AWWI TECHNICAL REPORT

Are Bat Activity and Mortality Best Predicted by Weather Measured On-Site or at Off-Site Regional Airports?

Prepared by:
Rhett E. Good, Goniela Iskali, Rebecca Clark, Paul Rabie, Karl DuBridge, Kevin Murray

October 14, 2020

AWWI Technical Report:

Are Bat Activity and Mortality Best Predicted by Weather Measured On-Site or at Off-Site Regional Airports?

American Wind Wildlife Institute
1990 K Street NW, Suite 620
Washington, DC 20006
www.awwi.org

For Release October 14, 2020

AWWI is a partnership of leaders in the wind industry, wildlife management agencies, and science and environmental organizations who collaborate on a shared mission: to facilitate timely and responsible development of wind energy while protecting wildlife and wildlife habitat.

Find this document online at https://awwi.org/resources/patterns-of-bat-activity-and-mortality

Acknowledgments

Thank you to AWWI's industry and conservation Partners for their support. AWWI thanks the project funders. Thank you to EDF Renewables for providing access to the site and help with important logistics, and NRG Systems for installing and supporting BAMM. Thank you to Mike Azeka, who designed the enclosure for the Anabat monitoring systems, and installed and maintained acoustic bat detectors. WEST also thanks Julie Bushey, Catherine Read, Steven Neumann, Jaclyn Adams, Jacob Ebersole, Gedaliah Krasner, Dustin Baldwin, Brian Beste, Emma Keuster, and Anne-Marie Rothermel for their work on this project.

Prepared By
Western EcoSystems Technology, Inc.
Rhett E. Good
Goniela Iskali
Rebecca Clark
Paul Rabie
Karl DuBridge
Kevin Murray

Suggested Citation Format
Good, R., G. Iskali, R. Clark, P. Rabie, K. DuBridge, and K. Murray. 2020. AWWI Technical Report: Are Bat Activity and Mortality Best Predicted by Weather Measured On-Site or at Off-Site Regional Airports? Washington, DC. Available at www.awwi.org.

Contents

Tables

Figures

Executive Summary

Curtailing the operation of wind turbines when wind speeds are low is a common and effective method used to reduce bat mortality. However, bats are not always present or killed during periods of lower wind, and additional research is needed to understand the factors that influence bat migration activity and mortality, which could be used to develop smarter curtailment regimes that maximize energy production while reducing bat mortality. Pilot Hill Wind, LLC is operating the Pilot Hill Wind Farm (PHWF) and Kelly Creek Wind, LLC is operating the adjacent Kelly Creek Wind Farm (KCWF; Projects) in Kankakee, Ford, and Iroquois counties, Illinois. Pilot Hill Wind, LLC and Western EcoSystems Technology, Inc. were awarded funding from the American Wind and Wildlife Institute to enhance ongoing research at both facilities in 2018 to quantify potential relationships between bat activity, bat fatalities, and weather patterns that could be used to implement cost-effective strategies for reducing bat mortality. Previous studies at the PHWF documented relationships between precipitation occurring on-site and bat fatalities recorded 48-hours later, and we hypothesized the lag in fatalities following precipitation could be because bat migration initiated outside the PHWF was being triggered by broader weather fronts in the region.

The objectives of this study were to 1) determine if weather data collected at off-site locations would be a better predictor of bat activity and fatalities than weather data collected on-site, 2) identify if weather variables could be used to optimize curtailment by increasing energy production when bats were not present, and 3) determine if bat activity and fatalities were concentrated in portions of the night.

Fifteen turbines were searched within 80 meters (m; 263 feet [ft]) of the turbine base at the PHWF; 10 of these were searched daily and five were searched twice a week. Anabat SD2 detectors were installed on eight turbines at the PHWF and four at the adjacent KCWF to record bat activity. Only bat carcasses estimated to have died the previous night from the PHWF were used to quantify relationships between bat mortality and weather. Acoustic data from PHWF and KCWF were used to quantify relationships between bat activity and weather. NRG Systems' Bat and Avian Mortality Monitoring System (BAMM), a camera based carcass detection system, was installed on 10 turbines at PHWF in an effort to determine the time of night when a fatality occurred.

The capabilities of logistic regression to predict migratory tree bat activity and fatalities were examined. Fatalities and activity data were divided into exploratory and validation data sets to test model performance. Barometric pressure and wind direction from 12 different airports located within 161 kilometers (km; 100 miles [mi]) of both Projects were used as measures of potential high and low pressure systems that may pass through the region and trigger bat activity and migration. Twelve weather variables collected from on-site meteorological towers and turbine sensors were included as potential covariates, including day of study, wind speed, air temperature, wind direction, precipitation, relative humidity, and barometric pressure. Estimated moonlight and peak moonlight measured at the Kankakee Airport, located 9.5–41.2 km (5.9–25.6 mi) from turbines, were included as variables, and assumed representative of conditions at both Projects. Wind direction recorded 48.0–121.0 km (29.8–75.2 mi) north of both Projects at airports along the Kankakee River were better predictors of hoary and silver-haired bat fatalities than weather variables recorded on-site. Eastern red bat activity was best predicted by combinations of changing barometric pressure and wind direction recorded on-site. Both the PHWF and KCWF lack significant forested areas within 10.0–19 km (6.2–1.8 mi) of both Projects. The lack of forested areas near the Project, the lack of bat calls recorded within 120 minutes (min) of sunset, and the selection of weather variables from airports located 48-121 km north of the Projects (as the best predictors of fatalities) suggest hoary and silver-haired bat migration and subsequent occurrence in both Projects were influenced by larger scale weather fronts away from both Projects. This was the first study to quantify data from broad scales, and suggests smart curtailment approaches for hoary and silver-haired bats could be improved by utilizing a combination of on-site variables such as wind speed and

temperature, with off-site measurement of broader weather fronts to develop smarter curtailment approaches.

The BAMM system identified the time of death of four hoary bat carcasses and one eastern red bat carcass; this was the first research study to assign a time of death to a bat carcass. The time of death for the five fatalities occurred between 2300 H and 0230 H. The wind speeds were variable on the nights when all five bat carcasses were found, ranging from 0 to approximately 12 meters/second (m/s; 26.8 miles per hour [mph]); all five fatalities occurred when wind speeds were between 2.8 and 3.9 meters per second. One of the five bats was killed when wind speeds were below cut-in speed (3.0 m/s [6.7 mph]). The five fatalities occurred during periods of the night when wind speeds were declining relative to periods just prior to the time of death. All five carcasses detected by BAMM occurred within 15.0 m (49.2 ft) of the base of wind turbines.

No bat activity was recorded until 90 min after sunset, and few calls were recorded until 120 min after sunset; activity occurred until sunrise. Both Projects lack significant forest cover within 10.0–19.0 km (6.2–11.8 mi) of turbines, which suggests bats have to fly significant distances before reaching turbines at both Projects. Our results suggest curtailment could be delayed until 90–120 min after sunset with little impact on bat fatalities at both Projects, and potentially other projects located long distances from significant amounts of forest habitat and roost sites could similarly delay curtailment.

Introduction

Migratory tree bat fatalities at wind-energy facilities throughout North America are a growing concern, as evidenced by recent work that modeled the potential population trajectories of the hoary bat (Lasiurus cinereus) relative to wind development (Frick et al. 2017). Wind turbine curtailment, a strategy involving automatically putting turbines in a stopped mode at night during high bat risk periods, is a documented method to reduce fatalities of nearly all bat species impacted by wind turbines (Arnett et al. 2009, Good et al. 2012, Arnett et al. 2013, Martin et al. 2017). This method, referred to as “cut-in speed curtailment” results in lost energy production at night and causes adverse impacts to wind project economics if not optimized. The wind industry is in need of strategies that reduce bat mortality while minimizing lost energy from curtailment unlikely to contribute to reducing bat fatalities. Martin et al. (2017) applied cut-in speed curtailment based only on date, sunset and sunrise times, wind speed, and air temperature to determine when turbines will be curtailed. Attempts to consider other environmental factors when triggering curtailment have been hampered by the high cost of intense carcass searches and difficulty in identifying when a fatality occurred.

Pilot Hill Wind, LLC owns and operates the Pilot Hill Wind Farm (PHWF) and Kelly Creek Wind, LLC owns and operates the adjacent Kelly Creek Wind Farm (KCWF) in Kankakee, Ford and Iroquois counties, Illinois. Western EcoSystems Technology, Inc. (WEST) has completed multiple years of post-construction monitoring and research at both facilities designed to estimate the effectiveness of curtailment and acoustic bat deterrents for reducing bat fatalities. Pilot Hill Wind, LLC and WEST were awarded funding from the American Wind and Wildlife Institute to enhance ongoing research at both facilities in 2018 to quantify potential relationships between bat acoustic activity, bat fatalities, and weather patterns that could be used to focus curtailment when it is most likely to be beneficial for reducing bat fatalities. Previous studies at the PHWF documented relationships between precipitation recorded on-site and bat fatalities recorded 48-hours later, and we hypothesized the lag in fatalities following precipitation could be because bat migration initiated outside the PHWF was being triggered by broader weather fronts in the region.

The objectives of this study were to 1) determine if weather data collected at off-site locations would be a better predictor of bat activity and fatalities than weather data collected on-site, 2) identify if weather variables could be used to optimize curtailment by determining what factors were associated with bat presence and bat fatalities, and 3) determine if bat activity or fatalities was concentrated in portions of the night. The ultimate goal of the study was to determine whether these factors could be applied to further refine cut-in speed curtailment and reduce energy loss.

Study Area

The PHWF and KCWF are adjacent wind-energy facilities in north-central Illinois. The PHWF became operational in 2015 and consists of 98 1.79-megawatt (MW) and five 1.85-MW wind turbines. Each turbine has an 80-meter (m; 263-foot [ft]) hub height; the 1.79-MW turbines have an 87-m (285-ft) rotor diameter and the 1.85-MW turbines have a 100-m (328-ft) rotor diameter. The KCWF became operational in 2017 and consists of 92 2-MW turbines with 80-m hub height and 100-m rotor diameter. All turbines have a manufacturer cut-in speed of 3.0 meters per second (m/s; 6.7 miles [mi] per hour [mph]).

The PHWF includes approximately 9,427.6 hectares (ha; 23,296.2 acres [ac]) within 1.0 kilometers (km; 0.6 mi) of turbines. According to the National Land Cover Database (Yang et al. 2018, Multi-Resolution Land Characteristics [MRLC] 2019), cultivated cropland and developed areas are the most dominant land use types, totaling 97.5% of the overall study area (Table 1, Figure 1). The remaining area (2.5%) is composed of small areas of hay/pasture, deciduous forest, open water, emergent herbaceous wetlands, shrub/scrub and herbaceous land.

The land cover types between the PHWF and KCWF are very similar. The KCWF includes 9,791.5 ha (24,195.4 ac) within 1.0 km of turbines. Cultivated cropland and developed areas are the most dominant land use types, totaling 98.4% of the overall study area (Yang et al. 2018, MRLC 2019; Table 1, Figure 1). Developed areas at both Projects are generally confined to residences and farms scattered throughout. The remaining area (less than 2%) is composed of small areas of hay/pasture, deciduous forest, herbaceous land, and woody wetlands.

Table 1. The land cover types, coverage, and percent (%) composition within 1.0 kilometer (0.6 miles) of turbine locations at the Pilot Hill (PHWF) and Kelly Creek Wind Farms (KCWF), Kankakee, Ford, and Iroquois counties, Illinois.

Land Cover Types	Coverage (Acres at PHWF)	% Composition at PHWF	Coverage (Acres at KCWF)	% Composition at KCWF
Cultivated Crops	21,461.6	92.1	22,417.7	92.7
Developed, Low Intensity	689.9	3.0	690.0	2.9
Developed, Open Space	546.4	2.3	652.1	2.7
Hay/Pasture	506.4	2.2	375.9	1.6
Deciduous Forest	48.0	0.2	22.7	0.1
Developed, Medium Intensity	13.3	0.1	24.6	0.1
Emergent Herbaceous Wetlands	12.0	0.1	0	0
Open Water	10.1	<0.1	0	0
Shrub/Scrub	5.6	<0.1	0	0
Herbaceous	1.3	<0.1	6.2	<0.1
Developed, High Intensity	1.5	<0.1	4.9	<0.1
Woody Wetlands	0	0	1.3	<0.1
Total*	**23,296.2**	**100**	**24,195.4**	**100**

Data from National Land Cover Database (Yang et al. 2018, Multi-Resolution Land Characteristics 2019).

*Totals may not equal values shown due to rounding.

