenance, and post-processing of database queries.

Avian activity index

We developed an avian activity index (AAI) using track IDs detected from the radar system in multiple steps. First, the 24-hour day was divided into hourly intervals starting at midnight (00:00 hours) on January 17, 2008, and continuing until 1500 hours on November 30, 2009. Avian activity indices were then calculated for each interval by summing the number of bird track IDs detected and tracked hourly by the radar. An interval length of 1.0 hour was chosen as a sampling unit to coincide with hourly meteorological data that was used in the modeling approach. It was possible for an individual bird to represent multiple track IDs. For example, a bird that intersected the radar beam during flight, landed, and then intersected the radar beam in a second flight within the 1-hour interval was assigned 2 track IDs. For this reason, AAI was developed to represent avian activity each interval as a function of both movement and abundance.

The overall objective was to estimate AAI as a relative value to examine variation in avian flight activity. The objective was not to estimate an absolute value for population abundance or density because allowing multiple tracks per individual per interval would likely bias those values. Additionally, because false positive errors were assumed to be random, AAI was the more appropriate measurement to understand relative differences between the influences of explanatory factors. Thus, potential biases associated with false positives are negligible under the condition that false positives are minimal and random. Missing data (<10%) which were usually caused by failure of the radar system, were not indexed and were excluded from the analyses. We conducted 2 separate analyses using AAI. We first investigated the relationship between activity and bird strikes, and then evaluated avian AAI models based on time effects and environmental variables.

Analysis 1: linking avian activity to bird strikes

We obtained records of bird strikes (n = 26) from Beale AFB from January 17, 2008, to November 30, 2009, from the U.S. Air Force Bird-Wildlife Aircraft Strike Hazard (BASH) database. These bird strikes were within the full range of horizontal radar. We included all species of birds in the analysis. We determined the hourly interval that each bird strike occurred and then collected the corresponding AAI for those intervals. Mean and variance of AAI for times when bird strikes occurred were computed.

We employed a generalized linear model (GLM) and a permutation resampling technique (Good 2000) to estimate the effects of AAI on bird strikes. Specifically, we first developed a GLM with a binomial distribution and specified the predictor variable as AAI value and the response (binary variable) as bird-strike interval (scored as 1) or all other intervals (scored as 0). We report the estimated model coefficients and interpreted those values as odds ratios. Second, we conducted 10,000 permutations of the GLM by randomly selecting 26 samples without replacement from the full dataset. In other words, these were not intervals of known bird strikes but were chosen at random. For each GLM permutation, the response variable consisted of 26 samples (scored as 1) and the remainder of the data set (scored as 0). Last, we report the percentile along the distribution of permutations where the coefficient of the analysis with bird-strike interval occurred. Because we are evaluating the hypothesis that AAI is higher during times of bird strikes than on average, we interpreted the results using a 1-tailed (directional hypothesis) evaluation. A similar approach was used to compare the mean and variance of AAI during bird-strike intervals to AAI mean and variance during intervals without known bird strikes. In this analysis, we first calculated the mean and standard deviation during bird-strike intervals. We then conducted 10,000 resamples of 26 AAI values from the full data set and calculated the means and standard deviations for each simulation. We report the percentile of the mean and variance of the sampled bird-strike data set within the approximated resampled distributions.

Analysis 2: modeling avian activity

Explanatory variables. We chose to examine variation in AAI based on *a priori* hypotheses regarding time-dependent effects and meteorological factors. We examined 2 sources of variation by seasonal effects on avian activity. The first seasonal effect was based on migration (MGR). We divided the year into 4 periods based on general migration patterns of multiple species that inhabited Beale AFB and the surrounding area within the Central Valley of California. We developed indicator variables for the 4 seasons, which consisted of fall migration (September 15 through November 15), winter (November 16 through February 20), spring (February 21 through May 20), and summer (May 21 through September 14). As an alternative *a priori* hypothesis that more effectively represented seasonal changes (e.g., daylight length, vegetation, and climate), we examined variation based on the calendar seasons (CSN). This variable consisted of fall (September 21 to November 20), winter (December 21 to March 20), spring (March 21 to June 20), and summer (June 21 to September 20).

We examined evidence for variation in AAI due to different daily light levels by classifying light levels in 2 ways. First, we separated the 24-hour day into 6 light periods (6LP) by grouping the minutes of the day into categories, comprised of 3 subintervals (i.e., early light [EL], mid-light [ML], and late light [LL]), and for dark (early dark [ED], mid-dark [MD], and late dark [LD]). The intervals were calculated by dividing the total minutes of daylight (sunrise to sunset) into the 3 groups and those of dark (sunset to sunrise) into the 3 groups during the 24-hour day using sunrise and sunset data (U.S. Navy Observatory, Astronomical Department, Washington, D.C.). We grouped each day separately because of differing lengths of daylight through the year. We used only 1 randomly assigned hourly sampling interval for each group per day for our analyses to prevent temporal autocorrelation and to meet the assumption of independence. If a sampling interval consisted of minutes from 2 categories, then we assigned the category with the greatest number of minutes. We also evaluated a less complex light pattern effect by specifying an indicator variable for 2 light periods (2LP) by reassigning 1 category as intervals between sunrise and sunset (light) and the other between sunset and sunrise (dark). The same randomly chosen intervals were used for this categorization.

We acquired meteorological data from the weather station at Beale AFB (U.S. National Climate Data Center, Asheville, N.C.). These data consisted of wind speed (mph), visibility (statute miles), relative humidity (%), ambient temperature (°C), precipitation (binary variable, 0 = no precipitation, 1 = precipitation), and cloud cover. Cloud cover consisted of 5 cover classes: clear (no clouds), few (1 to 25% cloud cover), scattered (26 to 50%), broken (51 to 75%), and overcast (76 to 100%). Variables were selected for this analysis based on *a priori* hypotheses of meteorological factors that have been thought to influence bird activity reported in the literature (Meinertzhagen 1955, Baldassare and Bolen 1984, Cain et al. 2004). We assigned each hourly time interval with the averaged value for each meteorological variable based on hourly data. To prevent multicollinearity in predictive models, we conducted correlation tests to exclude variables that co-varied ($r \geq |0.65|$).

