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Using Echolocation Monitoring to Model Bat Occupancy and Inform Mitigations at Wind Energy Facilities

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ABSTRACT Fatalities of migratory bats, many of which use low frequency (<35 kHz; LowF) echolocation calls, have become a primary environmental concern associated with wind energy development. Accordingly, strategies to improve compatibility between wind energy development and conservation of bat populations are needed. We combined results of continuous echolocation and meteorological monitoring at multiple stations to model conditions that explained presence of LowF bats at a wind energy facility in southern California. We used a site occupancy approach to model nightly LowF bat presence while accounting for variation in detection probability among echolocation detectors and heights. However, we transposed the spatial and temporal axes of the conventional detection history matrix such that occupancy represented proportion of nights, rather than monitoring points, on which LowF bats were detected. Detectors at 22 m and 52 m above ground had greater detection probabilities for LowF bats than detectors at 2 m above ground. Occupancy of LowF bats was associated with lower nightly wind speeds and higher nightly temperatures, mirroring results from other wind energy facilities. Nevertheless, we found that building separate models for each season and considering solutions with multiple covariates resulted in better fitting models. We suggest that use of multiple environmental variables to predict bat presence could improve efficiency of turbine operational mitigations (e.g., changes to cut-in speeds) over those based solely on wind speed. Increased mitigation efficiencies could lead to greater use of mitigations at wind energy facilities with benefits to bat populations.

KEY WORDS bats, bat detector, California, curtailment, detection probability, Mojave desert, renewable energy, site occupancy, wind turbine.

Concerns over pollution and climate change have inspired efforts to transition from fossil fuels to renewable sources of energy to meet the needs of humans. Wildlife populations are generally expected to benefit from increased use of renewable energy (Tsoutsos et al. 2005). Nevertheless, renewable energy is not free of impacts to wildlife (Kunz et al. 2007*b*, Kuvlesky et al. 2007, Rebelo and Rainho 2009, Horváth et al. 2010). Among renewable energy technologies, impacts of wind energy on wildlife are perhaps best understood. Wind energy developments have caused large numbers of bird and bat fatalities in some situations (Arnett et al. 2008, Smallwood and Thelander 2008). Fatalities of birds, in particular raptors, have been documented since the late 1980s (Orloff and Flannery 1992) and remain a concern today (Smallwood and Thelander 2008). However, impacts to birds have been ameliorated somewhat through changes in turbine designs and improved strategies for siting turbines (Drewitt and Langston 2006, Barclay et al. 2007, Smallwood and Karas 2009). Documentation of large numbers of bat fatalities at wind energy facilities is a more recent development (Johnson 2005, Arnett et al. 2008) for which the ultimate causes remain unclear (Kunz et al. 2007*b*, Cryan and Barclay 2009). As a result, fatalities of bats are now considered 1 of the primary wildlife concerns from utility-scale wind energy developments (Barclay et al. 2007, Kuvlesky et al. 2007).

Bat fatalities are regularly found at modern wind energy facilities in North America when searches specifically target their detection. However, magnitude of impact can vary by factors of $\geq$10 among facilities (Johnson 2005, Arnett et al. 2008, Baerwald and Barclay 2009). Despite differences in magnitude of animals killed, most studies have important traits in common: fatalities are primarily to migratory species and the majority of fatalities occur during migration season (Arnett et al. 2008). As such, impacts to bats could be minimized were it possible to locate wind energy developments away from their migratory routes (Baerwald and Barclay 2009). However, patterns of bat migration are poorly understood and hypotheses regarding relationships between fatalities at wind energy facilities and migratory behavior are only now being proposed and tested (Cryan and Brown 2007, Kunz et al. 2007*b*, Baerwald and Barclay 2009, Cryan and Barclay 2009).

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Efforts to minimize conflicts between wildlife and wind energy development have focused on 2 areas: risk avoidance and impact mitigation. Risk avoidance involves conducting surveys prior to construction in order to avoid sites, or areas within sites, with high levels of usage by wildlife. Compiled at the landscape level these data could allow developers and regulators to compare relative level of risk among multiple sites; within a site, information could be used to avoid areas of highest risk to wildlife (Smallwood et al. 2009). The foundation of this approach is that low indices of activity prior to construction should translate to low fatality rates because fewer animals are available to be killed (Baerwald and Barclay 2009). Impact mitigation has focused on developing methods to reduce wildlife fatalities at operational wind facilities. Proposed mitigations often involve deterrent devices or changes in facility operations. Both strategies have been recommended to reduce bird fatalities at wind energy facilities (Drewitt and Langston 2006, Hüppop et al. 2006, Smallwood and Karas 2009). For bats, proposed mitigations include acoustic and electromagnetic deterrents (Kunz et al. 2007*b*, Nicholls and Racey 2009) as well as changes in turbine operations (Kunz et al. 2007*b*, Arnett et al. 2008). Changes in turbine cut-in speeds, the wind speed at which turbine blades begin to rotate and generate electricity, has reduced bat fatalities in 3 separate studies (Baerwald et al. 2009; Arnett et al. 2011; O. Behr, University of Erlangen, unpublished report) and, to date, is the only mitigation measure for bats that has been tested at operational wind facilities.

Previous experiments manipulated turbine operations in response to a single variable, wind speed (Baerwald et al. 2009, Arnett et al. 2011). This was logical because more bats are killed at lower wind speeds (Kunz et al. 2007*b*, Arnett et al. 2008); and this strategy was relatively easy to implement because modern wind turbines can be programmed to cut-in or cut-out based on minimum and maximum wind speeds respectively (Baerwald et al. 2009, Arnett et al. 2011). Nevertheless, it is well known that bat activity patterns are influenced by other meteorological factors (e.g., temperature) as well as time of year (Erkert 1982, Erickson and West 2002). For example, fatality risk might be low on cold nights when bat activity is depressed (Erkert 1982), even if wind speeds are low. On such nights, changes to cut-in speeds based solely on wind speed might do little to reduce fatality risk to bats.

The desert region of southern California has been used for utility-scale wind energy developments since the early-1980s. Currently southern California, and indeed many areas of the southwestern United States, is targeted for further wind energy development but there have been no published accounts of bat activity or fatalities from existing or proposed facilities in this region (Kunz et al. 2007*b*). Impacts to bats are of concern in this region because this area contains the country's highest diversity and abundance of bats and the United States distribution of several species is limited to this region (Humphrey 1975). Additionally, southern California is considered a wintering area for migratory tree bats in the genus *Lasiurus* (Cryan 2003) which are frequently killed at wind energy developments elsewhere (Arnett et al. 2008). We speculated that bats might be active throughout winter in southern California due to relatively mild weather conditions and therefore may exhibit different seasonal activity patterns than those at wind energy facilities at higher latitudes.

We evaluated use of echolocation monitoring to address both risk avoidance and impact mitigation for bats at wind energy facilities. Although a variety of methods are useful for characterizing bat activity at wind energy developments (Kunz et al. 2007*a*), echolocation detectors are currently the most frequently employed because of their relatively low cost and capabilities for long-term deployment. The latter factor is extremely important because nightly bat activity levels vary greatly (Hayes 1997) and fatality events tend to be highly episodic (Arnett et al. 2008). Specific objectives of our study were to 1) characterize year round patterns of bat activity at a wind energy facility in southern California; 2) determine survey effort necessary to characterize bat activity levels at a wind energy facility in southern California; 3) model bat presence on-site with respect to date and meteorological conditions; and 4) determine whether incorporation of a full suite of meteorological conditions could improve predictions of bat presence.

STUDY AREA

Our study area was the Dillon Wind Energy Facility (DWEF) approximately 15 km north of Palm Springs, California (Fig. 1). The site was within the San Gorgonio Pass Wind Resource Area, 1 of the oldest and largest wind energy developments in the world. Approximately 3,000 wind turbines of various ages, sizes, and models were located in the San Gorgonio Pass area. Our site was located at the northeastern extreme of the existing wind energy development. We conducted our study on 2 separate approximately 2.5-km^2 parcels, on which 20 1-MW Mitsubishi turbines (Mitsubishi Heavy Industries, Ltd., Tokyo, Japan) were erected in each parcel during the study (Fig. 1). Turbine hub heights were 68 m with blade tip heights of 102 m. Turbine construction began in December 2007 and turbines began full operation on 26 March 2008.