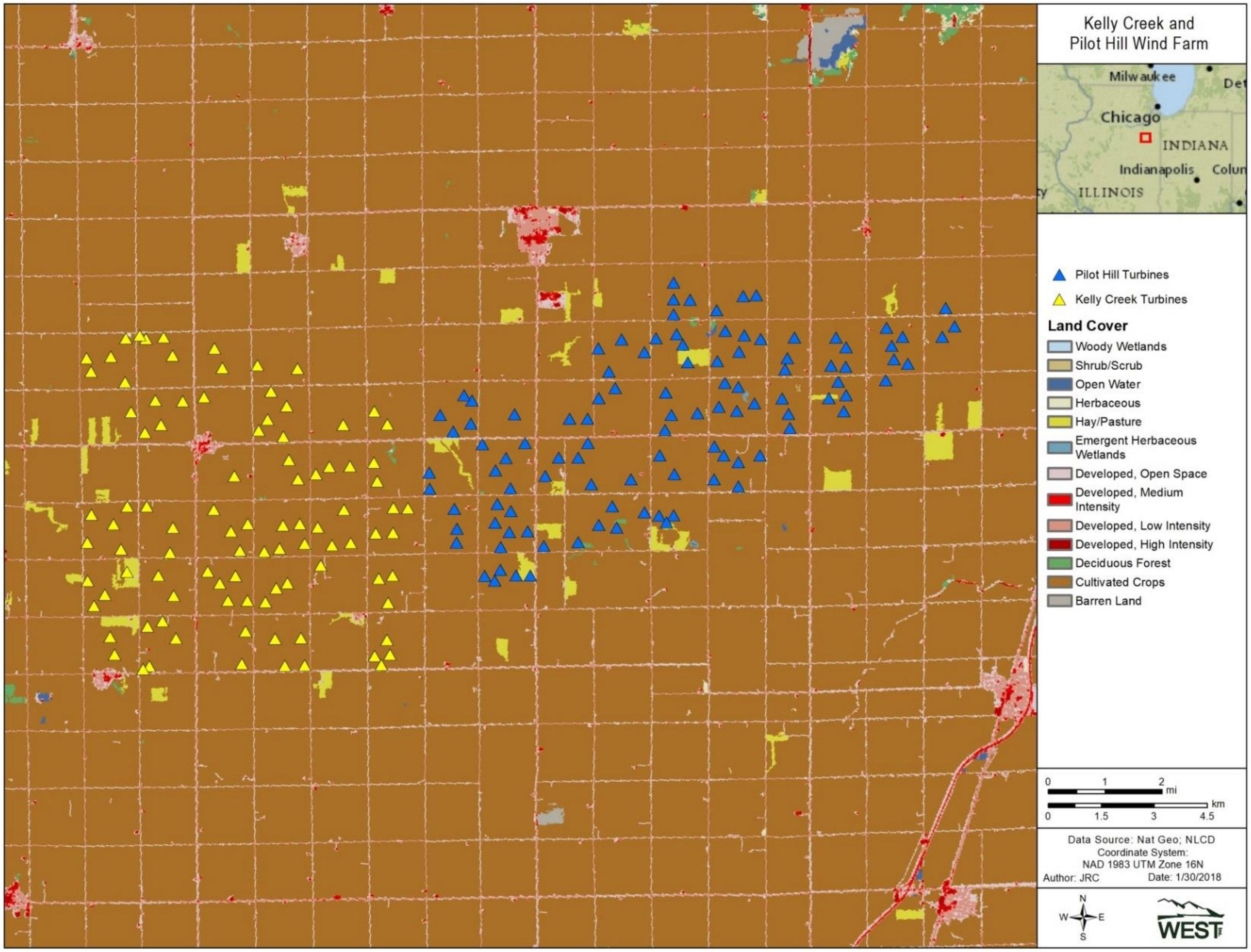

Figure 1. Land cover map and turbine locations for the Pilot Hill and Kelly Creek Wind Farms.

Twelve bat species have potential ranges that overlap the PHWF and KCWF (Feldhammer et al. 2015). The lack of forested habitat within both Projects limited the potential for many bat species to occur during the summer maternity season. Species most commonly detected within the PHWF and KCWF during previous acoustic and mortality surveys included the eastern red bat (*Lasiurus borealis*), hoary bat, silver-haired bat (*Lasionycteris noctivagans*), and big brown bat (*Eptesicus fuscus*; Iskali et al. 2019b).

Methods

Studies at the PHWF and KCWF were completed during the fall (August 1 – October 15, 2018), and included:

- Bat carcass surveys
- NRG Systems' Bat and Avian Mortality Monitoring System (BAMM)
- Bat acoustic monitoring surveys
- Regression analyses to determine potential relationships between:
    - Bat acoustic activity and environmental variables at Projects and surrounding airports
    - Bat fatalities and environmental variables at Projects and surrounding airports
    - Bat activity and fatalities

Bat Carcass Survey

Fifteen turbines were searched as circular cleared plots at the PHWF within 80 m of the turbines; 10 were searched daily to increase the probability of finding bats estimated to have died the previous night, and five were searched twice weekly (Figure 2a). Fifteen turbines were searched as circular cleared plots weekly at the KCWF within 60 m (197 ft) of turbines (Figure 2b).

We selected turbines for the study using a systematic sample with a random start. Turbines within PHWF were searched as part of a study designed to estimate the effectiveness of deterrents for reducing bat mortality (Iskali et al. 2019b). The study was limited to turbines within the eastern half of PHWF to reduce costs associated with the installation and operation of the acoustic bat deterrent (Figure 2a); all turbines were available for sampling at KCWF. All turbines included in the analysis described within this report operated at a manufacturer cut-in wind speed of 3.0 m/s, and were not outfitted with bat deterrents. Turbines were not feathered prior to reaching manufacturer cut-in speed.

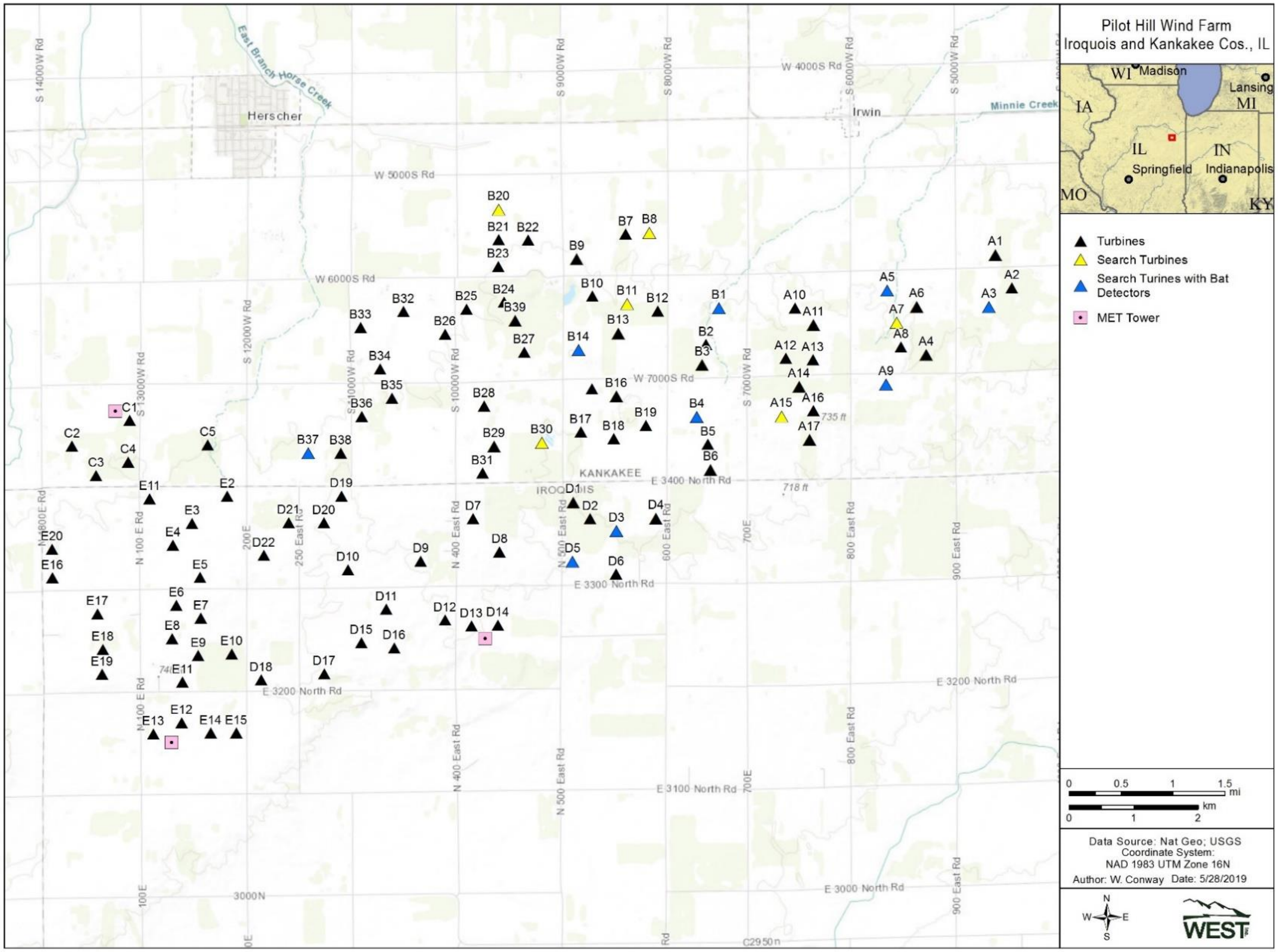

Figure 2a. Locations of meteorological tower and turbines, including search turbines and turbines outfitted with Anabat detectors at the Pilot Hill Wind Farm.

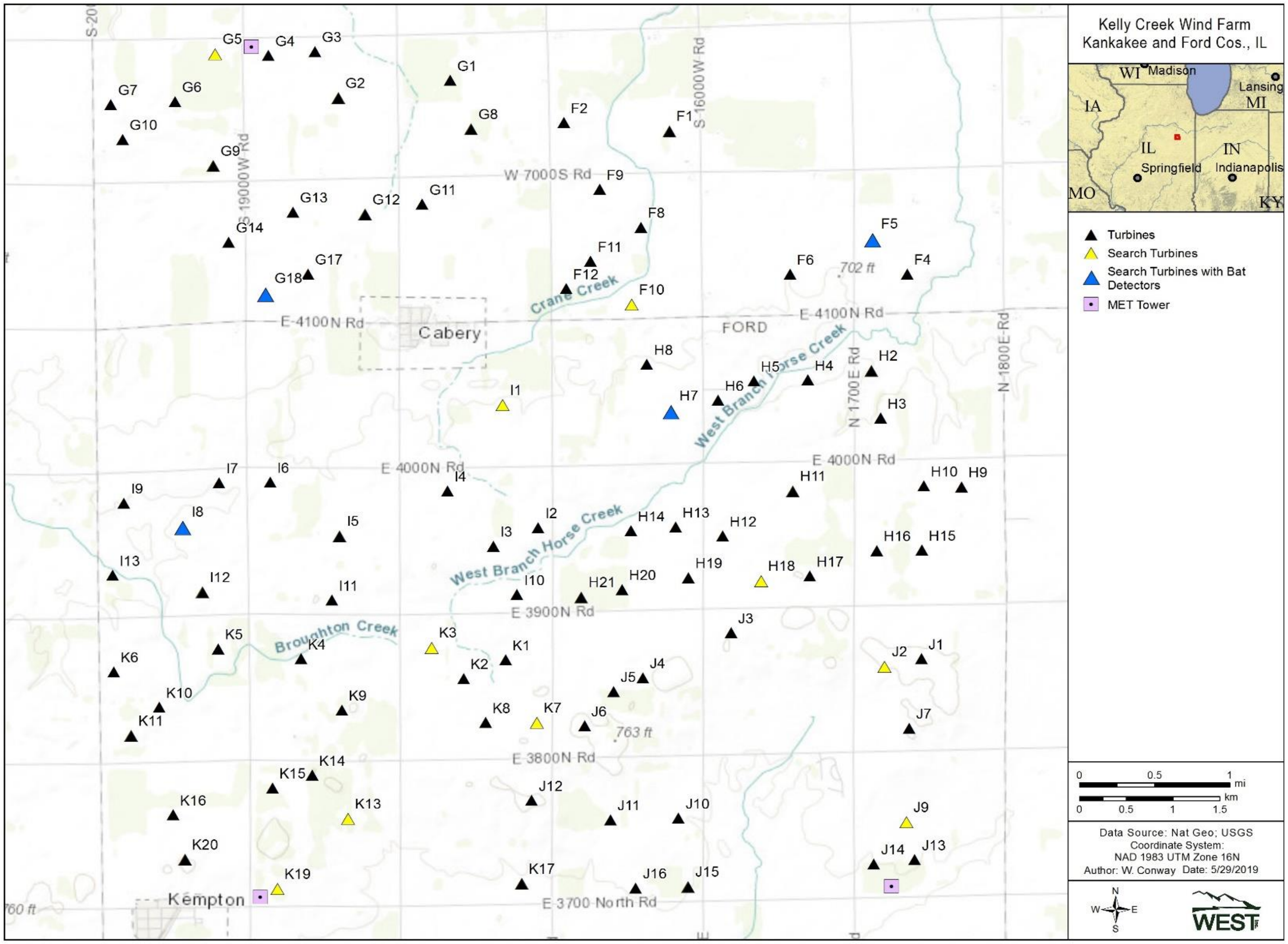

Figure 2b. Locations of meteorological tower and turbines, including search turbines and turbines outfitted with Anabat detectors at the Kelly Creek Wind Farm.