Model development. We took a 2-step approach to identify the most parsimonious inference models of AAI. In step 1, we determined whether or not a unique model would be developed for each season by comparing multiple models with different seasonal and light pattern effects. We used linear mixed effects models so that random effects could be specified, which accounted for variation that may otherwise confound the fixed effects (Faraway 2006, Gillies et al. 2006, Zuur et al. 2009). All models consisted of the logarithmic function of AAI as a response variable and a random intercept for year (i.e., random effect), but they differed by the structure of the fixed effects. The model notation took the form of:

$$y = \mathbf{X}\beta + \gamma_i + \varepsilon$$

where y is the vector of avian activity, $\mathbf{X}$ is a matrix containing the fixed effects regressors, β is a vector of fixed effects parameters, γ_i represents normally distributed random effects for year i = 1 and 2, and ε is a vector of normally distributed errors. The first candidate set of models consisted of 6 models with different light and seasonal fixed effects (variables are listed in Table 1). We randomly sampled 1 interval within each light period per day, obtaining 6 samples each day. Three models consisted of additive fixed effects (e.g., 6LP + MGR) and 3 models consisted of interactions (e.g., 6LP × MGR). The additive models represented the hypotheses that daily light periods and seasons explain variation in AAI, but the effect of light pattern is independent of season. The differences among the additive models were based on the 3 possible combinations of light periods (2LP and 6LP) and seasonal effects (MGR and CSN). The interaction models represented the hypothesis that the influence of light level periods was dependent on seasonal effects. The difference among the 3 interaction models was based on combinations of each type of light and season variables.

We evaluated evidence of support for the 6 models using differences in the information criterion (ΔAIC; Akaike 1971) with second-order bias correction (denoted as c; Anderson 2008). We calculated model probabilities (w; Anderson 2008) and compared the most parsimonious model (model i) to other models (model j) in the model set using evidence ratios (ER = $w_{\text{model } i}/w_{\text{model } j}$). At this stage of the model process, we specified maximum likelihood estimation to make unbiased comparisons among models (Zuur et al. 2009). During step 1, we included all the meteorological variables in the 6 models

Table 1. Explanatory variables for mixed effects models of avian activity indices using data collected from an avian radar system at Beale Air Force Base in the Central Valley of California during 2008 and 2009.

Effects	Abbreviation	Explanatory variable	Type	Treatment
Weather	PRC	Precipitation (yes or no)	ordinal	fixed
	SKY	Sky condition (5 categories: clear [no cover], few [<25%], scattered broken [50–75%], overcast [100%])	nominal	fixed
	WND	Wind speed (mph)	continuous	fixed
	VSB	Visibility (statute miles)	continuous	fixed
	TMP	Ambient temperature (℃)	continuous	fixed
Time	YR	Year	ordinal	random
	MGR	Season based on timing of general migration of most species within the area	ordinal	fixed
	CSN	Season based on calendar dates	ordinal	fixed
	2LP	2-category light periods (light [sunrise to sunset], dark [sunset to sunrise])	ordinal	fixed
	6LP	6-category light periods (EL = early light, ML = mid-light, LL = late light, ED = early dark, MD = mid-dark, LD = late dark)	ordinal	fixed

to prevent confounding effects. The rationale for this full inclusion was to prevent bias in the evidence for time-dependent effects by allowing variation to be explained by other variables of interest (Zuur et al. 2009). If we found support for an interaction between season and light pattern, then, in step 2, we modeled meteorological and light variables within each season. This 2-step approach was necessary for multiple reasons. First, it allowed us to evaluate the hypothesis that the magnitude of a light period effect differs by season. Second, it allowed us to investigate evidence for different seasons and light periods before exploring meteorological factors. Lastly, and perhaps most importantly, this 2-step process was thought to facilitate a relatively simple interpretation of the parameter

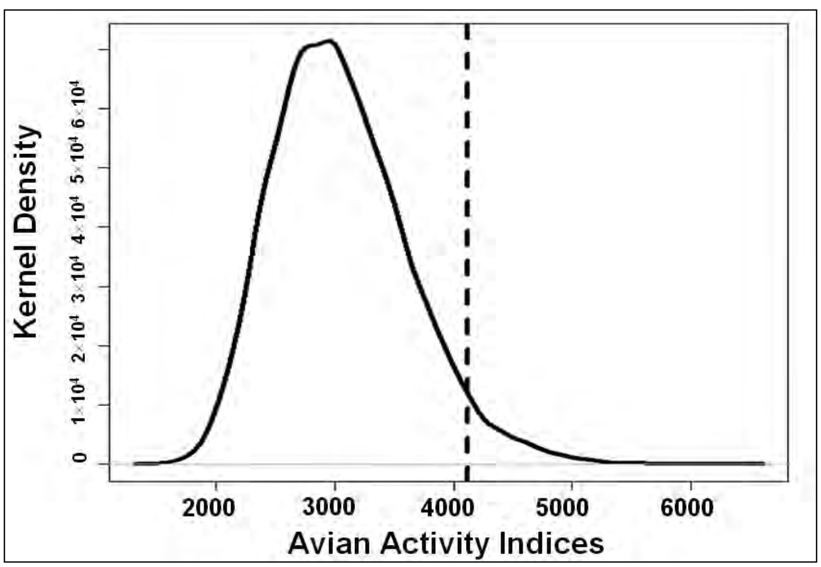

Figure 2. Distribution of avian activity indices computed using 10,000 resampled means (solid line) and mean avian activity index during bird strikes (dashed line)—from data collected using avian radar system at Beale Air Force Base in the Central Valley of California during 2008 and 2009.

estimates (i.e., coefficients) for flight planning authorities and wildlife managers. The light level period effect (2LP versus 6LP) that was found to have the most support was included in all models during the second step.

In step 2, we identified the most parsimonious model using an exploratory approach for each season that included meteorological and light level period effects. First, we included all the explanatory variables into 1 model for each season. We then removed variables that lacked support from each seasonal model until the most parsimonious models were identified using a modified information-theoretic-based technique described in Zuur et al. (2009). Within this procedure a series of steps were carried out. We started with a full model and dropped 1 term at a time to develop alternative models. Those models were compared to the full model using likelihood ratio tests (approximated by χ^2 distribution) and ΔAIC*c*. The alternative model with the lowest AIC*c* was retained and the process repeated. A single term was eliminated through each sequence until the AIC*c* could not be improved and the most parsimonious model was identified. The purpose of this approach was to account for the tradeoff between bias and variance in identifying the least complex but most explanatory model. Maximum likelihood estimation was specified for model comparison (Zuur et al. 2009). Although identifying the most parsimonious model in step 2 was exploratory, we based the terms in these models on factors that were thought to influence avian activity (*a priori* hypotheses).

Once the most parsimonious model was identified, we refit the models using restricted maximum likelihood to avoid biases in parameter estimation (Zuur et al. 2009). To account for similar evidence among models, we averaged the parameter estimates across models using model probabilities (Anderson 2008). We assessed model fit for the final seasonal models using 3 analyses. First, we conducted likelihood ratio tests (specified χ^2 distribution) between the most parsimonious model and a null model (random effect only) to compare model fits (Zuur et al. 2009). Second, we calculated likelihood R^2 values (Magee 1990, Kramer 2005) for the most parsimonious model to indicate the amount of explained variation by the time-dependent and meteorological effects. Lastly, we carried out a v-fold cross-validation technique (Burnham 1989) to estimate the prediction error. Specifically, we first grouped the data into 10 random subsets, and then fit the model after removing each subset in turn (50 simulations), and measured the difference between observed and expected values for the excluded subset. We reported the mean prediction error and standard deviation of the simulations. We also reported number of model parameters, log-likelihood, AIC*c* values, and model probabilities for each of the most parsimonious seasonal models. The estimated constant (β_0) and regression coefficients ($\beta_{1 \ldots p}$) associated with the best-approximating model were reported. All variables in models within 2 AIC*c* units from the most parsimonious model were considered to have support by the data (Arnold 2010). We reported values as means ± SE. All statistical analyses were conducted using Program R (model parameter estimation, "lme4" package, Bates et al. 2008; cross-validation, "boot" package, Canty and Ripley 2011; R Development Core Team 2008).