The site lies at the northwestern extreme of the Colorado desert, within the Sonoran Basin and Range ecoregion (United States Environmental Protection Agency 2007). Topography at the site was nearly flat and sparsely vegetated by desert scrub communities typical of the Mojave and Sonoran deserts. The plant community on-site was <2 m in height and dominated by creosote bush (*Larrea tridentata*) and white bursage (*Ambrosia dumosa*). Climate was characterized by hot dry summers with mean daily maximum temperatures $>38^\circ$ C from June through September and relatively mild winters with mean nightly minimum temperatures $>5^\circ$ C. Average annual rainfall in Palm Springs was 14 cm with the majority falling between December and February.

METHODS

We monitored bat activity using ANABAT II echolocation detectors (Titley Scientific, Lawnton, Australia). We at-

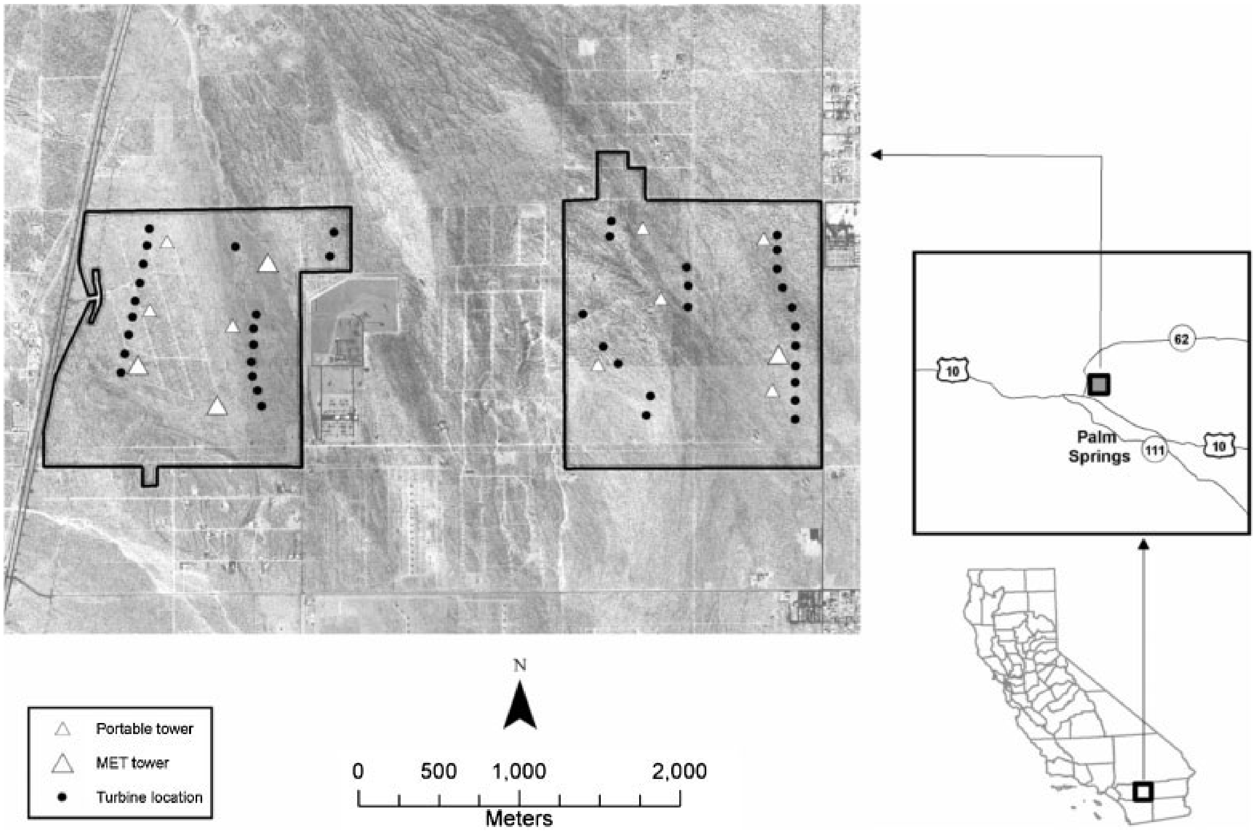

Figure 1. Location map and study design schematic for Dillon Wind Energy Facility, Riverside County, California. Echolocation detectors for bats were deployed on meteorological (MET) and portable towers prior to development (25 Oct 2007–25 Mar 2008) and during first year of site operations(26 Mar 2008–31 Mar 2009).

tached detector microphones to 4 meteorological (MET) towers at 3 heights (2 m, 22 m, and 52 m above ground) and to 8 temporary towers at 2 heights (2 m and 22 m above ground) for a total of 12 towers and 28 detectors (Fig. 1). The site developer (Iberdrola Renewables) selected the number and position of MET towers to characterize the wind resource on site. We added temporary tower locations to achieve uniform coverage of echolocation monitors within both parcels (Fig. 1). Distances between towers ranged from 350 m to 1,260 m.

Detector microphones were housed in weather proof casings (bat hats; EME System, Berkeley, CA) and directed straight down to protect them from precipitation and dust. Polycarbonate sound reflector plates on the microphone enclosures were positioned at 45° below horizontal so that angle of call reception was upward at 45° (Weller and Zabel 2002). We oriented all microphones to the west, into the prevailing wind direction. We connected microphones via Canare LE5-C microphone cable (Canare Corporation of America, Totowa, NJ) to bat detectors and Compact Flash Zero-Crossing Analysis Interface Modules (CF ZCAIMs; Titley Scientific) which were housed on the ground in weather and dust proof containers. We installed pre-amp drivers in each microphone enclosure to prevent loss due to cable length. We calibrated detectors relative to one another using the methods of Larson and Hayes (2000) and switched microphones on individual towers among detectors at each visit, as a further bias-prevention measure. We programmed detection systems to begin monitoring $\geq$30 min before sunset and continue until $\geq$30 min after sunrise. We visited detector systems approximately every 2 weeks to download data and ensure proper operation.

With exception of occasional malfunctions, detectors on MET towers operated nightly for 17 months from 25 October 2007 through 31 March 2009. Detectors on temporary towers operated intermittently from 14 December 2007 through 21 May 2008 with exception of 1 that operated nightly from 15 March 2008 through 23 March 2009. We divided our continuous sampling into 7 time periods, each corresponding to a season of the year (Table 1), because activity levels, species composition, and ecological needs of bats were expected to vary among seasons. The 7 time periods included 1 partial and 1 full autumn period (periods 1 and 5), 2 full winter periods (periods 2 and 6), 1 full and 1 partial spring period (periods 3 and 7), and 1 full summer period (period 4). Trends in bat activity corresponded well with dates selected to divide time periods (T. J. Weller, U. S. Department of Agriculture Forest Service, unpublished data).

Compact flash cards in CF ZCAIMs stored recordings of echolocation calls. We downloaded cards and viewed resulting time versus frequency sonograms using program ANALOOKW (version 3.7j; Titley Scientific). We defined bat passes as either a series of $\geq$2 echolocation calls each with duration $\geq$2 ms or a single echolocation call with duration $\geq$5 ms. Potential bat echolocations were separated from non-bat ultrasound via use of 2 filters. The first filter

Table 1. Allocation of bat echolocation monitoring effort at Dillon Wind Energy Facility, Riverside County, California.