The carcass surveys occurred August 1 – October 15, 2018, which encompasses the annual period during which bat mortality is highest in the US (Arnett et al. 2008). Standardized searches under turbines were used to count the number of bat carcasses observed. Vegetation within each search plot was mowed regularly to a height of approximately 10.0 centimeters (4.0 inches) to increase the probability of searchers detecting carcasses. A clearing search was conducted July 26 – 31, 2018, to remove carcasses estimated to have died prior to the beginning of the study. Field technicians were trained in proper search techniques prior to conducting carcass searches. Carcass searches began at first light and ended by 1700 H. Technicians walked transects five m (16 ft) apart at a rate of approximately 45–60 m per minute (min; 148–197 ft per min) along each transect, and scanned the area on both sides out to approximately 2.5 m (8.2 ft) for carcasses, thereby surveying the entire search area. The study was completed under Illinois Department of Natural Resources [IDNR] General Collection permit NH18.5223-1, USFWS Native Endangered and Threatened Species Recovery Permit TE234121-9, and IDNR Endangered and Threatened Species Permit 2514).

Bat and Avian Mortality Monitoring System

The BAMM was designed and installed by NRG Systems. This system used multiple cameras to detect the time when a bat carcass falls to the ground. The system was composed of six cameras temporarily mounted on the turbine tower, and pointed down toward the ground around the turbine pad (Figure 3). By using multiple cameras mounted around the turbine, the system was designed to detect bat carcasses within a full 360 degrees around the turbine out to 25 m (82 ft) from the tower; however the specifications of the system are proprietary. The system acquired images through the cameras every 30 seconds and then compared the most recent image to an average of the previously captured images (Figure 4). This allowed the system to detect if something in the field of view had changed (such as the arrival of a bat carcass). If a change was detected, the system classified the change using proprietary algorithms to determine if the change was a carcass or not, in order to reduce false positives. The BAMM systems were deployed at ten wind turbines at PHWF that a field technician searched daily; these are also a subset of the same 30 turbines that were searched for fatalities as described above. BAMM results were compared to carcasses found during carcass surveys to identify the time of night when bat fatalities occurred. Weather data collected from the time of death were summarized and compared to weather conditions over the entire evening.

Figure 3. A photograph showing NRG Systems' Bat and Avian Mortality Monitoring System. The cameras were mounted approximately 7.6 meters (25.0 feet) above the ground and pointed downward.

Figure 4. An example photograph recorded by NRG Systems' Bat and Avian Mortality Monitoring System.

Bat Acoustic Monitoring Survey

EDF Renewables (EDF) installed and maintained one Anabat SD2 detector (Anabat) per turbine at PHWF (A3, A5, A9, B1, B4, B14, B37, D3 and D5) and KCWF (F5, G18, H7, and I8) on turbines operating at manufacturer cut-in speed (3.0 m/s; Figures 2a and 2b). The Anabats were oriented toward the turbine rotor and equipped with newly developed filters (Anabat filters) by Titley Scientific™, Columbia, Missouri, designed to reduce wind turbine noise below bat call frequencies typically found at the Projects by sharply filtering the microphone signal below 19 kilohertz (kHz). The Anabats were also encased in noise-isolation enclosures developed by EDF. The combined noise control measures were designed to reduce mechanical, aerodynamic, and electrical noise from all wind turbine components including the gearbox, generator, blades, hydraulic system, inverters, blowers, and yaw motors. These measures allowed increased Anabat sensitivity settings in the lower half of the rotor-swept zone, tower, and under-nacelle areas, which have been shown to be areas of high bat activity by other studies. The Anabats operated July 31, – October 15, 2018 at both Projects.

A bat pass was defined as a sequence of at least two echolocation calls (pulses) produced by an individual bat with no pause between calls of more than one second. The terms “bat pass” and “bat call” are used interchangeably throughout this report. Bat pass rates represent indices of bat activity and do not represent numbers of individuals. An experienced bat biologist determined the number of bat passes using Analook software (Titley™ Scientific, Columbia, Missouri).

All sound files collected by the detectors were analyzed. Once the filtering process was completed, a qualified bat biologist with extensive acoustic identification experience visually identified all bat call sequences to species or species group. The bat biologist performed a visual comparison of echolocation call metrics (e.g., minimum frequency, slope, duration) to reference calls of known bats. Bat calls were identified to the following species or species groups 1) hoary bat, 2) big brown bat/silver-haired bat, 3) eastern red bat, 4) evening bat (*Nycticeius humeralis*, 5) tri-colored bat (*Perimyotis subflavus*), and 6) *Myotis* species. In some cases, bat calls were classified as species groups or as either high- (over 30 kHz minimum frequency) or low-frequency (under 30 kHz minimum frequency) unknowns if they lacked distinctive diagnostic characteristics, had fragmented calls, or if they contained approach-phase or feeding buzz calls.

Analyses of Bat Activity, Weather, and Bat Carcasses Found on Previous Evening

Regression Analysis of Bat Activity on Weather

Acoustic bat-call data from both the PHWF and KCWF were used to quantify relationships between bat activity and weather. Acoustic bat-call data were analyzed to determine if bat activity could be predicted by weather data collected on-site or weather data collected off-site at airports. EDF supplied on-site weather data gathered at meteorological (met) towers on the facility, summarized in 10-min intervals. Three met towers were present at each facility, but data gaps existed for each met tower. Anabat data were paired with met data to construct the most complete data set possible and to provide weather data from the nearest met tower to the acoustic detectors. Selection of on-site data source (i.e., which met tower or turbine sensors) followed advice from EDF in-house meteorologists. The advice was based on whether turbine wakes, location on the site, and distance to a met tower were likely to introduce errors or changing offsets in the data, and in consideration of data gaps. For example, barometric pressure, wind direction, and air temperature did not vary significantly across the distances between subject turbines, so met towers with fewer data gaps were used for these covariates. Conversely, rainfall and relative humidity may vary across the site based on location, so the nearest met tower was used for these data sources. Further, wind speed is known to vary based on location, wakes, wind direction, and anemometer offset, so a different method was used to develop the wind speed data, detailed below. It should be noted a met tower has multiple sensors, and one type of sensor may have failed to provide data for a few days, but the other sensors were working properly, so the met tower chosen and data sets considered these factors. The largest data gap was at met tower 8007, where a rain gage was missing 18% of the data.

Pilot Hill Anabat Data and Metrological Data Pairing — The study turbines at PHWF were grouped on the eastern half of the site, so one met tower located in the eastern portion of PHWF was chosen as representative for much of the data. The wind direction, air temperature, and barometric pressure data were taken from met tower 8003, while the relative humidity and rain gauge data were taken from the closest met tower, 8006. Wind speed was calculated as the mean of the nacelle wind speed sensors of the subject turbine and four nearby turbines. This was used in order to reduce the effects of turbine wakes, wind direction, and sensor offset differences between individual nacelle sensors.

Kelly Creek Anabat Data and Metrological Data Pairing — The air temperature, barometric pressure, and relative humidity data were taken from met tower 8006. The study turbines at Kelly Creek were spread around the site and were much farther from a single met tower than at Pilot Hill, so multiple met towers were chosen based on nearest location. The rain gauge, wind direction, and wind speed data were taken from met towers 8003, 8006, 8007 or PH Met 2, based on advice from EDF meteorologists.

For analysis, all weather and bat call data had to be on similar time intervals. Airport weather data were available on 20-min intervals (see below) so all weather variables except barometric pressure from the Projects were averaged over 20-min intervals. The maximum barometric pressure was recorded for the 20-min intervals.

Airport weather data from airports within approximately 161 km (100 mi) of the Projects (Figure 5) were used to determine if weather patterns outside of the Projects, such as storm fronts, affected bat migration and bat activity at the Projects (Table 2). Wind direction and barometric pressure were identified as two variables that would represent the passage of low or high-pressure systems and were used as predictive variables in this analysis. Barometric pressure entered our models as the change in barometric pressure over a 1-, 2-, or 3-hour period. For on-site weather variables, we used the current difference in pressure over the change period. For off-site weather variables, we used the same 1-, 2-, or 3-hour pressure change variable, but also tested time-lagged variables under the presumption that bats responding to weather fronts at distant locations would take some time to travel and encounter the wind farm.

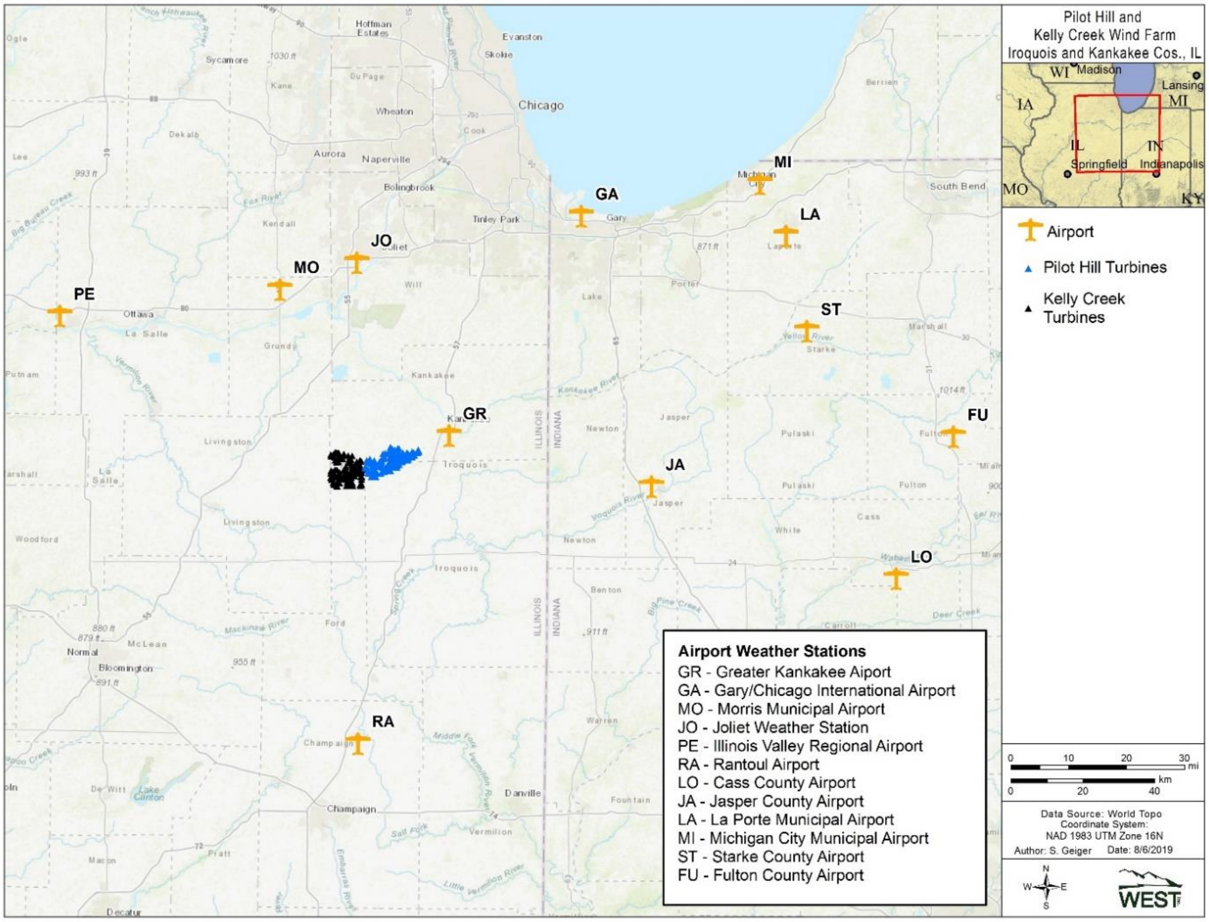

Figure 5. The location of the Pilot Hill and Kelly Creek Wind Farms relative to airports where data were used to assess regional weather pattern effects on bat activity and fatalities.