Results

Analysis 1: linking avian activity to bird strikes

We found evidence that AAI influenced the odds of a bird strike. Using the model parameter estimate, a 1,000-unit increase in AAI increased the odds of a bird strike by 8.3% (coefficient 0.08 ± 0.04). Therefore, the odds of a bird strike was 18.7% higher at a value that represented the third quartile (AAI = 3,642) than the value that represented the first quartile (AAI = 1,385) of the full data set. Using the permutation resampling technique, we found the coefficient intersected the distribution at the 95.3 percentile (Exact $P <$ 0.05), indicating that this model coefficient was significantly higher than those of the resampled permutations. The distribution of resampled coefficients was centered on zero, and 95.3% of the resampled coefficients fell below the mean value of AAI during a bird strike. The permutated distribution revealed a reasonably symmetrical shape, indicating a lack of evidence for bias in interpreting percentiles. During the intervals when bird strikes occurred, the AAI (4,112.9 ± 536.5) was substantially greater than the majority of resampled means from the full AAI dataset (Figure 2). The mean AAI during a

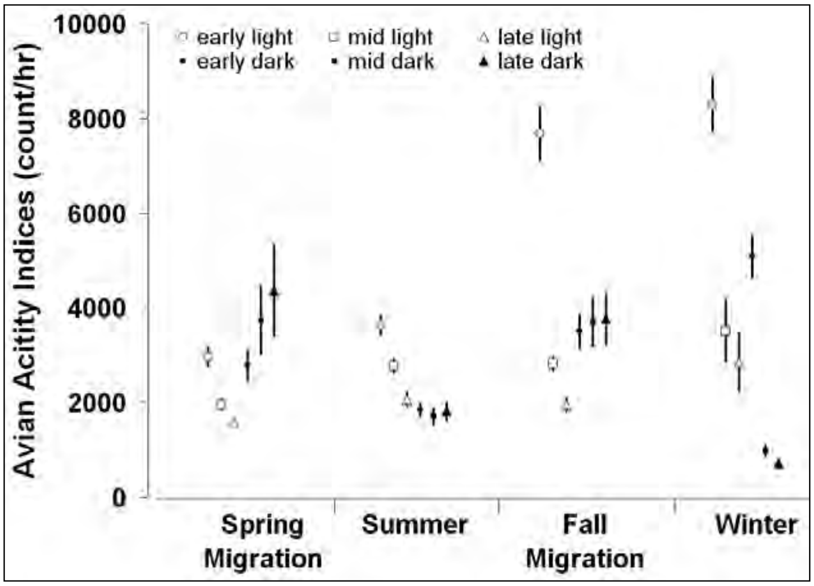

Figure 3. Interaction between 6-period light pattern and migration-based season at Beale Air Force Base in the Central Valley of California during 2008 and 2009. Vertical lines represent 95% confidence intervals.

bird strike was at the 95.4 percentile (Exact $P < 0.05$) of the overall sampling distribution. The AAI variance during bird-strike intervals was at the 56.2 percentile of the distribution of the resampled interval variances, which indicated no evidence of difference between AAI variance during a bird strike compared to the resampled variances.

Analysis 2: modeling avian activity

Model selection. In step 1, we found strong differences in evidence of support between the light period and season time-dependent models (Table 2). The most parsimonious model consisted of an interaction between 6LP and MGR ($w_{\text{model 1}} = 1.0$), meaning that the effect of light period varied among seasons (Figure 3). Most notably, avian activity indices during EL of the 2 seasons of fall migration (7,682.7 ± 289.5) and winter (8,297.0 ± 563.5) were substantially greater than indices during LD of the same seasons (fall, 3,776.6 ± 283.9; winter, 724.9 ± 43.5). However, avian activity indices during LD of the spring migration (4,363.4 ± 495.4) was greater than EL (2,974.0 ± 107.5) during spring. Thus, avian activity was greater before sunrise during spring migration but greater after sunrise during fall migration and winter. Also, we identified the most variation in activity by light periods within the winter months (see radar image in Figure 1b and c). Avian activity was highest during EL of fall migration and lowest during LD of winter. The least amount of variation among light periods occurred during summer season (Figure 3), which showed relatively low values of AAI.

Table 2. Evidence of model support for light pattern and time-dependent effects on avian activity indices from data collected using an avian radar system at Beale Air Force Base in Central Valley of California during 2008 and 2009. k = number of parameters, LL = log-likelihood, AIC*c* = Akaike's Information Criterion with second order bias correction, *w* = model probability.

No.	Model[a]	K	LL	ΔAIC*c*	*w*
1	6LP × MGR	36	-264.5	0	1.0
2	6LP × CSN	36	-331.7	134.5	0.0
3	2LP × MGR	25	-734.6	910.4	0.0
4	6LP + MGR	21	-742.6	926.3	0.0
5	6LP + CSN	21	-862.3	1163.8	0.0

[a] Meteorological explanatory variables were included in each model to prevent bias in evidence for light pattern and season effects. Number of samples was 3,659 (101.6 samples per parameter for most complex model). 6LP = 6-category light period, 2LP = 2-category light period, MGR = migration-based season, and CSN = calendar-based season.

Grouping seasons based on average migration dates was more informative than by calendar dates based on comparing model 2 (6LP × CLN) to model 1 (6LP × MRG; Table 2). Although model 2 had much greater support than the null model (without seasonal effects), we did not find evidence that this model had greater support than model 1 (Table 2, model 2, ΔAIC*c* = 134.5, $w_{\text{model 2}} = 0$). We also found that grouping light periods into 6 categories rather

Table 3. Variable reduction procedure for seasonal models of avian activity index at Beale Air Force Base in Central Valley, California, during 2008 and 2009. (k = number of parameters, n = sample size, AIC*c* = Akaike's Information Criterion with second order bias correction, LL = log-likelihood, *w* = model probability)

Season	Model	Iteration[a]	Covariate[b]	k	n	LL	ΔAIC*c*	*w*
Fall	1	1	-	17	798	-36.7	1.7	0.21
	2	2	HMD	16	798	-37.3	1.1	0.29
	3	3	VSB	15	798	-37.7	0.0	0.50
Winter	4	1	-	17	747	74.7	3.7	0.01
	5	2	WND	16	747	74.7	1.7	0.09
	6	3	TMP^2	15	747	74.5	0.2	0.40
	7	4	SKY	14	747	69.5	0.0	0.50
Spring [c]	8	1	-	17	878	-135.1	0.0	0.54
	9	2	VSB	16	878	-136.2	0.3	0.46
Summer	10	1	-	17	1236	151.4	8.2	0.01
	11	2	SKY	16	1236	150.3	2.4	0.17
	12	3	PRC	15	1236	149.7	1.6	0.25
	13	4	VSB	14	1236	149.5	0.0	0.57