	Time period						
	1	2	3	4	5	6	7
Start date	25 Oct 2007	16 Nov 2007	16 Feb 2008	18 May 2008	17 Aug 2008	16 Nov 2008	16 Feb 2009
End date	15 Nov 2007	15 Feb 2008	17 May 2008	16 Aug 2008	15 Nov 2008	15 Feb 2009	31 Mar 2009
Nights	22	92	92	91	91	92	44
Detector nights	205	1,500	1,517	1,128	1,031	1,107	471
Mean wind speed (m/s)[a]	5.07	5.22	9.06	9.45	6.35	4.86	8.20
Mean temperature (°C)[a]	21.1	11.4	17.8	28.9	25.6	13.4	15.2

[a] Mean of 92 values measured every 10 min between 1610 hours and 0730 hours.

identified sounds with frequencies $\geq$20 kHz and durations >2 ms. The second filter identified sounds $\geq$7 kHz and durations $\geq$5 ms. This second filter was designed to identify potential echolocation calls of southern California bat species that echolocate at low frequencies (e.g., family Molossidae) as they flew in open space. We visually inspected each file that passed either filter to determine whether it was a bat pass. We categorized bat passes as to whether they were produced by high ($\geq$35 kHz, hereafter HiF) or low (<35 kHz; LowF) frequency echolocating bats, based on minimum frequency. We established this distinction because most migratory species use LowF echolocation calls.

To understand the species composition of LowF and HiF groups we attempted to assign each bat pass to species. We developed a key that used visual inspection of quantitative (e.g., minimum frequency) and qualitative (e.g., shape) parameters of echolocation calls to assign them to species. We assigned 77% of HiF bat passes to species, all but 1 (*Lasiurus blossevillii*) of which was identified as *Parastrellus hesperus*. We assigned 22% of LowF bat passes to species. LowF bat passes identified to species were comprised of *Tadarida brasiliensis* (61.3%), *Nyctinomops femorosaccus* (16.0%), *L. cinereus* (12.8%), *Eumops perotis* (5.8%), *Eptesicus fuscus* (1.8%), and *L. xanthinus* (1.2%). We were not able to assign the remaining 78% of LowF bat passes to species because of overlapping call characteristics between species (e.g., *T. brasiliensis* and *E. fuscus*) and fragmentary call files that result from remote recording (O'Farrell et al. 1999). High frequency bat passes were not recorded between 15 November and 15 February and HiF bat pass rate varied from 0.02 to 0.18 bat passes/detector night (dn) during non-winter time periods. A separate study estimated fatalities during the first year of operations at DWEF (Chatfield et al. 2009) and all of the species found as fatalities use LowF calls. Therefore, our analyses focused on modeling seasonal and meteorological conditions which predicted presence of LowF bats.

Low levels and intermittent patterns of echolocation activity at DWEF made it clear that our primary concern should be distinguishing nights on which LowF bat passes were recorded from those in which they were not. Even on nights when LowF bat passes were recorded, they were usually only recorded by a subset of detectors. Thus, we employed a site-occupancy approach that allowed us to estimate probability of LowF bat presence on a given night while accounting for LowF bat passes being recorded by <100% of detectors on site (MacKenzie et al. 2002). Conventionally, the site occupancy approach has used multiple visits to a site to create a detection history that allows detection probability to be incorporated into estimates of proportion of sites occupied using a maximum likelihood approach (MacKenzie et al. 2002). However, the echolocation detection systems we used operated continuously over long periods of time, thereby negating concerns about temporal variability in detection probability. Hence, variability in our ability to characterize LowF bat presence occurred over space rather than time (i.e., among detector locations). Therefore, we transposed the standard detection history matrix such that individual nights composed rows, and columns were populated according to whether bat passes were recorded (1) or not recorded (0) at each operational detector. Occupancy analysis readily accommodates missing data (MacKenzie et al. 2002), which is important because failures of echolocation detectors in field settings are common.

We estimated both presence and detection probability as a function of covariates (MacKenzie et al. 2002) for time periods 2–6. We included detection probability as a function of detector height in all models and evaluated all possible combinations of mean nightly wind speed (m/s), wind direction, temperature (° C), and proportion of moon illuminated as predictors of presence of LowF bat passes. Ambient temperature, wind speed, and wind direction were recorded every 10 min from instruments 30 m above ground on each of the 4 MET towers. We calculated mean nightly values for meteorological variables as the mean of 92 measures between 1610 hours and 0730 hours at all 4 MET towers. We obtained nightly proportion of moon illuminated from the United States Naval Observatory Portal (http://aa.usno.navy.mil/data/docs/MoonFraction.php). Because mean nightly wind direction is a circular variable (e.g., difference between 359° and 1° is 2°), we included it as a covariate by inserting both sine and cosine of the unit vector, in radians, into models (Batschelet 1981). Both sine and cosine terms were necessary because inclusion of only 1 would describe 2 different directions (i.e., cos 270° = cos 90°). We expected bat activity patterns to change over the course of a time period, irrespective of meteorological conditions, so we also included ordinal date, within time period, as a covariate. We included both linear and quadratic (sum of date + date^2) forms of ordinal date in our models to account for nonlinear relationships (e.g., peaks mid-time period). Because date was included both individually and as part of the quadratic form, it appeared in 32 models per time period, whereas date^2 appeared in 16. We evaluated 48 models per time period. Models were batch-executed in SAS version 9.2 (SAS Institute, Inc., Cary, NC) using a custom script that used the maximum likelihood estimation capabilities of PROC NLMIXED. Function convergence was attempted over 20,000 iterations. One model in each of time periods 1 and 7 failed to converge and these were removed from model ranking and weighting calculations.

We ranked models using bias-corrected Akaike's Information Criterion (AIC_c; see Burnham and Anderson 2002) and calculated Akaike weights for each model. We present parameter estimates, odds ratios, detection, and occupancy probabilities as model-averaged values over the full set of models in each time period. We calculated relative importance of each predictor variable by summing Akaike weights over all models in which it appeared (Burnham and Anderson 2002). We normalized relative importance values by multiplying them by the total number of models ($n = 48$) and dividing by the number of models in which a variable was included (Burnham and Anderson 2002:169). We considered variables with normalized importance values >1.0 to be the most important variables for a time period. Further, we considered individual variables that had model-averaged odds ratios with 95% confidence intervals that did not overlap 1 to have the strongest support. Odds ratios for a unit increase in ordinal date (date + date^2) and wind direction (cos and sin) were each functions of 2 variables and a unique odds ratio was produced for each unit change (e.g., day 1 to day 2 odds ratio differs from day 2 to day 3). We present the mean odds ratio for wind direction and ordinal day in each time period and calculated upper and lower confidence intervals for the time period as the mean proportion of individual odds ratios represented by upper and lower confidence limits. We created an interactive plot to visualize changes in probability of LowF bat presence ($\hat{\psi}$) in response to multiple variables and to understand interactions among multiple covariates (http://www.fs.fed.us/psw/topics/wildlife/bat/batprob.shtml). We also created static plots of predicted probability values as a function of 2 variables by multiplying model-averaged parameter estimates for these variables by the range of values observed during a time period while holding remaining variables at their mean for the time period. We used the formula $p^* = 1 - (1 - \hat{p})^K$, where $\hat{p}$ is detection probability for a single echolocation detector and K = number of echolocation detectors (MacKenzie and Royle 2005), to estimate mean number of echolocation recorders required to obtain a 95% probability of detection when LowF bats were present.

We evaluated prediction success of our models by comparing predicted probabilities ($\hat{\psi}$) to nights when LowF bat passes were and were not recorded at DWEF by any detector. We applied model-averaged parameter estimates to the combination of meteorological conditions that occurred each night to estimate nightly probability of LowF bat presence in each full time period (periods 2–6). We divided probability classes into 5 equally sized bins then determined the proportion of nights in which LowF bats were and were not recorded that occurred within each bin (Boyce et al. 2002, Hirzel et al. 2006). If a model had good predictive capabilities, $\hat{\psi}$ would be greater on nights when LowF bat passes were recorded and lesser on nights when LowF bat passes were not recorded. We selected this method because it does not require use of an arbitrary cut-off threshold (e.g., $\hat{\psi} > 0.5$) to assign correct classification (Hirzel et al. 2006). We used area under the curve (AUC; Fielding and Bell 1997) to quantitatively assess classification success.