Table 2. Airports included in the analysis within 161 kilometers (km; 100 miles [mi]) at the Pilot Hill (PHWF) and Kelly Creek Wind Farms (KCWF), Kankakee, Ford and Iroquois counties, Illinois (IL).

		Distance from PHWF		Distance from KCWF	
Airport Location	**Airport Code**	**mi**	**km**	**mi**	**km**
Kankakee, IL	GR	5.9	9.6	15.9	25.6
Gary, Indiana (IN)	GA	49.3	79.4	57.1	91.8
Morris, IL	MO	33.1	53.2	29.8	48.0
Joliet, IL	JO	32.5	52.2	33.1	53.2
Peru, IL	PE	58.7	94.4	52.6	84.7
Rantoul, IL	RA	46.2	74.4	44.6	71.8
Logansport, IN	LO	85.5	137.7	94.0	151.3
Rensselaer, Jasper County, IN	JA	40.7	65.6	50.0	80.4
La Porte, IN	LA	73.7	118.6	83.3	134.0
Michigan City, IN	MI	75.0	120.7	84.1	135.4
Starke County, IN	ST	70.3	113.1	80.4	129.3
Fulton County, IN	FU	92.6	149.0	102.3	164.7

The distances that bats encountering the Projects in our study had to travel in a single night was unknown and has received little study. Weller et al. (2016) tagged three hoary bats at Humboldt Redwoods State Park, California in September 2014 during fall migration and documented nightly movements ranging from 6.4 km (3.9 mi) to 67.8 km (42.1 mi). Castle et al. (2015) documented nightly movements of a hoary bat in California of up to 70.0 km (43.5 mi) during fall migration. Therefore, the 161 km (100 mi) distance used in this analysis was assumed to represent up to two days of migration.

Weather variables, barometric pressure, and wind direction from airports were summarized in 20-min intervals with some data gaps. It was necessary to have all the weather data on the same time intervals in order for the Anabat data to be correctly paired for the analysis. Across all airports, 5.9% of the data was missing for barometric pressure and 2.2% for wind direction data was missing. Imputation, a multivariate technique for modeling missing data values, was applied to the airport weather data to account for these data gaps. Time stamps on the weather data from airports were adjusted to match the nearest 20-min intervals that matched the time stamps on the weather data from the Projects. Data available for regression analysis are summarized in Tables 3a (data from the Projects) and 3b (data from airports). Moonlight conditions have been proposed as correlates of bat activity (Cryan and Brown 2007). Estimated moonlight (Sunset to 1 AM) and peak moonlight (Sunset to Sunrise) data from Kankakee, Illinois were also used as possible predictors for the regression analysis (Time and Date AS 2018, WeatherForYou.com 2019). The estimated moonlight (Sunset to 1 AM) was calculated by multiplying the following three variables: percent illumination at highest point overhead (percent of maximum moonlight due to moon phase), visibility estimate from hourly weather (Sunset to 1 AM), and moonrise timing factor (Sunset to 1 AM). Peak moonlight (Sunset to Sunrise) was calculated by multiplying the following three variables: percent illumination at highest point overhead (percent of maximum moonlight), visibility estimate from hourly weather (Sunset to Sunrise), and moonrise timing factor (Sunset to Sunrise).

Table 3a. On-site predictor variables available for regression analysis.

Variable and Units	Use in the Model
Day of Study	as a continuous variable
Quadratic of Day of Study	as a continuous variable
Wind speed (meters per second [m/s])	as a continuous variable
Quadratic of Wind speed (m/s)	as a continuous variable
Air temperature (degrees Celsius)	as a continuous variable
Wind direction (compass degrees; measured at the meteorological tower)	Cardinal direction: N (315-45), E (45-135), S (135-225), and W (225-315)
Precipitation (millimeters)	as a continuous variable
Cumulative proportion of one night with no rain	as a continuous variable
Cumulative proportion of two nights with no rain	as a continuous variable
Cumulative proportion of three nights with no rain	as a continuous variable
Relative Humidity (percent)	as a continuous variable
Barometric Pressure (millibar)	as a continuous variable to account for barometric pressure changes from 1 hours, 2 hours, and 3 hours prior to the time stamps
Estimated Moonlight (Sunset to 1 AM)	as a continuous variable
Peak Moonlight (Sunset to Sunrise)	as a continuous variable

Table 3b. Off-site airport predictor variables available for regression analysis.

Variable and Units	Use in the Model
Barometric Pressure (millibar)	as a continuous variable to account for barometric pressure changes from 1 hours, 2 hours, and 3 hours prior to the time stamps with 0-, 6-, 12-, 18-hour time lags
Wind Direction (compass degrees)	Cardinal direction: N (315-45), E (45-135), S (135-225) and W (225-315) with 0-, 6-, 12-, 18-hour time lags

Anabat data were summarized to match the temporal resolution of the weather data, with counts of bat calls summed over 20-min intervals. Bat calls were summarized to represent periods of “high” bat activity and periods of “low” bat activity, because high and low activity periods are likely more applicable management classifications than counts of bat calls. To identity periods of high bat activity, the bat activity data were transformed to a binary response where a “success” was scored as counts exceeding a particular number of bat calls per 20-min interval (i.e. “time interval with high activity”) and a “failure” was scored as counts not exceeding that particular number of bat calls per 20-min interval (i.e. “time interval with low activity”). Thresholds for “high bat activity” were developed by examining plots that showed the fraction of the total observed bat calls that were scored in “high activity” periods as a function of the chosen threshold (e.g., Figure 6). Higher thresholds are often associated with easier-to-fit models, but lower thresholds are more useful in that they have the potential to predict more of the total bat activity, and our choice of thresholds was an attempt to balance these two competing concerns. In this sense, the terms “high activity” and “low activity” are relative terms of convenience. The use of the particular number of bat calls per interval resulted in 83–100% of all bat calls falling within time intervals with “high” activity (Table 4).

Table 4. Binary Response Transformation for Bat Activity.

Facility	Species	High Activity (Number of calls in a 20-minute period)	Percent of Bat Calls Falling Within High Activity
Both	All	>1	83
Both	Eastern red bat	>0	100
Both	Hoary bat	>1	80
Both	Big brown/silver-haired bat	>0	100
Pilot Hill	All	>0	100
Pilot Hill	Eastern red bat	>0	100
Pilot Hill	Hoary bat	>0	100
Pilot Hill	Big brown/silver-haired bat	>0	100
Kelly Creek	All	>0	100
Kelly Creek	Eastern red bat	>0	100
Kelly Creek	Hoary bat	>0	100
Kelly Creek	Big brown/silver-haired bat	>0	100

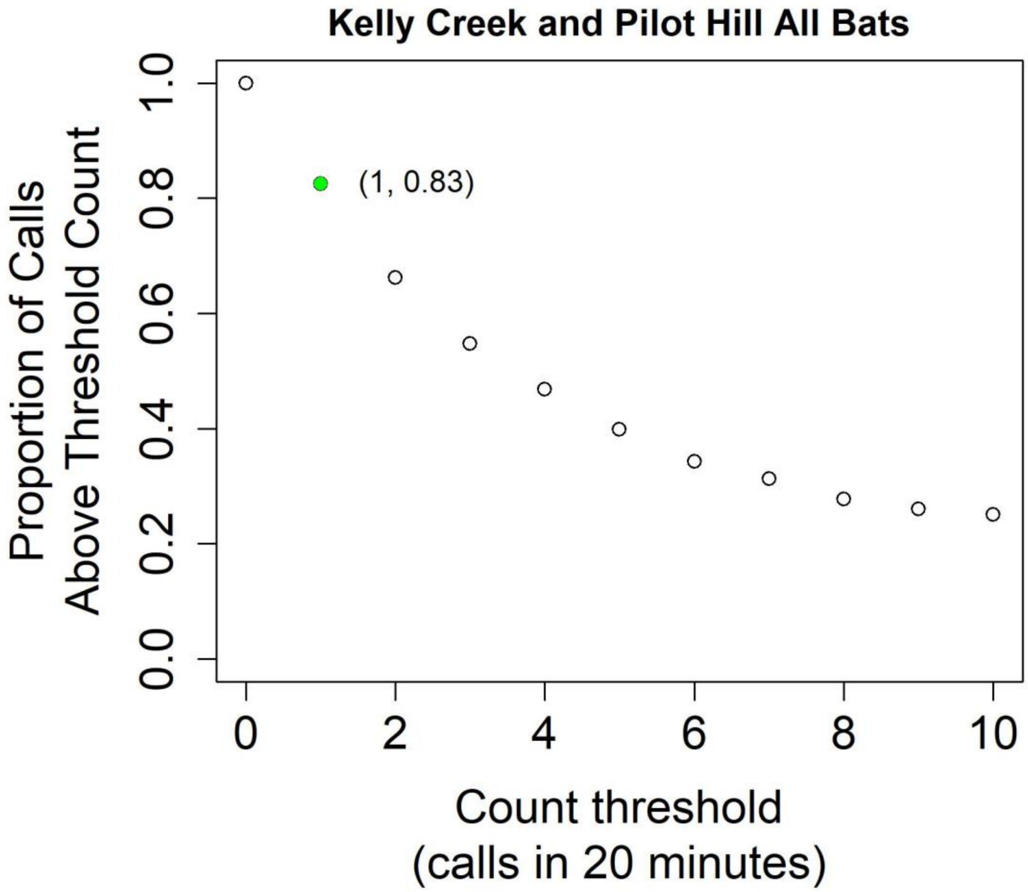

Figure 6. Illustrates the total observed bat calls for both Kelly Creek and Pilot Hill scored in “high activity” periods as a function of the chosen threshold of 1.

Converting the Anabat data summary to presence-absence data permitted the use of logistic regression to investigate the relationship between environmental conditions and bat activity. Although alternative models (multinomial or count-based regression models) were possible, logistic models are simpler and so tend to provide more stable fits to the data and provided output (high versus low activity period) directly applicable in the context of a turbine curtailment decision. Nine predictors (day of study, wind speed, temperature, wind direction, precipitation, relative humidity, barometric pressure, estimated moonlight, and peak moonlight) were included in the model selection process (Tables 3a and 3b). In addition to those main effects, models were tested that included the interaction between an indicator variable for rain (i.e., whether rain was occurring at that moment) and the proportion of the previous one, two, and three nights that had not been raining, because bat response to rain may be mediated by recent weather. The quadratic of day of study was included to capture the seasonal effect of bats. The quadratic of wind speed was included in order to model the nonlinear relationship between bats and wind speed. Models were also tested that included an interaction between wind direction and the change in barometric pressure, because past research at the PHWF (Good et al. 2018) and Arnett et al. (2013) suggest bat migration may be related to the presence of weather fronts. Anabat data were trimmed to include nighttime hours (defined here as 30 min before sunset to 30 min after sunrise) during the date range of interest: 6 PM August 1 through 8 AM October 15, Central Daylight Time.

Bat activity by species and by all bats was modeled (using logistic regression) with data pooled across facilities, and with each facility modeled separately. Data were subset to the facility of interest and divided into an exploratory data set and a validation data set in order to test model performance (Table 5). The exploratory data set was used to fit models, and models were tested using the validation data set. Comparisons of the observed responses in the validation data to the predicted responses using the model showed how well the models could predict bat activity. The data were divided between the exploratory and validation data sets in a stratified random sample such that the exploratory data set included two-thirds of the observations with high bat activity periods and two-thirds of the observations without high bat activity periods, and the validation data set included the remaining one-third of observations.

Table 5. Sample sizes in the pooled data set and by facility for the exploratory and validation data sets for acoustic bat activity.

Facility	Total observations (20-minute night time intervals)	Observations in exploratory data set	Observations in validation data set
Both	2963	1975	988
Pilot Hill	2960	1973	987
Kelly Creek	2961	1973	988

The data were a time series, and each observation was associated with one of 13 turbines, which suggests there may have been correlations in time and space. Typically, a statistical model would attempt to account for spatial and temporal autocorrelation in the data, but for the current case, the objective was to produce a model that could theoretically be used in real time as the basis of a theoretical adaptively managed curtailment program. To that end, no attempt was made to model the spatial or temporal autocorrelation structure in the data.