[a] Iteration was conducted to remove variables that lacked evidence of support from the data. Iteration 1 consisted of the global model that included cloud cover, temperature (quadratic), precipitation, humidity, wind visibility, and a 6-period light pattern.
[b] Covariate removed from models based on likelihood ratio test between nested models (Zuur et al. 2009). No variables were removed in iteration 1. SKY = cloud cover, WND = wind speed (mph), VSB = visibility (statute miles), HMD = relative humidity (%), TMP = ambient temperature (°C).
[c] Although similar evidence was found for spring models 8 and 9, model 9 was chosen based on "pretending variable" effect (Anderson 2008).

than two explained more variation in AAI. This difference was evident in comparing model 3 (2LP × MRG) to model 1 (6LP × MRG). Model 3 had substantially less support from the data (Table 2; model 3, ΔAIC*c* = 910.4, $w_{\text{model 3}} = 0$).

In step 2, we developed avian activity models that consisted of 6LP and also included meteorological factors as additive effects. The rationale for modeling each season separately was to reduce model complexity to assist in interpreting the estimated parameters, based on the interaction effect identified in step 1. We found seasonal variation in the effects of multiple meteorological factors. During the fall migration, the most parsimonious model consisted of cloud cover, temperature (quadratic function), precipitation, wind, and light period as explanatory variables (Table 3, model 3). In assessing model fit, this model performed substantially better than a random-effect only model ($\chi^2 = 429.7$, df = 13, $P < 0.001$) and explained a reasonable amount of variation ($R^2_{LR} = 0.41$). We found that mean prediction error of 50 simulations was 0.0673 (SD = 0.0004) using cross-validation.

Avian activity during fall tended to be greatest at approximately 6 to 15°C (Figure 4a). After this temperature range, activity decreased with increasing temperatures. Increased wind speed (mph) and precipitation were associated with less AAI (Figure 4b and c). We found that avian activity was substantially greater during clear skies, and AAI decreased as cloud cover increased (Figure 4d). The global model (Table 3, model 1), which included humidity and visibility, had less support from the data (ΔAIC*c* = 1.7, $w_{\text{model 1}} = 0.21$) than the most parsimonious model ($w_{\text{model 3}} = 0.50$). Model 3 was 2.3 times ($w_{\text{model 3}}/w_{\text{model 1}}$) more likely to be better than the global model. Model 3 was also 1.7 times more likely to be better than a model consisting of the same additive effects as model 3 but with visibility (Table 3, $w_{\text{model 2}} = 0.29$).

A parsimonious model during the winter months consisted of temperature (linear effect), humidity, precipitation, visibility, and

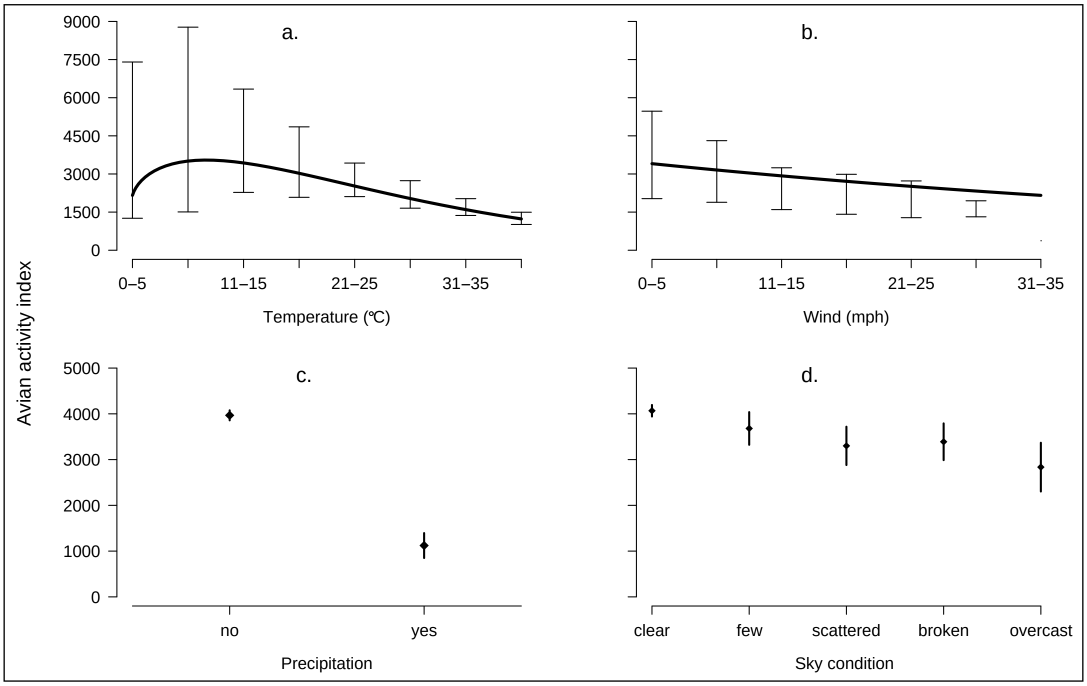

Figure 4. Effects of (**a**) temperature, (**b**) wind speed, (**c**) precipitation, and (**d**) sky condition on avian activity indices during the fall migration season at Beale Air Force Base in the Central Valley of California during 2008 and 2009. Vertical bars represent 25th to 75th percentiles for continuous variables (a and b) and standard error for categorical variables (c and d). Lines represent predicted values from the equation of the most parsimonious model. Lines may not appear to fit raw data because of back transformation from the logarithmic function, and all additive effects were included in the model. Continuous variables were held constant at the mean values and the most frequent group was used for categorical variables.

6LP (Table 3, model 7). This model performed substantially better than a null model (χ^2 = 1065.5, df = 9, P < 0.001) and explained the greatest amount of variation compared to other seasonal models (R^2_{LR} = 0.76). Using the cross-validation technique, the mean prediction error was 0.05 (SD = 0.0001) during this season. Increased avian activity was associated with lower temperatures and visibility (Figure 5a and c). Avian activity was greater during times with increased humidity (Figure 5b) and no precipitation (Figure 5d). The global model, which included temperature (quadratic function), wind speed, and cloud cover, had substantially less support from the data (Table 3, ΔAIC*c* = 3.7, $w_{\text{model 4}}$ = 0.01) than the most parsimonious model ($w_{\text{model 7}}$ = 0.50). Model 7 was 6.4 times ($w_{\text{model 7}}/w_{\text{model 4}}$) better than the global model. A model that also included sky cover had less support from the data (ΔAICc = 0.2, $w_{\text{model 6}}$ = 0.40). Increased cloud cover was associated with less avian activity.