RESULTS

On average, 13.3 (range 0–25) detectors per night were operational over a 17-month period at DWEF (Table 1). We recorded 1,798 LowF bat passes and 523 HiF bat passes during 6,959 detector nights (dn) for a mean rate of 0.26 and 0.08 bat passes/dn, respectively. Pass rates of LowF bats varied from 0.01 bat passes/dn in time period 2 to 0.62 bat passes/dn during time period 7 (Table 2). We recorded LowF bat passes on 18.5–69.6% of nights (Table 2). Excluding winter seasons (periods 2 and 6), LowF bat passes were recorded on 57.2% of nights. After accounting for variability in detection probability, we estimated LowF bats were present on 32.1–77.8% of nights depending on time period (Table 2).

Although all LowF species we identified, with exception of *L. xanthinus*, were recorded by microphones at 2 m, overall LowF bat passes rates increased with detector height from 2 m (0.14 bat passes/dn) to 22 m (0.26 bat passes/dn) to 52 m (0.43 bat passes/dn). Further, passes of LowF bats comprised 49.2%, 83.6%, and 98.5% of bat passes recorded at 2 m, 22 m, and 52 m, respectively. Detection probabilities ranged from 0.027 (SE = 0.014) at 2 m during time period 2 to 0.564 (SE = 0.032) at 52 m during period 3 (Fig. 2). In other words, the probability of detecting LowF bats, given they were present, with a single detector ranged from 3% to 56% depending on time period and height of detector. Detection probabilities for LowF bats were greater at 22 m and 52 m than 2 m in all time periods with no overlap in confidence intervals during time periods 3–5 (Fig. 2). Detection probabilities at 22 m and 52 m were similar in all time periods except period 3 where they were greater at 52 m Excluding winter time periods, the mean number of detectors at 52 m required to achieve a 95% probability of detection ranged from 4 in period 3 to 14 in period 4. However, for detectors at 2 m obtaining a 95% probability of detection, when LowF bats were present, would have required from 10 to >30 detectors depending on time period.

Table 2. Number of low frequency (<35 kHz) bat passes per detector night (dn) and observed and estimated proportion (with lower [LCL] and upper [UCL] confidence limits) of nights with bat activity ($\hat{\psi}$) at Dillon Wind Energy Facility, Riverside County, California 25 October 2007–31 March 2009. Time periods defined in Table 1.

Time period	Passes/dn	ψ (obs)	$\hat{\psi}$	LCL $\hat{\psi}$	UCL $\hat{\psi}$
1	0.19	0.636	0.679	0.618	0.740
2	0.01	0.185	0.321	0.291	0.351
3	0.51	0.696	0.696	0.678	0.714
4	0.19	0.659	0.778	0.752	0.803
5	0.38	0.659	0.706	0.684	0.727
6	0.05	0.272	0.527	0.526	0.528
7	0.62	0.545	0.557	0.535	0.578

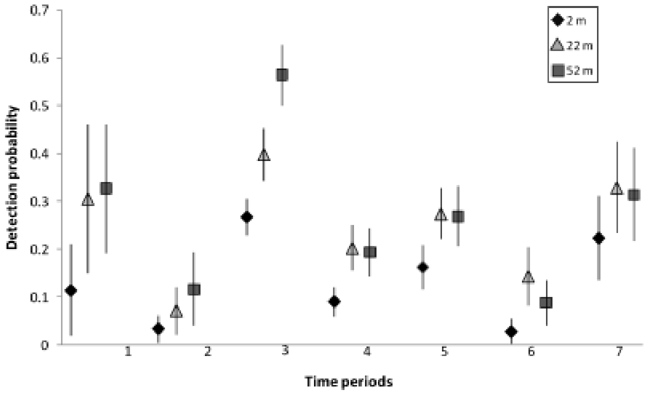

Figure 2. Model-averaged estimated detection probabilities (±SE) for low frequency (<35 kHz) bat passes using ANABAT echolocation detectors deployed at 3 heights above ground level at Dillon Wind Energy Facility, Riverside County, California. Time periods as defined in Table 1.

The top-ranked models for explaining presence of LowF bat passes had weights ranging from 0.167 to 0.460 indicating relatively high model uncertainty in all time periods (Table 3, see Table S1 available online at www.onlinelibrary.wiley.com for the 95% confidence set of models). Nevertheless, in most time periods, 1–3 variables were heavily represented among the top models. Mean wind speed had the highest relative importance for predicting LowF bat activity in all but periods 4 and 6 (Table 4). Mean wind speed and temperature had the highest and second ranked relative importance, respectively in time periods 2, 3, and 7. Mean nightly wind speeds were lower on nights when LowF bat passes were recorded than on nights when they were not in all time periods; however, confidence intervals overlapped in time periods 1 and 6 (Fig. 3A). Though there were overlaps in confidence intervals in most time periods, mean nightly temperatures were higher on nights when LowF bat passes were recorded in all but time period 6 (Fig. 3B). Ordinal date had the highest relative importance in periods 4 and 6 and high relative importance in periods 5 and 7. In periods 4–7, the quadratic form of ordinal date provided a better fit to the data than did the linear form (Table 4). Proportion of moon illumination was important for predicting bat activity in time periods 3, 4, 6, and 7. Our confidence was highest for models where we had data for a full season (time periods 2–6) and where variables with high relative importance also had odds ratio confidence intervals that did not overlap 1 (Table 4; time periods 2, 3, 5).

Understanding the impact of multiple variables on predicted probability of LowF bat presence ($\hat{\psi}$) can best be visualized via the use of interactive plots (http://www.fs.fed.us/psw/topics/wildlife/bat/batprob.shtml). Nevertheless, evaluating models using pairs of variables, while holding others at their mean for the time period, provided interesting insights into how individual variables affected $\hat{\psi}$ and how threshold values varied among periods (Figs. 4 and 5). For instance, wind speed and temperature were the 2 most important predictors of LowF bat presence in time periods 2 and 3. However, values of $\hat{\psi}$ increased more gradually over time and were lesser for a particular temperature in period 2 compared to period 3 (Fig. 4). Although date within time period did not always have high relative importance, it interacted with meteorological conditions to impact $\hat{\psi}$ in most seasons (e.g., Fig. 5). Peak probabilities occurred in the middle of time period 3 (Fig. 5A) but at the beginning of period 5 (Fig. 5B).

Table 3. Top-ranked models of low frequency bat occupancy (ψ) and detection probability (p) at Dillon Wind Energy Facility, Riverside County, California during 5 time periods from 16 Nov 2007–15 Feb 2009. We present models within 2 bias-corrected Akaike's Information Criterion points (<2 ΔAIC_c) of the model with the lowest AIC_c. K = number of estimable parameters, ω_i = Akaike weights of individual model, and Cum wt. = cumulative Akaike weights of the top-ranked models.

Time period[a]	Model[b]	K	AIC_c	ΔAIC_c	ω_i	Cum wt.
2	ψ(ws + temp) p(ht)	3	242.595	0.000	0.312	0.312
	ψ(ws + temp + wd) p(ht)	5	244.301	1.706	0.133	0.444
	ψ(ws + temp + moon) p(ht)	4	244.488	1.894	0.121	0.565
3	ψ(ws + temp + moon) p(ht)	4	1397.123	0.000	0.313	0.313
	ψ(ws + temp + date + date^2 + moon) p(ht)	6	1398.303	1.180	0.174	0.487
	ψ(ws + temp + date + moon) p(ht)	5	1398.530	1.407	0.155	0.641
	ψ(ws + temp + wd + moon) p(ht)	6	1398.622	1.498	0.148	0.789
4	ψ(date + date^2 + wd + moon) p(ht)	6	784.506	0.000	0.263	0.263
	ψ(ws + date + date^2 + wd + moon) p(ht)	7	785.232	0.725	0.183	0.447
	ψ(date + date^2 + wd) p(ht)	5	785.872	1.366	0.133	0.580
5	ψ(ws + date + date^2) p(ht)	4	873.035	0.000	0.167	0.167
	ψ(ws + date) p(ht)	3	873.267	0.232	0.149	0.315
	ψ(ws + date + date^2 + moon) p(ht)	5	874.215	1.180	0.092	0.408
	ψ(ws + temp + date) p(ht)	4	874.496	1.461	0.080	0.488
	ψ(ws + temp + date + date^2) p(ht)	5	874.508	1.473	0.080	0.568
	ψ(ws + temp + date + date^2 + moon) p(ht)	6	874.719	1.684	0.072	0.640
	ψ(ws + temp) p(ht)	3	874.978	1.943	0.063	0.703
6	ψ(wd + date + moon) p(ht)	5	299.259	0.000	0.460	0.460
	ψ(wd + date + moon + ws) p(ht)	6	299.687	0.428	0.372	0.832

[a] Time periods as defined in Table 1.
[b] ws = mean nightly wind speed (m/s); temp = mean nightly temperature (°C); date = ordinal date within time period; wd = wind direction: entered into a model as sin and cos components; moon = proportion of moon illuminated.