There were 686 predictors, including interactions, available for model selection. Due to the high number of predictors and substantial correlation between them, variable selection was performed using elastic net regression (glmnet package; R Core Team 2018). Elastic net regression is a technique that can be used to reduce the number of predictors in a regression model by imposing penalties for more complex models. It is useful in high-dimensional data sets because it is computationally faster than information theoretic methods such as Akaike's Information Criterion (AICc). All predictors with nonzero coefficients from the elastic net regression were selected for further testing (Hastie and Qian 2014) using AICc (Arnold 2010).

AICc (Arnold 2010) scores were calculated for each model using the predictors selected with elastic net regression, and the model with the lowest AICc score that also produced finite confidence intervals for all parameters of interest was selected as the best model. Predicted probability of high bat activity periods was estimated for the validation data set and used to assess model performance. Model performance was assessed graphically with the Receiver Operating Characteristic (ROC) curves. These curves plot the reliability of the model at predicting bat presence against the likelihood the model falsely predicts bat presence.

Regression Analysis of Bat Carcasses Found on Previous Evening's Weather

Data from the PHWF were used to quantify relationships between bat fatalities and weather because daily carcass searches were only completed at PHWF. Counts of bat fatalities from carcass searches were analyzed in a framework similar to the acoustic data, to determine if bat fatalities during a night were well predicted by weather conditions the evening before. Carcass count data were restricted to turbines operating at manufacturer's cut-in speed and to carcasses estimated to have arrived on the evening immediately prior to the search (Appendix A).

Applying the same approach used for bat activity, bat fatalities were summarized to represent periods of "high" bat fatalities and periods of "low" bat fatalities across nights. The rationale for transforming the fatality data was similar to the rationale for transforming the activity data. Categories of "high" and "low" were more readily useful in a management context than counts, and logistic regression required fewer parameters so produces more stable model fits than multinomial or count-based regression models. Therefore, counts of bat fatalities were transformed to a binary response to allow the data to be analyzed using a logistic regression (Table 6). Weather conditions from Tables 3a and 3b were summarized on a nightly basis and used to model bat carcasses found during searches. Weather variables were summarized by taking an average over the night with one exception; change in barometric pressure was summarized by taking the maximum absolute value through the night. Models were constructed for each species at each site separately, and for both sites combined. Variable selection was carried out in the same manner as the acoustic data using elastic net regression (glmnet package; R Core Team 2018). Models were constructed that included all possible combinations of the nonzero coefficients from the glmnet function.

Table 6. Binary Response Transformation for Bat Fatalities Across Nights.

Facility	Species	High Fatalities	Percent of Fatalities Falling Within High Fatalities
Pilot Hill	All	>1	95
Pilot Hill	Eastern red bat	>1	76
Pilot Hill	Hoary bat	>0	100
Pilot Hill	Silver-haired bat	>1	82

AICc scores were calculated for each model and the model with the lowest AICc score that also produced finite confidence intervals for all parameters of interest was selected as the best model. Bat fatalities could not be assigned to 20-min intervals of the night, so sample units for the analysis were calendar nights. Unlike the 20-min interval bat activity data, there were too few night interval fatality data to divide the data into exploratory and validation data sets (n = 75 nights [PHWF]). Therefore, a jackknife procedure (Efron 2013) was used to examine the accuracy of the models; for each of the "n" data points, the model was trained on the remaining n-1 data points and tested on the n^{th} data point. Model performance was assessed using the same methods as for the regression analyses of bat activity on weather.

Regression Analysis of Bat Carcasses Found on Bat Activity the Previous Night

Bat fatality data were compared to bat activity and time of year to determine if the number of bat passes was related to the number of carcasses found. Carcass count data from each facility were restricted to turbines with functioning acoustic detectors, those operating at manufacturer's cut-in speed, and to carcasses estimated to have arrived on the evening immediately prior to the search (Appendix A). After this restriction, KCWF did not have sufficient carcasses for modeling, so only counts of bat fatalities from carcass searches at PHWF were analyzed.

Counts of acoustic calls were included in the analysis for all working detectors from 30 min before sunset to 30 min after sunrise. Bat activity was then summed for three time periods in each night (early night: 30 min before sunset–10 PM, midnight: 10 PM–2 AM, and late night: 2 AM–30 min after sunrise) to examine whether timing of bat activity played a role in the number of bat fatalities. Acoustic data from periods when turbines were not spinning and revolutions per min (rpm) was zero were excluded from this analysis in order to provide a more accurate comparison between activity and fatalities during the risk period of operating turbines.

Counts of bat fatalities were analyzed in a Poisson regression model using count of acoustic calls occurring in each period of the previous evening and Julian date as predictor covariates. A quadratic term was also included for Julian date. The number of turbines (with detectors) searched and the probability of a carcass being detected were included as offsets in the model to account for unequal search effort from day to day. The probability of a carcass being detected was calculated as the product of the probability the carcass was detected by observers ($\hat{p}$) multiplied by an adjustment for the searched area ($\hat{a}$) as determined using the methods for the Huso estimator (Iskali et al. 2019a). This detection probability omits an accounting of the persistence probability typically included in fatality estimates. Omission of the persistence probability was appropriate because only fresh carcasses were included in our analysis, and so we could assume persistence probability was constant for all carcasses.

Searcher efficiency trials were used to estimate $\hat{p}$ using logistic regression. Potential covariates for this logistic model included turbine operation (control versus treatment turbines). The logistic regression modeled the natural logarithm of the odds of finding an available carcass as a function of the above covariates. The $\hat{p}$ used for each night was the mean of the $\hat{p}$ values for each turbine with an operating acoustic detector on that night.

The area adjustment was estimated as the product of the unsearched area around each turbine and a carcass-density distribution. The carcass-density distribution predicts the likelihood a carcass fell a given distance from the turbine base. A truncated weighted maximum likelihood modeling approach (Khokan et al. 2013) was used to estimate the carcass-density distribution. Truncation accounts for carcasses beyond the search radius and weights account for unequal search effort. Distributions considered were normal, gamma, Gompertz, Rayleigh, and Weibull. The proportion of area searched was calculated in a Geographic Information System as the amount of area searched divided by the total area searched at each 1.0-m (3.2-ft) annulus around the turbine. The area adjustment was estimated by combining the carcass-density distribution with the proportion of area searched for each 1.0-m annulus across the search area and summarizing across the distances. The mean â value for all turbines with functioning detectors on a given night was used to calculate the offset for a particular night. For further information on the calculation of $\hat{p}$ and $\hat{a}$ see Iskali et al. 2019a.

Models were fitted for all bat species combined, and for the following species individually: 1) hoary bat, 2) eastern red bat, and 3) silver-haired bat. Many silver-haired bat calls are indistinguishable from big brown bat calls, therefore, calls that were either big brown or silver-haired bat, but could not be distinguished, were included in the analysis of all bat and silver-haired bat fatalities.

AICc scores were calculated for each model and the model with the lowest AICc score was selected as the best model. Unlike for the bat activity data, there were too few fatality data to divide the data into exploratory and validation data sets (n = 75 carcass search dates at PHWF). Therefore, k-fold cross-validation was used to test the efficacy of the fatality models. K-fold cross validation with 1,000 55-night randomly drawn samples used to fit the selected model and 1,000 complimentary 20-night samples used to test the fitted models (Boyce et al. 2002). Model performance was assessed by plotting the model-predicted counts from the validation data sets against the observed counts from the validation data sets.

Data Summaries

The relative number of bat calls and fatalities were also summarized by variables regression models used as significant predictors. The goal of summarizing the data was to explore if minimization measures could be further refined to reduce bat fatalities while increasing energy production. Data from both PHWF and KCWF were summarized.

Results

Bat Carcass Survey

Two hundred sixty-eight bat carcasses estimated to have died the previous night were included in the analyses, including 225 from PHWF and 43 from KCWF. Eighty-five eastern red bats, 60 hoary bats, 61 silver-haired bats, 18 big brown bats, and one Seminole bat (*Lasiurus seminolus*) were included from PHWF, and 16 eastern red bats, 15 silver-haired bats, 11 hoary bats, and one big brown bat from KCWF (Appendix A).

Bat and Avian Mortality Monitoring System

Five BAMM systems were installed prior to the start of the study, while the remaining five BAMM systems were installed several weeks after August 1. The BAMM systems did not function reliably, reducing the availability of the system and resulting in several carcasses being missed due to system unavailability. This issue also led to engineering resources being diverted from improving the detection algorithm to trying to improve the system availability. Additionally, the detection algorithm produced too many false positives, so it could not be used to independently determine when a carcass arrived around the wind turbine.

A manual review process was implemented by NRG Systems to review the images from the sectors around turbines where carcasses were found by human searchers. The time of death of one eastern red bat and four hoary bat carcasses were determined by the manual review resulting in four of the five bats killed within one hour of midnight and the fifth bat killed at 0230 hours (Table 7). All five carcasses detected by BAMM occurred within 15.0 m (49.2 ft) of turbines.

The weather conditions for the entire night when fatalities occurred were plotted to examine how the conditions at the time of death compared to conditions throughout the night. Wind speeds were variable on the nights when all five bat carcasses were found, ranging from zero to approximately 12.0 m/s (26.8 mph); all five fatalities occurred when wind speeds were between 2.8–3.9 m/s (6.3–8.7 mph). One of the five bats was killed when wind speeds were near cut-in speed. The five fatalities occurred during periods of the night when wind speeds were declining relative to the minutes prior to the time of death (Figures 7a, 7b, 7c). Rotor speed varied from zero up to approximately 15 rpm on the five nights; the rotor speed ranged from 6.0–9.6 rpm at the time of death for the five bat carcasses. Wind direction varied less than wind speed throughout most nights, although some variability was observed. Winds were out of the northeast for three of the carcasses, southeast and southwest for the remaining two carcasses. Barometric pressure also varied during the night from 33169.7 to 33406.7 mbar, with barometric pressure increasing close to dawn on four of the five nights. The barometric pressure at the times of death ranged from 33193.4 to 33366.1 mbar.

Table 7. On-site weather and other attributes associated with five bat carcasses where the time of death was identified by the Bat and Avian Mortality Monitoring System.

Turbine	Date and Time	Species	Bearing from Turbine (°)	Distance from Turbine (m)	Air Temperature (C)	Barometric Pressure (mbar)	Wind Direction (compass degrees)	Wind Speed (m/s)	Rotor Speed (RPM)	Nacelle Position (°)
A09	8/6/2018 00:30 H	Eastern Red Bat	2	7	25.1	984.8	206	3.67	7.48	118
A09	8/16/2018 00:20 H	Hoary Bat	20	3	20.3	980.2	160	3.89	9.27	315
B01	8/17/2018 02:30 H	Hoary Bat	24	10	19.3	980.6	58	3.23	9.61	8
B01	8/17/2018 23:00 H	Hoary Bat	140	8	20.6	982.6	68	3.47	9.27	39
B04	8/12/2018 00:50 H	Hoary Bat	96	15	20.9	985.3	82	2.83	6.06	77

° = degrees; m = meters; C = Celsius; mbar = millibar; m/s = meters per second; RPM = revolutions per minutes.