We found that a parsimonious model during the spring migration consisted of all variables except visibility (Table 3, model 9), which were cloud cover, temperature (quadratic function), humidity, wind, precipitation, and 6LP. Removal of any 1 of the 6 explanatory variables resulted in a higher AIC*c* value. The spring model fit those data substantially better than a null model (χ^2 = 243.5, df = 14, P < 0.001) and explained a relatively high amount of variation compared to other seasonal models (R^2_{LR} = 0.51). By cross-validation, mean prediction error was 0.0828 (SD = 0.0004) during spring. A global model had nearly equal support from the data (Table 3, $w_{\text{model 8}}$ = 0.54). During the spring, a strong quadratic relationship revealed less activity during low and high temperatures (Figure 6a). Avian activity appeared to be greatest at 16 to 25°C. Low activity was associated with increased wind and precipitation (Figure 6b and d) and decreased humidity (Figure 6c). Less activity was associated with cloud cover (Figure 6e).

The most parsimonious model during the summer season consisted of temperature (quadratic function), wind, humidity and 6LP

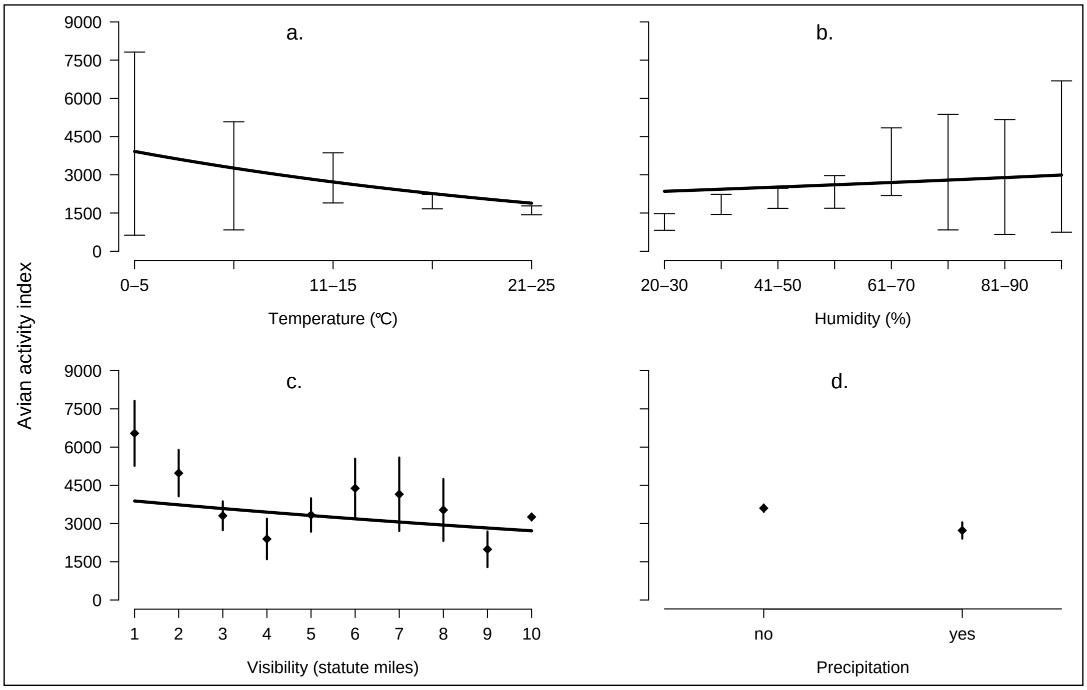

Figure 5. Effects of (**a**) temperature, (**b**) humidity, (**c**) visibility and (**d**) precipitation on avian activity indices during the winter season at Beale Air Force Base in the Central Valley of California during 2008 and 2009. Vertical bars represent 25th to 75th percentiles for continuous variables (a and b) and standard error for categorical variables (c and d). Lines represent predicted values from the equation of the most parsimonious model. Lines may not appear to fit raw data because of back transformation from the logarithmic function and all additive effects were included in the model. Continuous variables were held constant at the mean values and the most frequent group was used for categorical variables.

(Table 3, model 13). This model was supported by the data substantially better than a null model ($\chi^2 = 522.0$, df = 9, $P < 0.001$). Although explained variation by this model was lower than other seasonal models, the model represented a reasonable amount of variation (R^2_{LR} = 0.34). Mean prediction error for the summer model was 0.050 (SD = 0.0001). In interpreting parameter estimates, we found evidence for a quadratic effect, where the temperature range with the greatest avian activity was approximately 16 to 25°C (Figure 7a), and less activity was found at temperatures lower and higher than this range. Also, increased wind speed was associated with less activity (Figure 7b). The global model did not have support from the data (Table 3, ΔAICc = 8.2, $w_{\text{model 10}}$ = 0.01) compared to the most parsimonious model ($w_{\text{model 13}}$ = 0.57). However, a model with all of the same additive effects as the most parsimonious model that included visibility showed support from the data (model 12, ΔAICc = 1.6, $w_{\text{model 12}}$ = 0.25) but less than model 13 (Table 3).

Model implementation. To facilitate interpretation, we provided 2 ways to apply the results of these analyses: (1) a general interpretation of light pattern and season effects without including meteorological data and (2) a more specific model implementation using forecasted weather information. The reason for the former was a matter of convenience on the part of the safety officer or resource manager, mostly because of time limitations and unavailability of forecasted weather, while the reason for the latter was to predict avian activity with a relatively greater degree of accuracy and precision. For the former application, we classified the light periods into 3 categories related to a relative risk of bird strike (i.e., low, medium, and high) during aircraft flights. Light periods scored as high risk met 2 criteria: (1) the 95% CI of the mean did not include the mean during bird strike and (2) the mean activity during light period was greater than the mean activity during bird strike. Those light periods scored as medium risk met 1 criterion: 95% CI of mean activity during light period included the mean activity during bird strike. Light