Table 4. Model-averaged parameter estimates, unconditional standard errors, odds ratios with 95% confidence intervals, and relative importance of variables resulting from 48 models of nightly low frequency ($\leq$35 kHz) bat occupancy at Dillon Wind Energy Facility, Riverside County, California 25 Oct 2007–31 Mar 2009.

Time period[a]	Variable[b]	Coeff.	SE	Odds ratio	CI	Importance
1	Wind speed	−0.560	0.411	0.571	0.255, 1.279	0.568[c]
	Temp	0.431	0.324	1.538	0.814, 2.905	0.245
	Date	−1.017	0.806	0.640	0.267, 1.700	0.377
	Date^2	0.124	0.010			0.070
	CosWindDir	11.268	8.297	1.013	0.791, 1.312	0.036
	SinWindDir	−6.462	7.844			0.036
	Moon	11.210	7.023	1.119	0.975, 1.284	0.294
2	Wind speed	−0.455	0.207	0.634	0.423, 0.952	0.909[c]
	Temp	0.345	0.163	1.412	1.025, 1.945	0.935[c]
	Date	−0.009	0.012	0.998	0.983, 1.014	0.295
	Date^2	3.0×10^{-4}	7.0×10^{-5}			0.079
	CosWindDir	1.757	0.384	1.000	0.989, 1.012	0.331
	SinWindDir	0.099	0.271			0.331
	Moon	−0.844	0.349	0.992	0.985, 0.998	0.278
3	Wind speed	−0.553	0.172	0.575	0.411, 0.807	1.000[c]
	Temp	0.444	0.161	1.558	1.138, 2.135	0.959[c]
	Date	0.097	0.049	1.037	0.986, 1.092	0.523
	Date^2	−0.001	2.2×10^{-4}			0.290
	CosWindDir	−4.531	0.881	1.002	0.976, 1.028	0.239
	SinWindDir	1.523	0.728			0.239
	Moon	−3.287	1.268	0.968	0.944, 0.992	0.889[c]
4	Wind speed	−0.320	0.125	0.726	0.568, 0.928	0.402
	Temp	0.197	0.081	1.218	1.040, 1.426	0.308
	Date	−0.670	0.463	1.807	0.914, 4.617	0.993[c]
	Date^2	0.013	0.007			0.936[c]
	CosWindDir	22.487	11.047	1.223	0.682, 2.307	0.850[c]
	SinWindDir	47.294	24.487			0.850[c]
	Moon	−4.246	1.942	0.958	0.923, 0.996	0.672[c]
5	Wind speed	−0.488	0.169	0.614	0.441, 0.855	0.999[c]
	Temp	0.143	0.047	1.154	1.051, 1.266	0.434
	Date	-8.3×10^{-4}	0.053	0.955	0.897, 1.018	0.891[c]
	Date^2	-9.1×10^{-4}	3.0×10^{-4}			0.484[c]
	CosWindDir	1.585	0.220	1.000	0.994, 1.006	0.194
	SinWindDir	−0.147	0.117			0.194
	Moon	1.234	0.492	1.012	1.003, 1.022	0.319
6	Wind speed	−0.137	0.053	0.872	0.786, 0.968	0.258
	Temp	−0.020	0.031	0.980	0.922, 1.042	0.216
	Date	−0.060	0.094	1.158	0.978, 1.378	0.999[c]
	Date^2	0.002	0.001			0.958[c]
	CosWindDir	−3.955	2.365	1.003	0.929, 1.085	0.959[c]
	SinWindDir	5.290	2.459			0.959[c]
	Moon	−13.817	6.730	0.871	0.763, 0.994	0.989[c]
7	Wind speed	−4.884	4.856	0.007	5.56×10^{-7}, 102.9	1.000[c]
	Temp	1.087	0.673	2.966	0.794, 11.08	0.951[c]
	Date	3.812	3.417	6.682	0.965, 611.8	0.817[c]
	Date^2	−0.095	0.057			0.644[c]
	CosWindDir	7.491	0.621	1.013	0.979, 1.048	0.066
	SinWindDir	−11.066	1.345			0.066
	Moon	13.528	5.056	1.145	1.037, 1.264	0.455[c]

[a] Time periods as defined in Table 1.
[b] Wind speed = mean nightly wind speed (m/s); Temp = mean nightly temperature (°C); Date = ordinal date within time period, odds ratio calculated as mean of 1-night increments in date and date^2 over course of the Time Period; CosWindDir = mean cosine of nightly wind direction; SinWindDir = mean sine of nightly wind direction, odds ratio calculated as mean of 1° increments in wind direction; Moon = nightly proportion of moon illuminated.
[c] Relative importance values > expected based on number of models in which variable appeared.

Our models were relatively successful at classifying nights when LowF bat passes were recorded and not recorded at DWEF (Fig. 6). On nights when LowF bats were recorded in the field, the highest proportion of estimates had $\hat{\psi} > 0.8$ in time periods 2–6 (Fig. 6). Similarly on nights when LowF bats were not recorded in the field, the highest proportion of estimates had $\hat{\psi} < 0.2$ in all but period 3 (Fig. 6). AUC values ranged from 0.76 to 0.84 in all but period 3 (AUC = 0.69). That is, nights when a LowF bat pass was recorded had a >76% chance of having a greater $\hat{\psi}$ value than nights when LowF bat passes were not recorded.

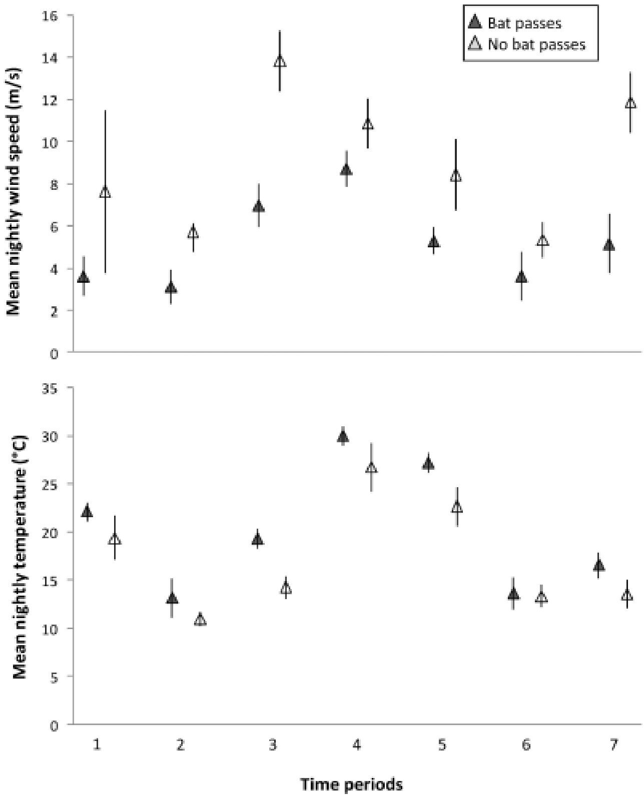

Figure 3. Comparisons of mean (±SE) wind speed (A) and temperature (B) on nights when low frequency (<35 kHz) bat passes were and were not recorded at Dillon Wind Energy Facility, Riverside County, California. Time periods as defined in Table 1.