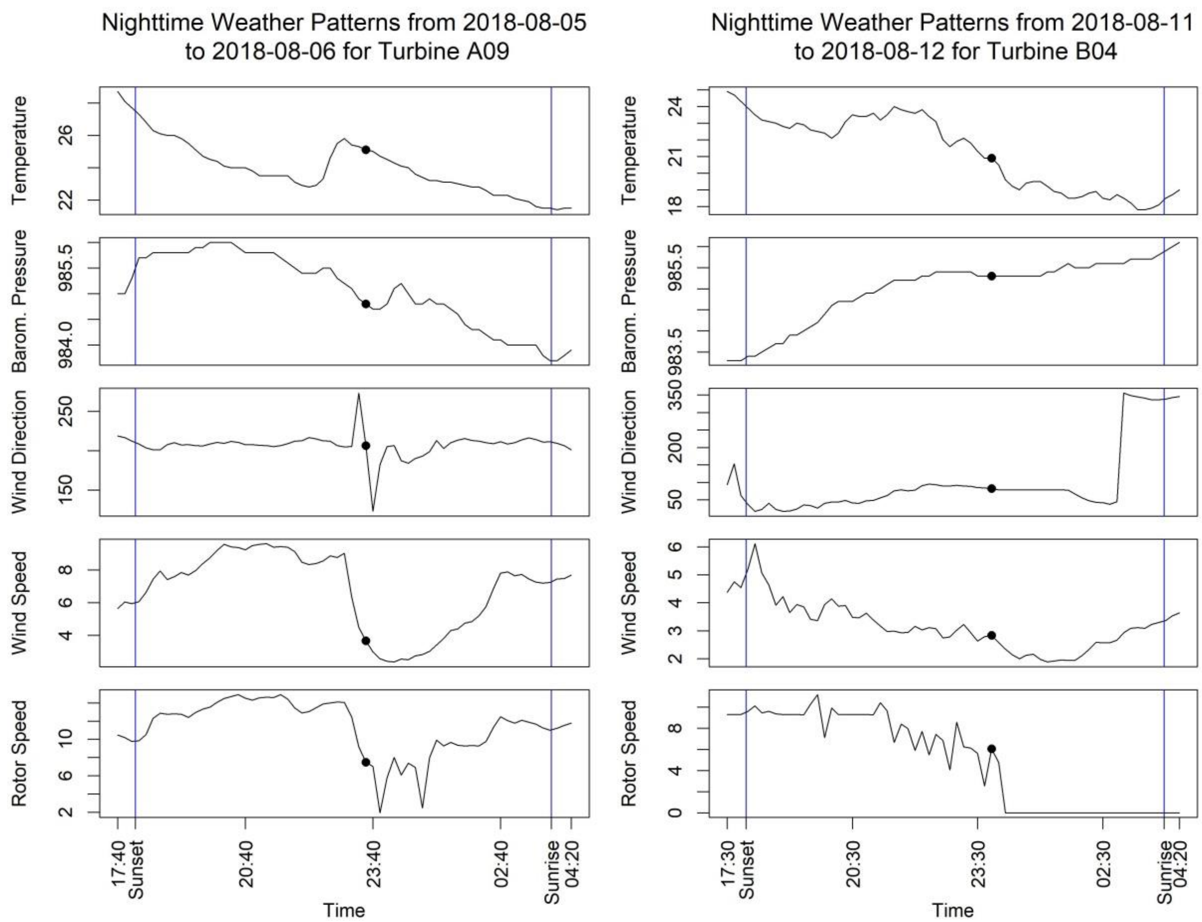

Figure 7a. Variability in on-site weather and rotor speed for turbines on nights where the time of death of an eastern red bat and hoary bat found at turbines A09 and B04, respectively, were identified by the Bat and Avian Mortality Monitoring system. The solid black circles idenitfy the time of death for the selected bat. Note, the y-axes are scaled differently for each bat to improve readability.

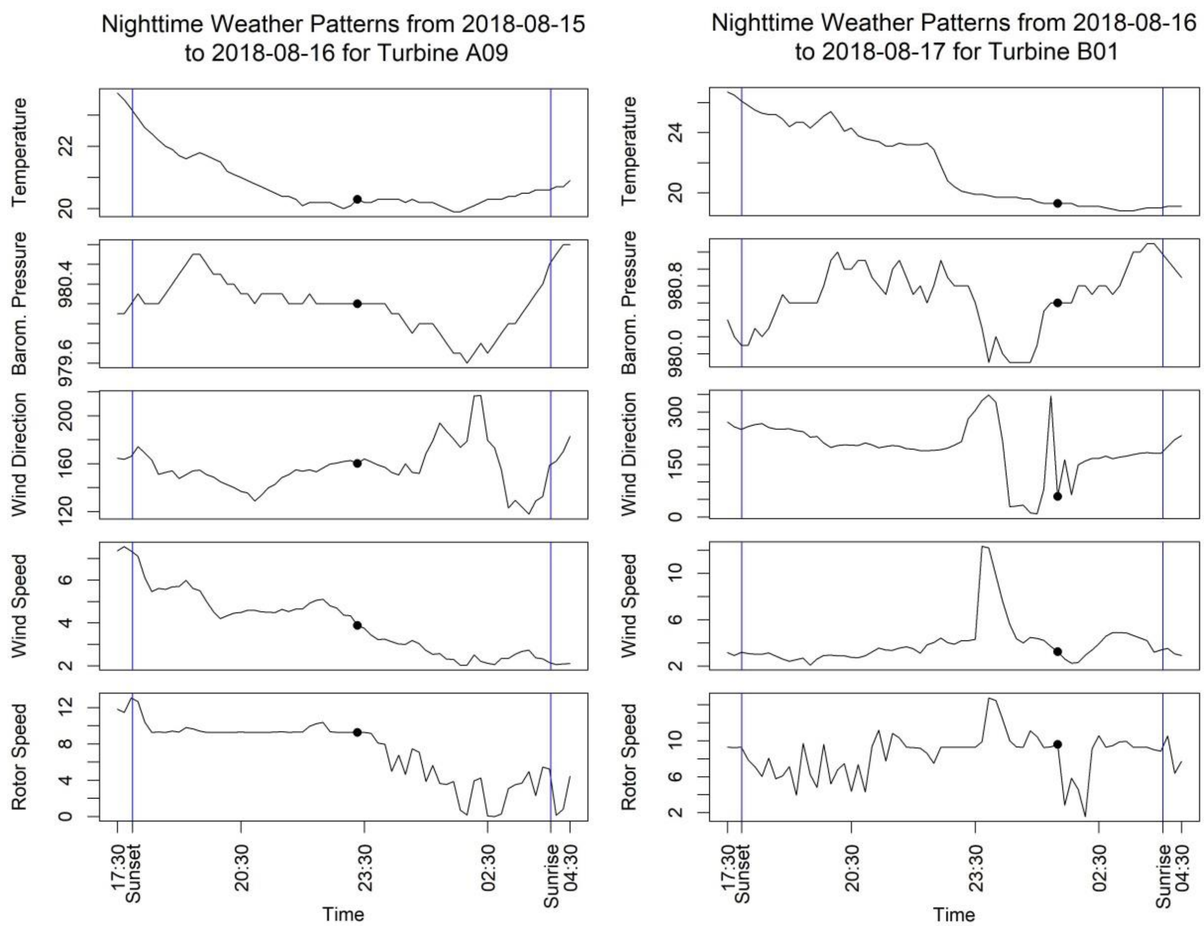

Figure7b. Variability in on-site weather and rotor speed for turbines on nights where the times of death of two hoary bats at turbines A09 and B01 were identified by the Bat and Avian Mortality Monitoring system. The solid black circles idenitfy the time of death for the selected bat. Note, the y-axes are scaled differently for each bat to improve readability.

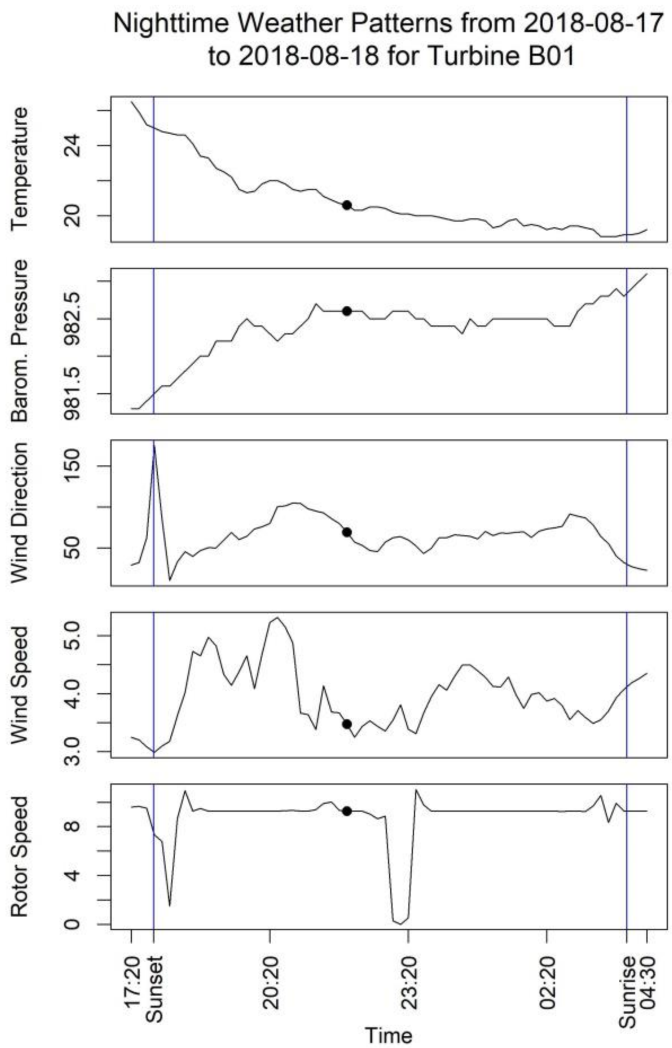

Figure 7c. Variability in on-site weather and rotor speed for turbines on nights where the time of death of one hoary bat at turbine B01 was identified by the Bat and Avian Mortality Moniting system. The solid black circles idenitfy the time of death for the sele selected bat. Note, the y-axes are scaled differently to improve readability.

Acoustic Bat Activity

Anabats at the PHWF recorded 1,588 bat passes over 463 detector nights during the fall migration period. The majority of all bat passes recorded (77.1%) were by low-frequency bats (e.g., hoary, big brown, and silver-haired bats). The majority of the low-frequency calls could not be identified to species or species group due to the quality of the calls or overlap in the call characteristics of low-frequency bat species. Bat passes per night ranged from a mean ± the standard error of 0.95 ± 0.24 to 6.64 ± 1.55 bat passes per detector night, with the lowest activity recorded at Turbine A3 and the highest activity recorded at Turbine B1. Nightly pulses in bat activity were relatively consistent between detectors at the PHWF (Figure 8). The Anabats at turbines A3 and A5 only operated approximately 26% of the survey period. All other detectors operated 43% or more for the entire study period and the lowest bat passes per night recorded within those detectors was 2.31 ± 0.40 (Table 8a). Five of the nine detectors stopped collecting data at various times from August 21 to September 25. Stopped data collection was due to data cards full because of turbine noise (three units), Anabat malfunction (one unit), and 12-volt power loss (one unit) (Figure 9).

Anabats at the KCWF recorded 494 bat passes over 185 detector nights. The majority of all bat passes recorded (68.6%) were by low-frequency bats. The majority of the low-frequency calls could not be identified to species or species group due to non-search-phase echolocation calls or the quality of the calls. Bat passes per night ranged from 0.44 ± 0.20 to 4.38 ± 0.75 bat passes per detector night, with the lowest activity recorded at Turbine I8 and the highest activity at Turbine F5. Nightly pulses in bat activity were relatively consistent between detectors at the KCWF (Figure 10). The Anabat at Turbine I8 operated only 23% of the survey period, which may explain the lower bat activity at this turbine. All other detectors recorded 50% or more for the entire study period (Table 8b, Figure 11).

Bat activity rates were similar between the PHWF and KCWF, ranging from 0.44 to 6.64 bat passes per detector night. This indicates no concentration of activity was detected at PHWF compared to KCWF. One Seminole bat carcass was identified during the surveys; Seminole bats have call characteristics that are indistinguishable from eastern red bats. It is possible that some of the calls identify as eastern red bats were made by Seminole bats; however, Seminole bat calls are expected to comprise a small proportion of identified eastern red at calls based on the low number of Seminole bat carcasses found during surveys.