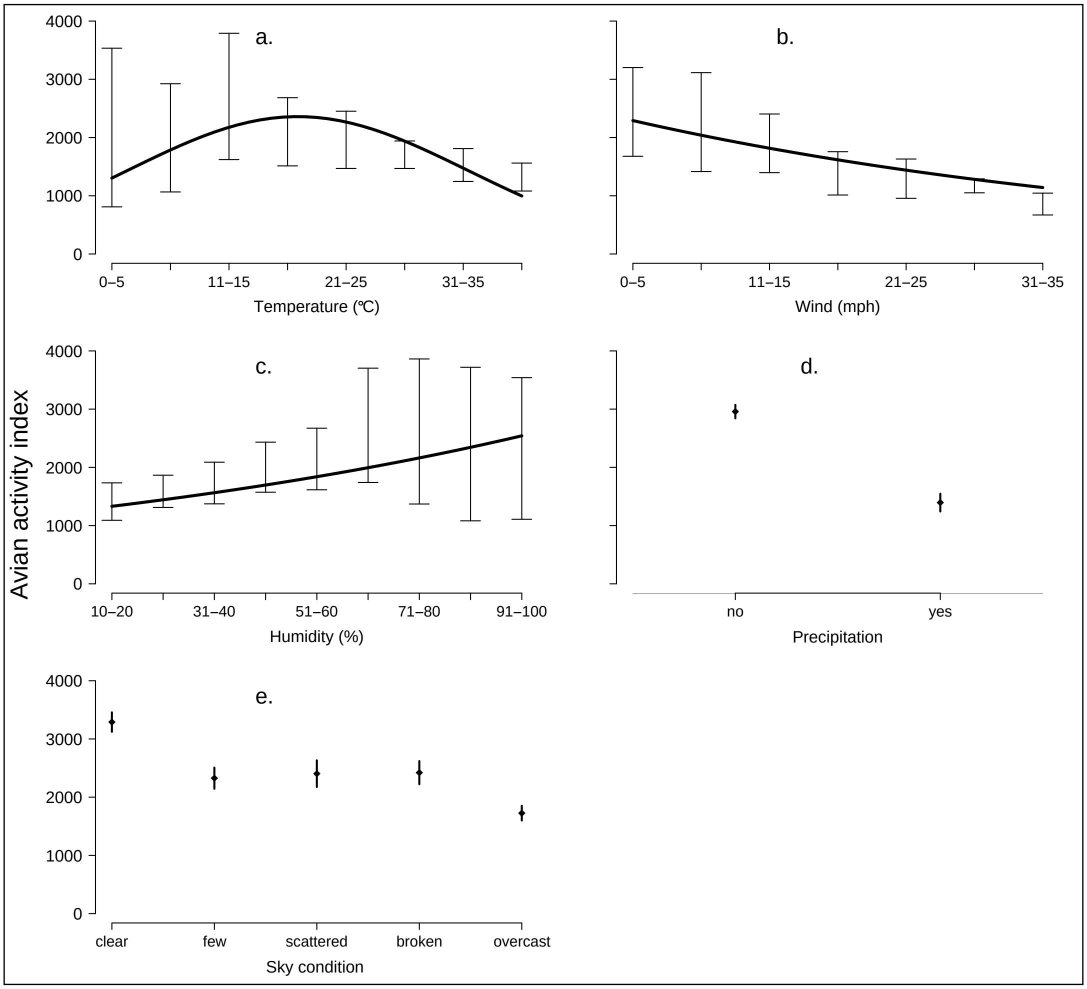

Figure 6. Effects of (**a**) temperature, (**b**) wind speed, (**c**) humidity, (**d**) precipitation, and (**e**) sky condition on avian activity indices during the spring migration season at Beale Air Force Base in the Central Valley of California during 2008 and 2009. Vertical bars represent 25^{th} to 75^{th} percentiles for continuous variables (**a, b,** and **c**) and standard error for categorical variables (**d** and **e**). Lines represent predicted values from the equation of the most parsimonious model. Lines may not appear to fit raw data because of back transformation from the logarithmic function and all additive effects were included in the model. Continuous variables were held constant at the mean values and the most frequent group was used for categorical variables.

periods scored as low risk met 2 criteria: (1) the 95% CI of the mean did not include the mean during bird strikes and (2) the mean activity during light period was less than the mean activity during bird strikes. The high-risk group consisted of EL during the fall migration and EL and ED (5,082.7 ± 440.4) during the winter. The medium risk group consisted of MD and LD during spring (3,744.6 ± 723 and 4,363.4 ± 971.0, respectively) and fall migration (3,706.1 ± 520.5 and 3,776.6 ± 556.5, respectively) and ML during winter (3,514.3 ± 665.1). All other light periods were classified as low risk.

The latter application was more specific and preferred and entailed using the derived inference models to predict avian activity based on season, light pattern, and meteorological characteristics. This was a superior approach because it accounted for additive effects among light patterns and meteorological variables. Inference using this technique was a 2-step process. Forecasted model-averaged values of light pattern and weather were inputted for any given interval of interest into the model equations (Figure 8). The resulting AAI value then was related to the mean and 95% CIs of the sample distribution of activity during intervals when bird strikes occurred. An interval was scored relatively high risk if the predicted AAI value was greater than or equal to the mean AAI

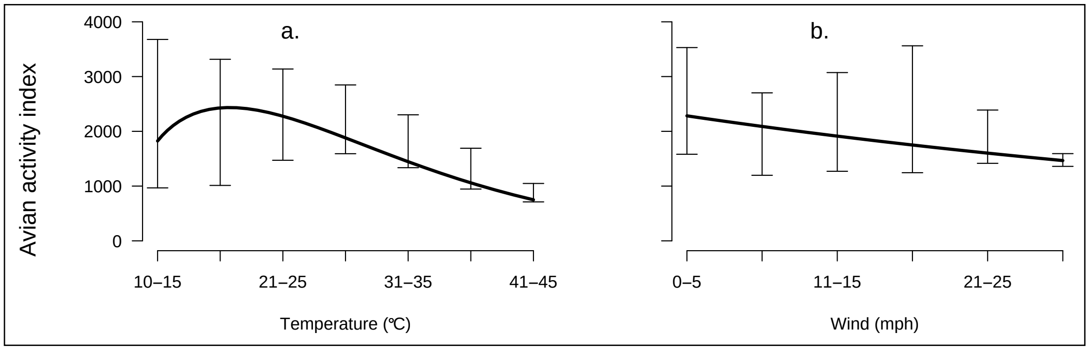

Figure 7. Effects of (**a**) temperature and (**b**) wind speed on avian activity indices during the summer season at Beale Air Force Base in the Central Valley of California during 2008 and 2009. Vertical bars represent 25th to 75th percentiles. Lines represent predicted values from the equation of the most parsimonious model. Lines may not appear to fit raw data because of back transformation from the logarithmic function and all additive effects were included in the model. Continuous variables were held constant at the mean values and the most frequent group was used for categorical variables.