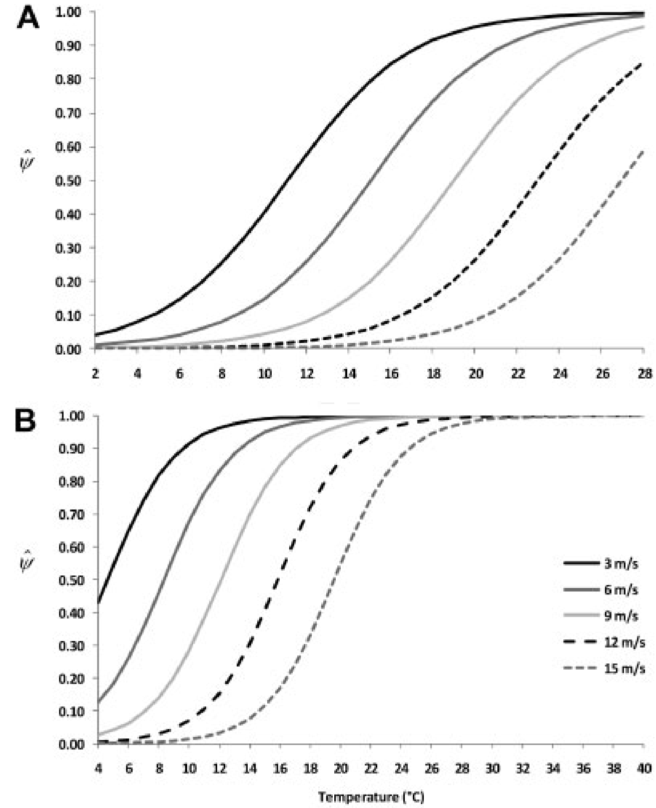

Figure 4. Effects of wind speed (m/s) and temperature (°C) on model-averaged probability of bat presence ($\hat{\psi}$) at Dillon Wind Energy Facility, Riverside County, California. A) Time period 2 (16 Nov 2007–15 Feb 2008). B) Time period 3 (16 Feb 2008–17 May 2008). Temperature scaled to range of values observed during each time period.

DISCUSSION

Bat activity levels at DWEF were low compared to other studies at wind energy facilities. Previous estimates of bat activity at wind energy facilities include: 0.78–14.81 migratory bat passes/dn in southern Alberta, Canada (Baerwald and Barclay 2009), >1.0 bat pass/dn during spring in western New York (Reynolds 2006), >18 bat passes/dn during autumn in south-central Wisconsin (Redell et al. 2006), and >3 bat passes/dn during autumn in south-central Pennsylvania (Arnett et al. 2006); all of which were greater than the highest seasonal LowF bat pass rate we documented (0.62 passes/dn in time period 3). Bat activity at DWEF was extremely low during winter (time periods 2 and 6), addressing 1 of our questions about bat activity patterns in this area, at least for this flat, windy, sparsely-vegetated site.

Despite low overall bat activity levels, we were able to build models that successfully predicted conditions when LowF bats were present. Our models confirmed results from studies of wind energy developments in other regions and habitats which have demonstrated that bat activity is generally higher at lower wind speeds and higher temperatures (Arnett et al. 2006, Redell et al. 2006, Reynolds 2006). Nevertheless, wind speed alone was only the top-ranked model in time period 1 and time period 2 was the only 1 in which the combination of mean wind speed and mean temperature was the top-ranked model. Although we found lower wind speeds and higher temperatures associated with greater probabilities of presence in every time period, model performance generally increased with inclusion of additional variables (e.g., date and moon illumination). This suggests that using model-averaged parameter estimates for a broad suite of variables will provide better predictions of LowF bat presence than those limited to 1–2 variables. We created bivariate plots as a simple way of visualizing how variables with high relative importance influenced probability of presence and how their influence was often co-dependent (Figs. 4 and 5). However interactive visualization tools that allow users to visualize changes in $\hat{\psi}$ in response to multiple variables are much more effective for understanding performance of models with multiple covariates (e.g., http://www.fs.fed.us/psw/topics/wildlife/bat/batprob.shtml).

Our results highlight the importance of modeling conditions that explain bat activity on a seasonal basis. Not only were there marked differences in activity levels, but the top models and relative importance of explanatory variables differed among time periods. This is not surprising given that behavioral and energetic needs of bats change seasonally (Weller et al. 2009). For example, conditions conducive to foraging during summer may differ from those that favor migration during spring and autumn. Further, the ecological context of meteorological variables differs among seasons. For instance, a temperature of 15° C in February might be a relatively warm night, favoring bat activity, whereas the same

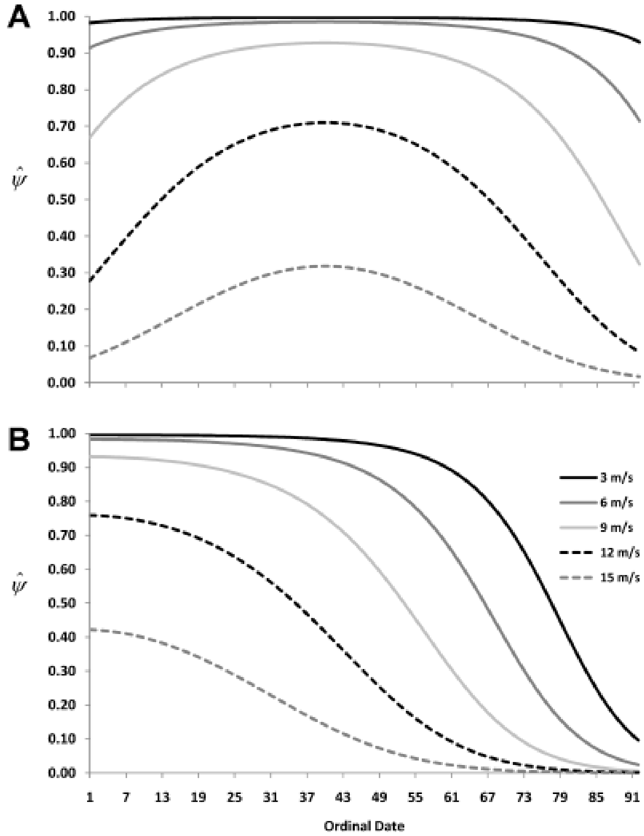

Figure 5. Effects of wind speed (m/s) and night within time period on model-averaged probability of bat presence ($\hat{\psi}$) at Dillon Wind Energy Facility, Riverside County, California. A) Time period 3 (16 Feb 2008–17 May 2008). B) Time period 5 (17 Aug 2008–15 Nov 2008).

temperature in August may depress bat activity levels. Hence, although bat activity may be positively associated with ambient temperature in every season, model coefficients may differ markedly and season-specific models are likely to increase predictive power.

Although mean nightly wind speed was negatively associated with LowF bat presence in every time period, those periods with high occupancy estimates also had the highest mean wind speeds (i.e., periods 3 and 4), whereas periods with the lowest estimates had low mean wind speeds (periods 2 and 6). A similar result was observed in Alberta, Canada where highest bat activity levels were at the site with the lowest mean minimum temperature and second highest mean maximum wind speed among 7 sites evaluated (Baerwald and Barclay 2009). This suggests that nightly meteorological conditions, rather than mean seasonal (or annual) values will be better predictors of bat activity levels. Accordingly, we found that inclusion of ordinal date as a covariate improved model performance in several time periods. That is, there were changes in LowF bat presence within a time period that occurred irrespective of meteorological conditions. For example, probabilities of bat presence decreased as autumn progressed into winter (Fig. 5B). Changes in probability of bat presence within a time period could result from transitions in species composition or predominant activities (e.g., foraging vs. migration) of bats present in response to seasonal changes. Although explanations remain speculative, our results highlight the need to consider night within time period as a covariate in models of bat activity.