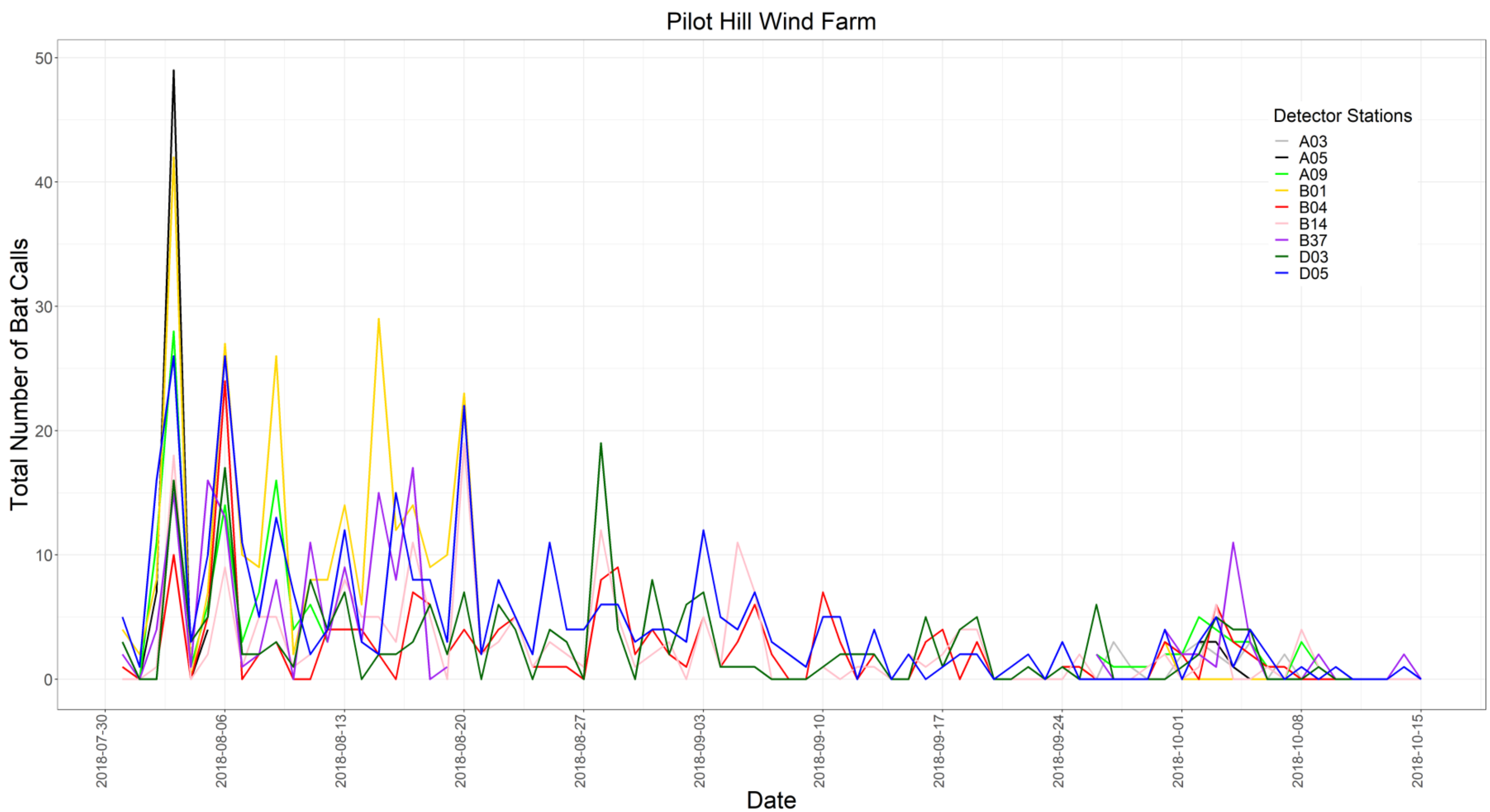

Figure 8. The number of bat calls recorded by calendar date at Pilot Hill July 31 – October 15, 2018.

Table 8a. The total number of bat passes recorded in lower rotor swept zone and under turbine nacelles within the Pilot Hill Wind Farm July 31 – October 15, 2018. Passes were separated by species or species group and call frequency; low frequency and high frequency.

Detector Stations	A3	A5	A9	B1	B4	B14	B37	D3	D5	Total
					Low-Frequency Bats					
big brown bat	1	5	4	3	4	0	1	1	0	19
big brown bat/silver-haired bat	6	5	36	20	50	32	23	36	66	274
silver-haired bat	1	2	4	0	2	2	6	3	4	24
hoary bat	0	18	33	134	0	15	65	6	97	368
low-frequency unknown	8	31	18	65	68	97	37	112	103	539
Low-Frequency Total	**16**	**61**	**95**	**222**	**124**	**146**	**132**	**158**	**270**	**1,224**
					High-Frequency Bats					
eastern red bat	1	2	21	48	36	39	17	20	42	226
tri-colored bat	0	0	0	0	0	0	0	0	1	1
high-frequency unknown	2	7	12	9	18	17	9	29	34	137
High-Frequency Total	**3**	**9**	**33**	**57**	**54**	**56**	**26**	**49**	**77**	**364**
All Bats Total	**19**	**70**	**128**	**279**	**178**	**202**	**158**	**207**	**347**	**1,588**
Detector-Nights	**20**	**20**	**33**	**42**	**77**	**77**	**40**	**77**	**77**	**463**
Bat Passes/Night*	**0.95±0.24***	**3.50±2.35***	**3.88±1.00**	**6.64±1.55**	**2.31±0.40**	**2.62±0.45**	**3.95±0.89**	**2.69±0.42**	**4.51±0.62**	**3.45±0.68**

*± bootstrapped standard error.

*Detector only operated during 26% of the survey period.

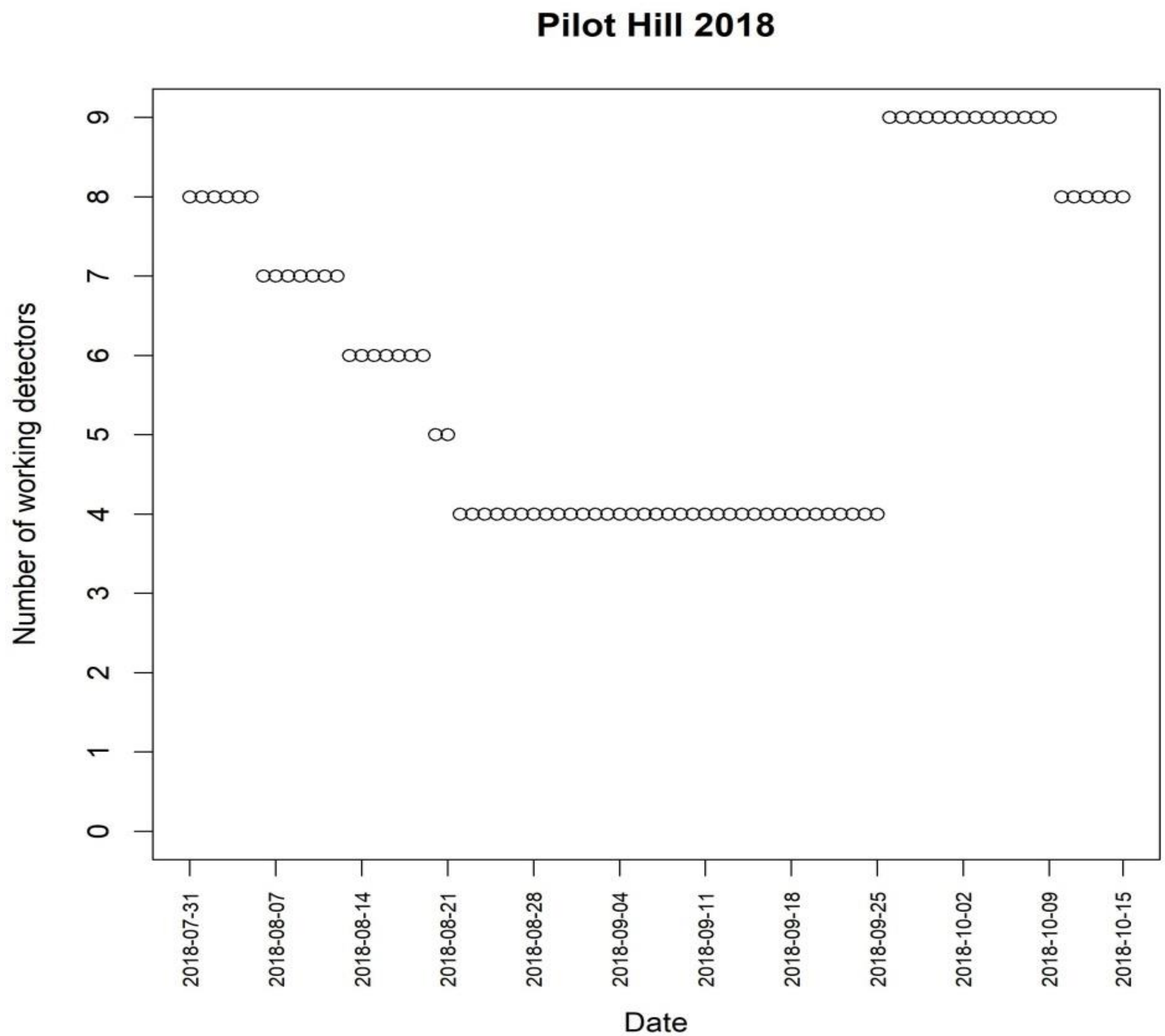

Figure 9. The number of working bat detectors at Pilot Hill by calendar week July 31 – October 15, 2018.

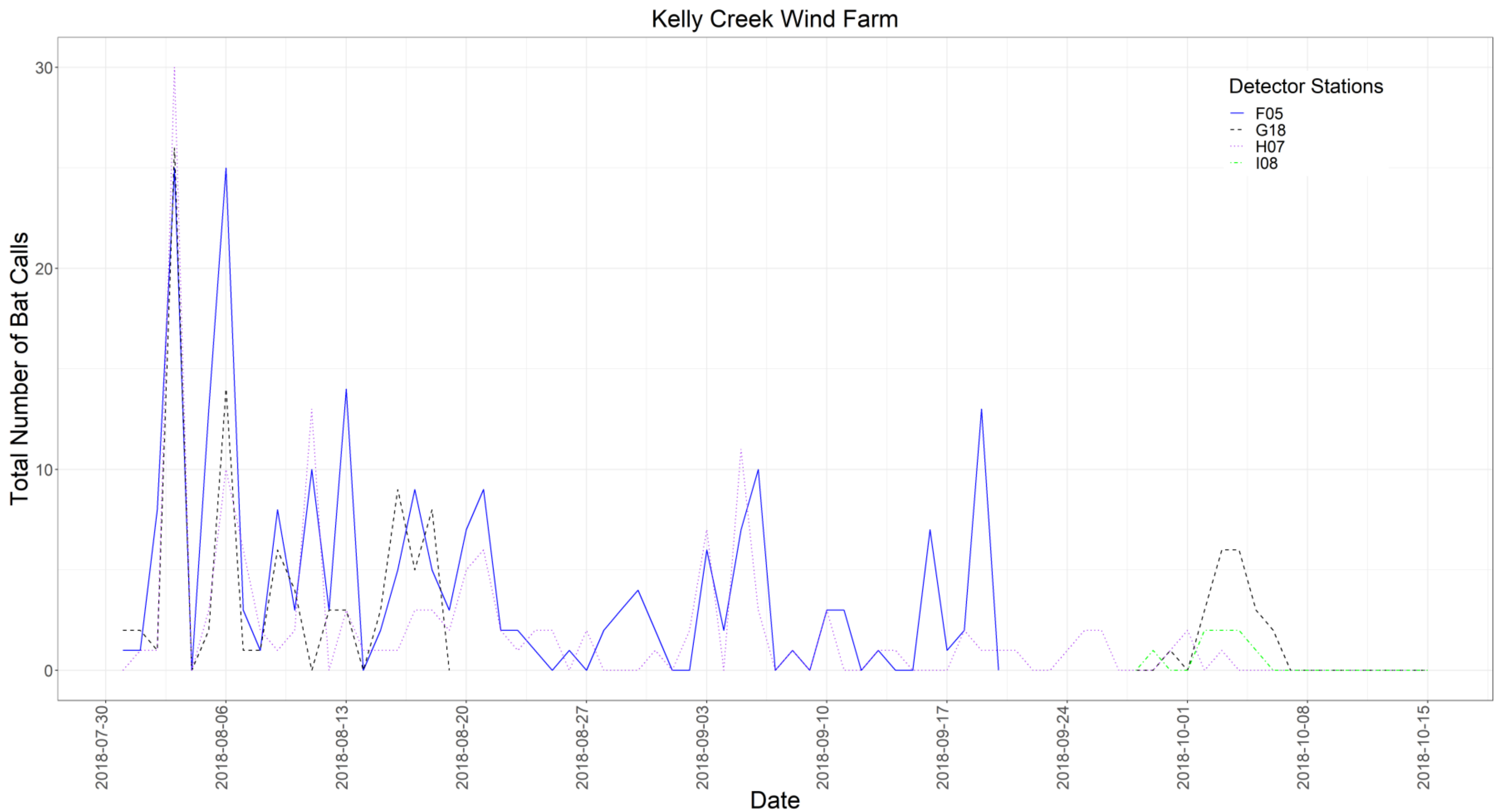

Figure 10. The number of bat calls recorded by calendar date at Kelly Creek July 31 – October 15, 2018.