A. Fall

$$Log(Y) = 3.518 + \begin{bmatrix} 0.155, \text{if } SKY \text{ is clear} \\ 0.085, \text{if } SKY < 25\% \\ 0.012, \text{if } SKY\ 25-50\% \\ 0.000, \text{if } SKY\ 50-75\% \\ -0.091, \text{if } SKY\ 75-100\% \end{bmatrix} + (0.034 \times TMP) - (0.001 \times TMP^2) - \begin{bmatrix} 0.531, \text{if } PRC \\ 0.000, \text{if no } PRC \end{bmatrix} - (0.007 \times WND) - \begin{bmatrix} 0.000, \text{if } EL \\ 0.363, \text{if } ML \\ 0.478, \text{if } LL \\ 0.365, \text{if } ED \\ 0.415, \text{if } MD \\ 0.438, \text{if } LD \end{bmatrix}$$

B. Winter

$$Log(Y) = 3.784 - (0.012 \times TMP) + (0.002 \times HMD) - \begin{bmatrix} 0.085, \text{if } PRC \\ 0.000, \text{if no } PRC \end{bmatrix} - (0.015 \times VSB) - \begin{bmatrix} 0.000, \text{if } EL \\ 0.306, \text{if } ML \\ 0.357, \text{if } LL \\ 0.138, \text{if } ED \\ 0.939, \text{if } MD \\ 1.092, \text{if } LD \end{bmatrix}$$

C. Spring

$$Log(Y) = 2.684 + \begin{bmatrix} 0.049, \text{if } SKY \text{ is clear} \\ 0.018, \text{if } SKY < 25\% \\ -0.002, \text{if } SKY\ 25-50\% \\ 0.000, \text{if } SKY\ 50-75\% \\ -0.161, \text{if } SKY\ 75-100\% \end{bmatrix} + (0.067 \times TMP) - (0.001 \times TMP^2) - \begin{bmatrix} 0.225, \text{if } PRC \\ 0.000, \text{if no } PRC \end{bmatrix} + (0.003 \times HMD) - (0.010 \times WND) - \begin{bmatrix} 0.000, \text{if } EL \\ 0.242, \text{if } ML \\ 0.318, \text{if } LL \\ 0.177, \text{if } ED \\ 0.094, \text{if } MD \\ 0.101, \text{if } LD \end{bmatrix}$$

D. Summer

$$Log(Y) = 3.495 + (0.033 \times TMP) - (0.001 \times TMP^2) - (0.003 \times HMD) - (0.007 \times WND) - \begin{bmatrix} 0.000, \text{if } EL \\ 0.009, \text{if } ML \\ 0.031, \text{if } LL \\ 0.236, \text{if } ED \\ 0.363, \text{if } MD \\ 1.357, \text{if } LD \end{bmatrix}$$

Figure 8. Averaged model parameters of bird activity by season based on daily light patterns and meteorological factors at Beale Air Force Base in the Central Valley of California during 2008 and 2009. To facilitate interpretation, random intercept for year was not included. SKY = cloud cover, WND = wind speed (mph), VSB = visibility (statute miles), HMD = relative humidity (%), TMP = ambient temperature (°C), EL = early light, ML = mid light, LL = late light, ED = early dark, MD = mid dark, LD = late dark.

during intervals with bird strikes (i.e., ≥4,112.9). An interval was scored as medium risk if the AAI value was between the mean and the lower limit of the 95% CI of AAI at intervals with bird strikes (i.e., >3,061.5 and <4,112.9). Lastly, an interval was scored as relatively low risk intervals if the predicted AAI value was below the lower limit of the 95% CI. For example, consider that cloud cover was approximately 15%, temperature is 28°C, no precipitation, humidity was 22%, wind speed was 5 mph, the period was late dark (before sunrise) during the spring migration. According to the spring equation (Figure 8, Equation C), the logarithmic function of avian activity was computed as: 2.684 + 0.018 (<25% cloud) + 0.067 × 28 (temperature) − 0.001 × 28^2 (quadratic function for temperature) + 0 (no precipitation) + 0.003 × 22 (humidity) − 0.010 × 5 (wind speed) − 0.101 (late dark period) = 3.709. By calculating $10^{3.709}$, the value was back transformed to a predicted AAI of 5,117. Because this value was greater than the mean AAI during a bird strike, aircraft flight during this time interval *ws* relatively high risk.

Discussion

We used a portable avian radar system to investigate links in avian activity, bird strikes, and time-dependent and meteorological factors. This study provided useful statistical inference models with environmental covariates using an hourly sample unit that explained substantial variation in avian activity. The relatively fine-scale of inference throughout a 24-hour day could not have been achieved with conventional field survey methods. For example, surveys conducted in the field often are limited by sample size, sampling duration, sampling area, inter- and intra-observer errors, and detection probabilities that vary through time (Celis-Murillo et al. 2009). Further, aircraft often fly during hours of darkness when inferences derived from data generated by radar technology are essential.

Modeling an avian activity index at the local scale as demonstrated here is an effective approach to mitigate the risk of bird strikes. Avian activity index is more informative than estimating abundance or density because activity naturally accounts for variation in the amount of movement by individuals. To develop an avian activity index, data must be collected directly at airfields using methods that result in continuous fine-scale measurements, such as the portable avian radar system. Understanding local scale activity is important because 74% of bird strikes occur at ≤150 m above ground level (Dolbeer 2006) and majority of strikes are near airports (Burger 1985). Further, 66% of low altitude strikes cause substantial damage (Dolbeer 2006). Airports are usually in rural or suburban settings and often adjacent to wetland environments that consists of open water areas, which have been shown to strongly influence abundance of waterfowl and other water birds (Bell et al. 1997, Hart et al. 2009).

We found that most activity occurred during the crepuscular periods of fall migration and the winter season, which coincides with feeding behavior of multiple species of ducks and geese. The Central Valley supports about 60% of the waterfowl within the Pacific Flyway during the winter (Miller 1985). Annually, 10 to 12 million waterfowl and hundreds of thousands of other water birds will fly into the valley (Gilmer et al. 1982). Variation in waterfowl activity recently has been reported as a significant bird-strike hazard at Beale AFB, and this variation appears to be related to their foraging strategies (Cain et al. 2004). For example, rice fields, especially those flooded after harvest to aid in decomposition of rice straw, provide a valuable winter food source for waterfowl during September through March. Many airfields were adjacent to rice fields in the Central Valley near Beale AFB, and waterfowl frequented rice fields (Cain et al. 2004). Agriculture has been shown elsewhere to attract birds and increase bird activity within airfields (Elphick and Oring 1998, Kuenzi and Morrison 1998, Sodhi 2002, Cain et al. 2004).

Northern pintails (*Anus acuta;* hereafter, pintails) probably are of particular importance in explaining variation in activity based on their abundance and daily foraging behavior. California regularly winters >50% of the pintail population in North America (Bellrose 1980), and these birds feed nocturnally and return to open water sites for loafing and roosting during morning hours (Miller 1985). Flights by pintails to feeding grounds during the winter months occur approximately 30 minutes after sunset (Miller 1985, Cox and Afton 1996), which was consistent with our finding that activity was relatively high in the early period of darkness in December. Many other waterfowl species, including Canada goose (*Branta Canadensis*; Raveling et al. 1972), greater white-fronted goose (*Anser albifrons*; Ely 1992), mallard (*A. platyrhynchos*; Meissner and Remisiewics 2008), and green-winged teal (*A. carolinensis*; Tamisier 1976) also are common in the Central Valley and frequently have been reported to conduct forage-related flights during morning and evening hours. These birds appear to reduce their activity during midday and night. Additionally, our findings using radar are consistent with another study that found waterfowl numbers were greatest during morning hours using visually-based point surveys at Beale AFB during winter (Cain et al. 2004). Other airfields located within landscapes dominated by agriculture or wetlands likely experience similar time-dependent patterns, as shown here, based on feeding patterns of Anatidae species.