Modified Occupancy Approach

A site-occupancy analysis approach was a logical choice for us because LowF bat activity at DWEF was detected on a little over half (57%) of the nights and median number of LowF bat passes recorded per night ranged from 0 (periods 2,6) to 1.5 (period 1). Thus, it was sensible to reduce data from each detector night at DWEF to a detected/non-detected outcome and apply the site-occupancy approach. A similar approach should be applicable to other studies at wind energy facilities as they frequently report high proportions of nights when no bats were detected (Reynolds 2006, Baerwald and Barclay 2009). Further, a site-occupancy approach may be an effective way to model bat activity even at sites where bat activity levels are greater. In such cases, the threshold for what is considered a detection will require modification. For instance, detection (1) and non-detection (0) have been assigned according to whether number of bat passes or echolocation pulses were above or below pre-established thresholds (e.g., seasonal medians; Gorresen et al. 2008, 2009).

One advantage of the site-occupancy framework is that variability in detection rates among echolocation recorders is incorporated directly into models that attempt to explain bat activity with respect to covariates (e.g., meteorological conditions; MacKenzie et al. 2002). Activity patterns of bats are notoriously variable over both space and time and accounting for this variability is critical for obtaining credible estimates of activity (Hayes 1997, 2000; Weller 2007). Use of site occupancy approaches to analyze data collected by automated echolocation detection devices is not new (Yates and Muzika 2006; Gorresen et al. 2008, 2009). Nonetheless, our method of transposing the spatial and temporal components of the encounter history matrix was a unique modification of the conventional occupancy approach. Although we applied it to echolocation detectors, this modification should be more broadly applicable to any continuously operated equipment used to monitor ecological systems. Typically, monitoring program designs must weigh tradeoffs between spatial and temporal replication necessary to obtain estimates with desired levels of precision (MacKenzie and Royle 2005, Gorresen et al. 2008, Weller 2008). However, because echolocation detectors operate continuously we were able to focus solely on the number of detectors on site and the height at which to deploy them.

Detection Probabilities and Survey Effort

Detection probabilities of LowF bats varied both by time period and detector height with important implications for design of echolocation monitoring programs at wind energy facilities. Our results reflect patterns observed elsewhere that bat species that echolocate at lower frequencies are detected more frequently at greater heights above the ground (e.g., $\geq$30 m; Arnett et al. 2006, Baerwald and Barclay 2009, Collins and Jones 2009). Most migrant bat species in North America echolocate at low frequencies and are the

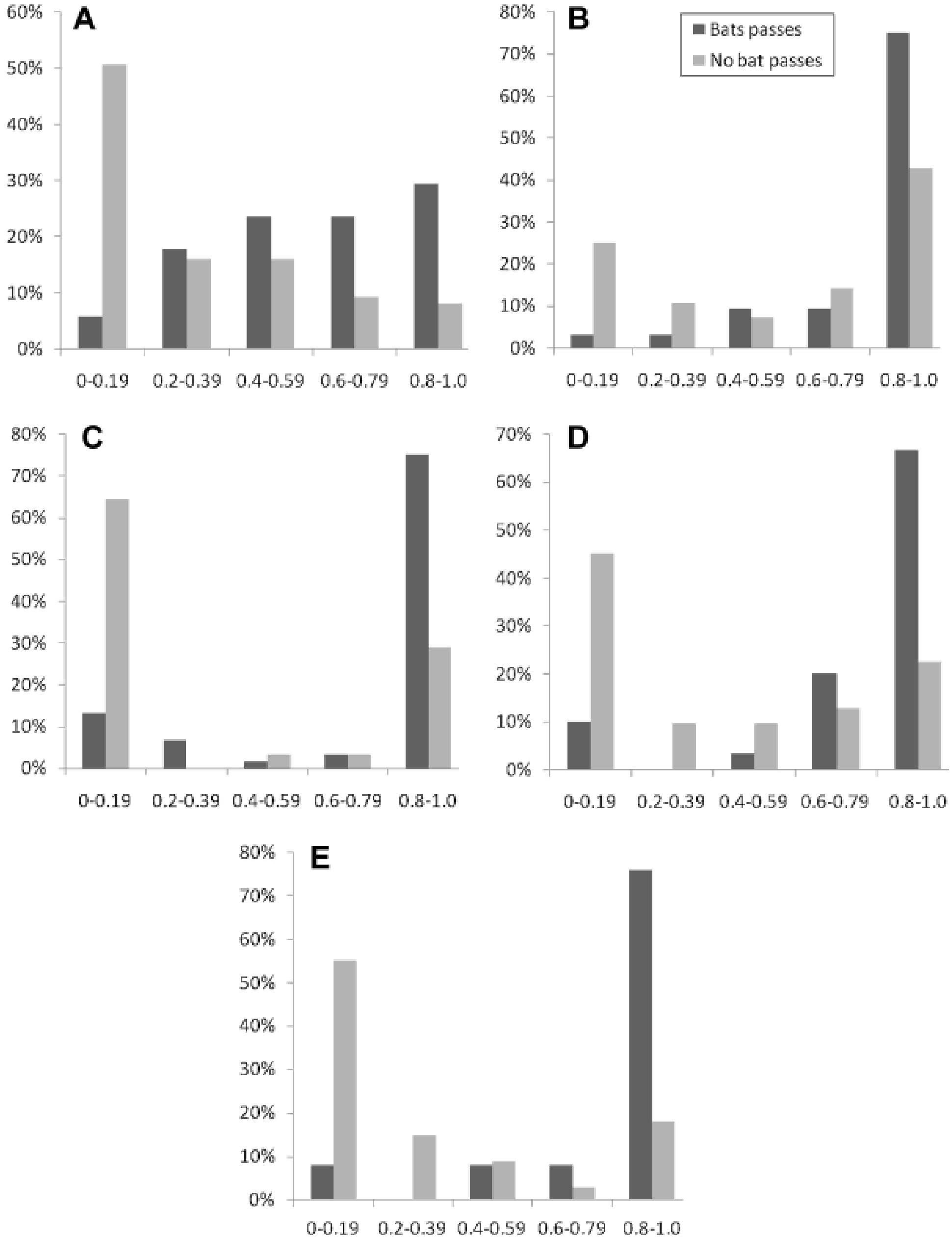

Figure 6. Distribution of model-averaged predicted probabilities of low frequency bat presence, on nights when bat passes were and were not recorded at Dillon Wind Energy Facility Riverside County California. A) Time period 2 (16 Nov 2007–15 Feb 2008). B) Time period 3 (16 Feb 2008–17 May 2008). C) Time period 4 (18 May 2008–16 Aug 2008). D) Time period 5 (17 Aug 2008–15 Nov 2008). E) Time period 6 (16 Nov 2008–15 Feb 2009).

species most impacted by wind energy development (Arnett et al. 2008). Hence, our findings contribute to a growing consensus that accurate characterization of migratory bat activity levels at wind energy facilities requires deployment of detectors well above ground level (Reynolds 2006, Kunz et al. 2007*a*). For instance, Baerwald and Barclay (2009) found a significant relationship between migratory bat activity measured at 30 m and fatalities at facilities with turbines >65 m tall but no relationship for activity measured at ground level.

Much less attention has been paid to the density of echolocation detectors that must be deployed to accurately characterize activity patterns of LowF bats. Even at a relatively small (40 MW), topographically and vegetatively homogenous facility, our deployment of 4 detectors at 52 m was only able to achieve a cumulative detection probability of 95% in 1 time period (period 3). Achieving 95% confidence in estimates may not be necessary to meet objectives at other wind energy facilities. However, we expect that most studies would desire detection probabilities greater than the approximately 30% we observed with single detectors at DWEF. Future work should assess density of detectors required to achieve robust estimates of bat presence or activity in other habitats and geographic regions.

Using Echolocation Monitoring to Inform Mitigations

We suggest that a model-based approach could be used to improve effectiveness and efficiency of mitigations for bat fatalities at wind energy facilities. Previous studies have documented that increasing cut-in wind speeds from approximately 3 m/s to approximately 6 m/s resulted in about half as many bat fatalities with relatively modest reductions in power production (Baerwald et al. 2009, Arnett et al. 2011). Nevertheless, uncertainty remains regarding the cost-effectiveness of changing turbine cut-in speeds to reduce bat fatalities (National Wind Coordinating Collaborative [NWCC] 2010). Our findings suggest that use of season-specific, multivariate models, rather than basing operational changes on wind speed alone, could decrease the amount of time that turbine operations must be changed to protect bats. For instance, during time period 5 there were 33 nights with mean wind speeds from 3–6 m/s (i.e., nights when turbine operations would be curtailed); though, only 19 of these nights had $\hat{\psi} > 0.9$. Hence, if $\hat{\psi} > 0.9$ was selected as the value for which turbines were curtailed, this would result in 42% fewer nights of curtailment. In other words, a model-based approach that prescribed changes in turbine operations based on a full suite of environmental conditions could minimize turbine shut down times.

Our models were relatively successful at classifying nights when LowF bat passes were recorded and were not recorded. Nevertheless, nights when LowF bat passes were not recorded at DWEF sometimes had high $\hat{\psi}$ values (Fig. 6). This result was not entirely unexpected because $\hat{\psi}$ will always be greater than observed levels of presence because it accounts for non-detection (MacKenzie et al. 2002). Nevertheless, we were surprised at the proportion of nights when LowF bat passes were not recorded at DWEF with $\hat{\psi} > 0.8$. Our models' prediction of bat presence on nights on which we did not record bats may be troubling for those wishing to base changes in turbine operations on models of echolocation activity. That said, our comparisons of observed data to model predictions were similar to other studies which considered their models to have sufficient predictive power to inform management decisions (Zielinski et al. 2006, Dunk and Hawley 2009). Uncertainty is systemic in the modeling of biological systems and individual data points will not always conform to predictions. The key question becomes how best to incorporate model uncertainty into management actions. In our case, basing curtailment on too low a threshold for bat presence (e.g., $\hat{\psi} > 0.5$) would increase turbine downtime, whereas selection of too high a threshold (e.g., $\hat{\psi} > 0.95$) may result in additional fatalities that reduce perceived benefits of curtailment.

This paper does not prescribe a particular number of fatalities, bat passes, or model probability levels (e.g., $\hat{\psi} > X$) that should trigger mitigation actions. It does describe a scientific process that can be followed to predict conditions when bat presence, and presumably fatality risk, is highest. Arnett et al. (2011) demonstrated the technical feasibility of altering turbine operations, in response to wind conditions, on a nightly basis to reduce bat fatalities. Thus, it should be feasible to program turbine operations to respond to a wider suite of environmental variables. Although our models are more complicated and would require additional programming to implement, costs should be quickly recovered through reduced losses of power generation time. In the future, installation of echolocation detectors directly within turbine nacelles and programming shutdowns to occur when levels of bat activity exceed pre-determined thresholds, in real-time, may offer an even more focused and direct mitigation alternative. Nevertheless, a model-based solution to calculating the costs of doing so, based on bat echolocation patterns recorded on site, would remain a useful tool.

Model-based approaches to informing mitigations will not be effective if the environmental conditions that predict bat activity vary greatly from year to year. Our study was not designed to evaluate inter-annual variation in bat activity. Winter, which had the lowest occupancy rates, was the only season in which we sampled over 2 complete time periods. Nevertheless, applying model results from full time periods 2, 3, and 5 to subsequent (time period 6) or partial (time periods 7 and 1) time periods resulted in AUC values of 0.65, 0.69, and 0.89, respectively. This provides some indication that our models were reasonably robust to inter-annual variation in conditions that predict bat activity. Multiple years of pre-construction echolocation monitoring will improve understanding of seasonal bat activity patterns and the environmental conditions used to predict them.

A model-based approach to prescribing mitigations is predicated on the assumption that there is a strong positive relationship between bat activity, as measured by echolocation recorders, and bat fatalities. Validity of this assumption has yet to be conclusively demonstrated and in some cases questioned (Cryan and Brown 2007, Cryan and Barclay 2009). Our study was not designed to explicitly test this assumption and statistical comparisons were not possible because we did not know on which night fatalities occurred. Nevertheless, the following observations provide cautious support for its validity. Bat echolocation activity at DWEF was low but corresponded well with the magnitude, timing, and species composition of bat fatalities found during a separate study of the first year of operations (Chatfield et al. 2009). Weekly and bi-weekly fatality searches, corrected for searcher efficiency and scavenger removal, resulted in an estimate of 2.17 bat fatalities/MW/year (90% CI: 1.37–3.41; Chatfield et al. 2009). This places DWEF on the low end of observed fatality rates in North America (Arnett et al. 2008, NWCC 2010) and is consistent with the low echolocation activity rates we observed. The 21 observed bat fatalities were comprised by *T. brasiliensis* ($n = 10$), *L. xanthinus* ($n = 3$), *L. cinereus* ($n = 2$), *E. fuscus* ($n = 1$), *N. femorosaccus* ($n = 1$), and 4 bats of undetermined species. The relative contribution of these species roughly corresponds to the proportion of echolocation recordings we were able to assign to each of these species. In particular, *T. brasiliensis* accounted for the largest proportion of fatalities and echolocation recordings assigned to species. Further, most fatalities were observed in either autumn ($n = 16$) or spring ($n = 2$; Chatfield et al. 2009) which corresponds well with peaks in echolocation activity in our study. Echolocation activity of LowF bats during the week prior to observation of a fatality was twice as high (0.54 passes/dn, SD = 0.52, $n = 12$) than in weeks prior to a survey in which no fatalities were observed (0.23 bat passes/dn, SD $= 0.39$, $n = 42$). Further, for 13 of 17 fatalities identified to species, we assigned $\geq$1 bat pass to that species during the week prior to it being found as a fatality. We only identified 5 *L. xanthinus* bat passes, yet 4 of these were recorded during the week prior to observation of *L. xanthinus* bat fatality.

These findings contribute to a growing notion that echolocation monitoring, if properly conducted, may provide a reliable index to expected bat fatality levels at wind energy facilities (Kunz et al. 2007*a*, Baerwald and Barclay 2009). Establishing a link between pre-construction echolocation monitoring and expected fatality levels once turbines are built and operational is more difficult because bats may be attracted to turbines (Cryan and Brown 2007, Kunz et al. 2007*b*, Horn et al. 2008). Although timing of our study was such that we could not fully address this question, there was no obvious trend in patterns of bat presence or activity to indicate bat activity patterns changed in response to presence of turbines on site. However, the location of DWEF near a large existing wind energy development may have dampened any attraction effect relative to facilities sited in previously undeveloped areas. Consequently, evaluating links between pre-construction bat activity and fatality rates across a variety of locations and habitats should remain a monitoring and research priority.

MANAGEMENT IMPLICATIONS

Our findings suggest that combining data from thoughtfully deployed, continuously operated, echolocation detectors with meteorological data is an effective way to predict presence of LowF bats at wind energy facilities. In fact, though echolocation monitoring is frequently used as a tool to predict where risk to bats might be high, its more effective use may be to predict when risks are high. In other words, echolocation monitoring may be at least as important for informing mitigations (e.g., changes in turbine operations) as it is for avoiding sites that may pose greater risk to bats. Importantly, because monitoring of bat echolocation activity, in addition to meteorological conditions, has become standard practice at proposed wind energy facilities, the components necessary to model bat activity are now available from most facilities. A key consideration is that detectors must be placed at heights suitable for detecting bats at greatest risk and in sufficient densities to accurately characterize bat activity levels. We found that 4–14 detectors at an elevation of 52 m were required to achieve a 95% detection probability for LowF bats at a 40 MW wind energy facility in the southern California desert. We suspect that similar densities of detectors would be required to describe LowF bat activity at other wind energy facilities of similar size, in homogenous habitats, of the southwestern United States. Further work is necessary to quantify effective detector heights and densities in other habitats and geographic regions.

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