We found that most meteorological factors explained variation in avian activity, and we identified differences between these effects among seasons. Perhaps one of the most important findings related to risk of bird strikes was the apparent negative relationship between visibility and avian activity in the winter season. The amount of time spent flying in a 24-hour period by waterfowl species in the Central Valley is thought to increase with less visibility, especially caused by fog, because birds likely have difficulty identifying food sources and loafing areas. Waterfowl are thought to gradually fly above the fog line until they locate clear areas to land, often aggregating into larger flocks. This may not always be the case with species other than waterfowl (Meinertzhagen 1955). For example, herring gulls (*Larus argentatus*) have been shown to fly below fog during periods of low visibility (Williams et al. 1974). Nevertheless, most waterfowl are large-bodied birds with powerful flight that often leads to ascent during fog conditions. With low visibility, pilots might be less likely to detect and avoid flocks of birds. Aircraft flight during low visibility, especially early morning hours of winter, is perhaps the riskiest time for aircraft to encounter birds.

The variation in temperature (i.e., quadratic and linear) among seasons may be partly explained by differences in responses by bird communities that occupy the Central Valley. Because waterfowl and other large-bodied waterbirds are generally most abundant during winter, patterns in time budgets by waterfowl species likely explain the linear relationship during this season. For example, cold temperatures have been shown to be associated with early morning feeding departures by mallards and other waterfowl (Jorde et al. 1983, Baldassare and Bolen 1984). The positive increase we observed at the lower temperature range during summer and fall and spring migrations may be partly explained by the behavior of birds other than waterfowl that are sensitive to daily variation in temperature. For example, shorebirds and passerines tend to be less active during relatively cold weather conditions than waterfowl, perhaps because of low prey availability (Shuford et al. 1998) and greater energy demands (Evans 1976).

Aviation safety officers and resource managers could use the avian activity inference models developed here to better understand risk associated with bird strikes. For example, these models could serve as a useful tool to schedule flights, in advance, based on information regarding the timing and weather forecast. However, differences in the usefulness of these models likely exist between military and civil airports. For example, military flights are largely based on training exercises, and scheduling is relatively flexible. Use of these models by civil aviation safety officers may be limited because flights are scheduled in advanced and generally fixed.

Manipulation of airport landscapes can be a useful means to discourage bird activity and reduce the risk of bird strikes (Linnell et al. 2009, Blackwell et al. 2009, Hart et al. 2009, Hoehn et al. 2009). Adjusting aircraft flight schedules using inference models could be used in conjunction with land planning actions or, in some cases, as an effective alternative to mitigate risk of bird strikes while maintaining biodiversity. For example, in some circumstances discouraging the protection and enhancement of general land cover types (e.g., permanent wetland) that serve as habitat for specific avian species and, thus, support population growth counteract the resource manager's stewardship mission aimed at enhancing wildlife populations and their habitats. Removal or modification of land cover is particularly detrimental to species where habitats at airports contribute to source populations (Brown et al. 2001). For example, a loss of those habitats for source populations may disrupt source-sink metapopulation dynamics and lead to population declines at larger spatial scales (Blackwell et al. 2009).

A recent review indicated that guidelines produced for land planning at airports are generally not supported by scientific studies and often do not consider bird collision hazards (Blackwell et al. 2009). The integrated natural resource management plan for Beale AFB (U.S. Army Corps of Engineers 1999) consists of actions directed at protecting wetlands and enhancing multiple areas that benefit wildlife species including annual grasslands with vernal pools, riparian deciduous woodland,

and marshes. Additionally, 12 bird species that occur at Beale AFB are considered special-status fish and wildlife species, and 7 habitat conservation areas are designed to increase biodiversity. Actions of conservation must coincide with those that reduce the risk of bird strikes to meet common goals by land stewards and aviation safety officers.

Successful airport management and planning that focuses on minimizing bird-strike hazards should incorporate multiple types of information regarding bird-strike hazards. These include (1) high-quality bird strike data, (2) differential use in land cover type by seasonal demographic cycle (Blackwell et al. 2009), (3) flight frequency of different types of aircraft, and (4) bird activity patterns (as a function of abundance and movement) as related to time-dependent and meteorological factors. Additionally, implementing buffer areas that are thought to allow avoidance of aircraft by birds at the landscape and patch scale likely contributes to conservation planning for non-hazardous species (Blackwell et al. 2009). Although implementing the inference models developed in this study are likely more cost effective than modifying and managing land cover, a combination of these techniques are perhaps the most effective.

Inferences based on these models are not without constraints. First, data used to estimate the model parameters were obtained in the Central Valley of California at Beale Air Force Base. Therefore, inferences could be made beyond these geographic areas, but those inferences have a greater potential to be misleading. Second, variation associated with year could not be incorporated into the final equations to keep the model interpretation relatively simple and applicable to predicting avian activity. We accounted for variation in year by fitting a random intercept to reduce potential bias on the parameter estimates. Although additional annual variation that was not accounted for here may present potential bias in the model parameter estimates, this effect is likely negligible. Third, weather forecast data used to calculate avian activity could be misleading because of variation in forecast confidence. For long-term planning, we suggest using hourly averages over multiple years from local weather stations and inputting these values into the model well in advance. Flight schedules subsequently should be adjusted based on more accurate short-term weather forecasts. Fourth, this study included all bird strikes in the analysis at Beale AFB regardless of variation in aircraft damage. For example, some periods of avian activity (e.g., migration of larger birds) may produce greater risk than that of other periods. Unfortunately, identifying these patterns was beyond the scope of this study because of limited sample size of bird strikes during the 2 years of avian radar deployment at Beale AFB. However, the use of avian radar at Beale AFB is an ongoing effort, and research that investigates these patterns would be beneficial.

The model parameters that we estimated should be viewed only as a baseline for ongoing studies. With additional data collected by avian radar systems, model parameter estimates for the effects identified in this study could be fine-tuned periodically. Additional factors that were not considered in our analysis contribute to unexplained variation in avian activity, and, thus, we encourage challenging the current model fit by incorporating additional environmental covariates based on *a priori* hypotheses. Further, more rigorous models that define relationships between avian activity and risk of bird strikes would be beneficial. The odds ratios reported here should be interpreted with caution because of a limitation in the number of known bird strikes during radar monitoring at Beale AFB. With robust sample sizes of known bird strikes, models that investigate additive and multiplicative effects between activity indices and other hypothesized explanatory variables, such as flight altitude and air traffic (number of aircraft in flight), would be very informative and could be interpreted in terms of odds ratios based on model coefficients. At this time, we suggest assessing risk with the method described in the model implementation section instead of odds ratios until sample sizes of known bird strikes during radar deployment are larger. Nevertheless, the relationships identified here between avian activity and bird strikes, coupled with the estimated model parameters of avian activity using time-dependent and meteorological variables, provide an important tool in mitigating the risk of bird strike at Beale AFB and other airfields that share similar characteristics.

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