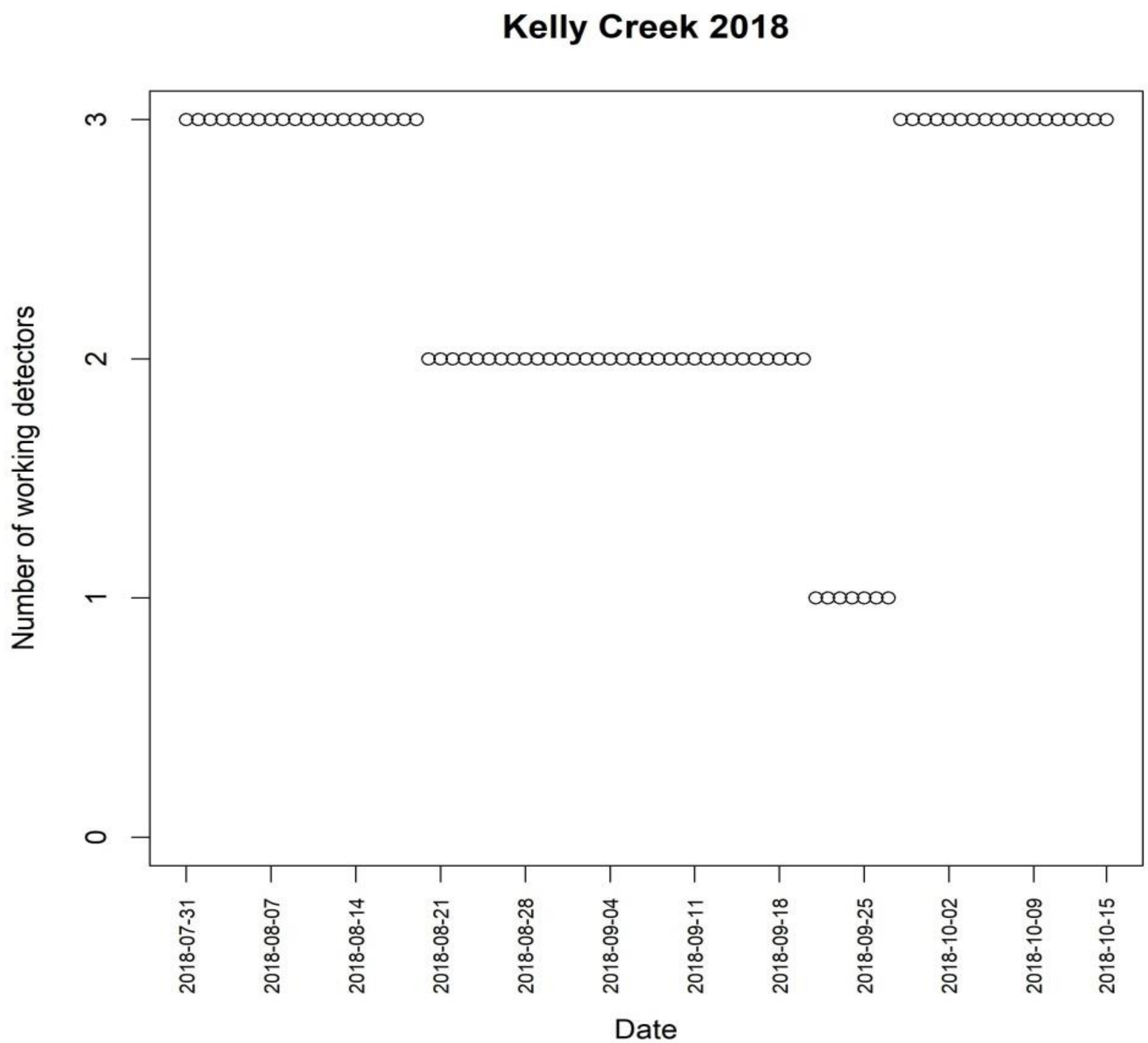

Figure 11. The number of working bat detectors at Kelly Creek by calendar week July 31 – October 15, 2018.

Table 8b. The total number of bat passes recorded in the lower rotor swept zone and under turbine nacelles within the Kelly Creek Wind Farm July 31 – October 15, 2018. Passes are separated by species or species group and call frequency; low frequency and high frequency.

Detector Stations	F5	G18	H7	I8	Total
		Low Frequency Bats			
big brown bat	2	2	4	1	9
big brown bat/silver-haired bat	46	20	25	2	93
hoary bat	48	31	5	0	84
low frequency unknown	88	39	65	3	195
Low Frequency Total	**184**	**92**	**99**	**6**	**381**
		High Frequency Bats			
eastern red bat	16	4	25	1	46
tri-colored bat	1	1	0	0	2
high frequency unknown	27	14	23	1	65
High Frequency Total	**44**	**19**	**48**	**2**	**113**
All Bats Total	**228**	**111**	**147**	**8**	**494**
Detector-Nights	**52**	**38**	**77**	**18**	**185**
Bat Passes/Night±	**4.38±0.75**	**2.92±0.76**	**1.91±0.47**	**0.44±0.20***	**2.41±0.45**

*± bootstrapped standard error.

Regression Analyses of Bat Activity, Bat Fatalities and Weather

Regression Analysis of Bat Activity and Weather

Top models to predict bat call detections by weather conditions for each combination of site and species are described in Appendix B. The combined-site acoustic model results from KCWF and PHWF are presented below. Species-specific models (e.g., eastern red bat and hoary bat) had lower false positive rates and comparable correct prediction rates than models that grouped species, such as all bats, and silver-haired bat/big brown bat. The ROC curve for the model predicting high bat activity for all bats shows it was possible to correctly predict 72% of high activity bat periods with a false positive rate of 28% (Figure 12). For eastern red bats, it was possible to correctly predict 71% of high activity bat periods with a false positive rate of 19% (Figure 13), and for hoary bats, it was possible to correctly predict 79% of high activity bat periods with a false positive rate of 18% (Figure 14). The silver-haired bat/big brown bat model was less accurate; the correct prediction of high silver-haired/big brown bat activity periods was 77%, while the false positive rate was 53% (Figure 15).

On-Site Weather Analyses

Wind direction, temperature, barometric pressure, relative humidity, and precipitation were measured at on-site Project met towers. Wind speed was the most common on-site predictor for all of the species models; bat activity was higher when wind speeds were lower for all bats (Figure 16), eastern red bat (Figure 17), hoary bat (Figure 18), and silver-haired/big brown bat (Figure 19), and confidence intervals for the parameters did not overlap with zero; the relationship being strongest for hoary bats (Figure 18). Wind direction and interactions between Project barometric pressure and wind direction were also selected as predictors for hoary bats (Figure 18), while barometric pressure was selected for eastern red bats (Figure 17). Other Project variables, including relative humidity, temperature, moonlight, and precipitation, had relatively minor influences on the predicted model outputs of bat activity.

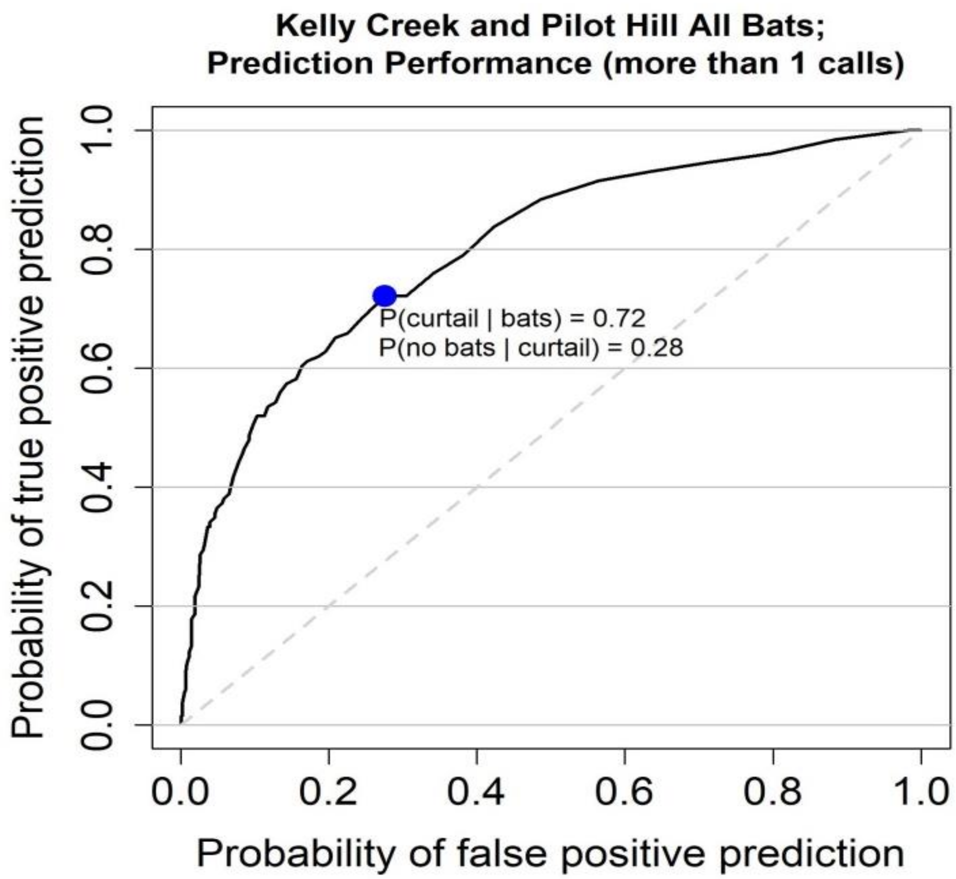

Figure 12. Model performance for the logistic regression model predicting the probability of a bat call detection at both sites.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting a high activity bat period (on the y-axis) versus the probability of falsely predicting a high activity bat period (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts high bat activity periods with 72% fidelity, and generates 28% false positive predictions.

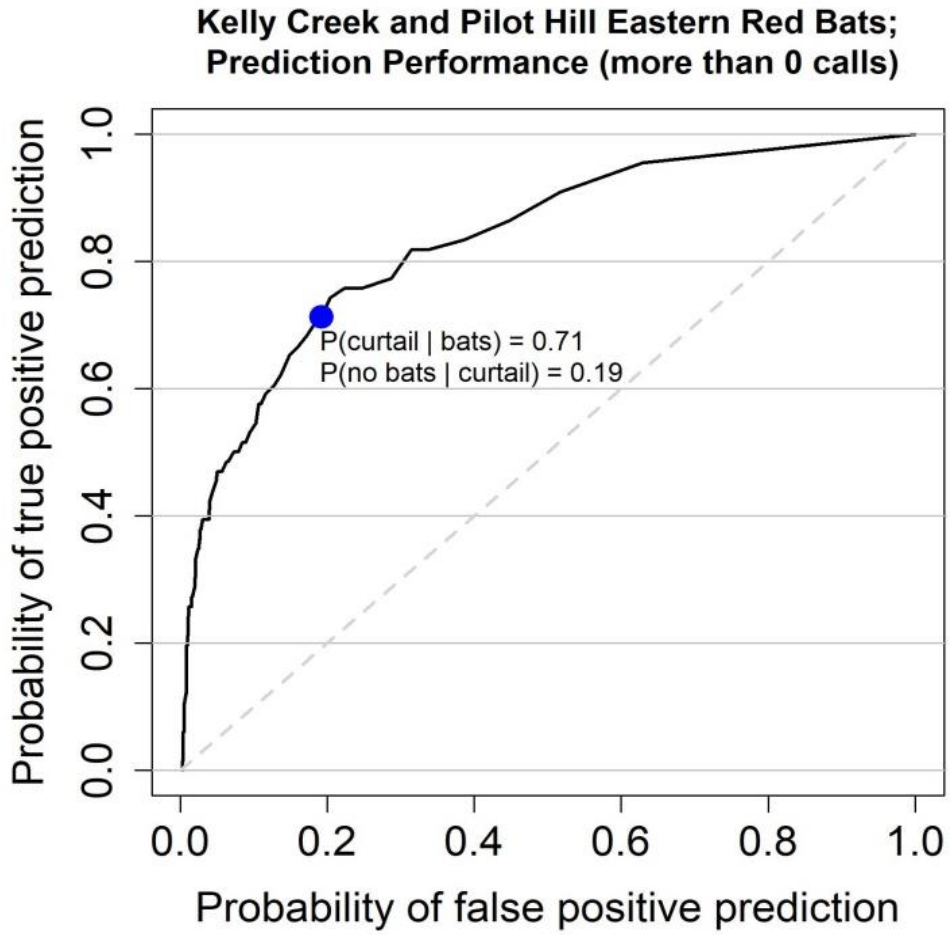

Figure 13. Model performance for the logistic regression model predicting the probability of an eastern red bat call detection at both sites.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting a high activity bat period (on the y-axis) versus the probability of falsely predicting a high activity bat period (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts high bat activity periods with 71% fidelity, and generates 19% false positive predictions.

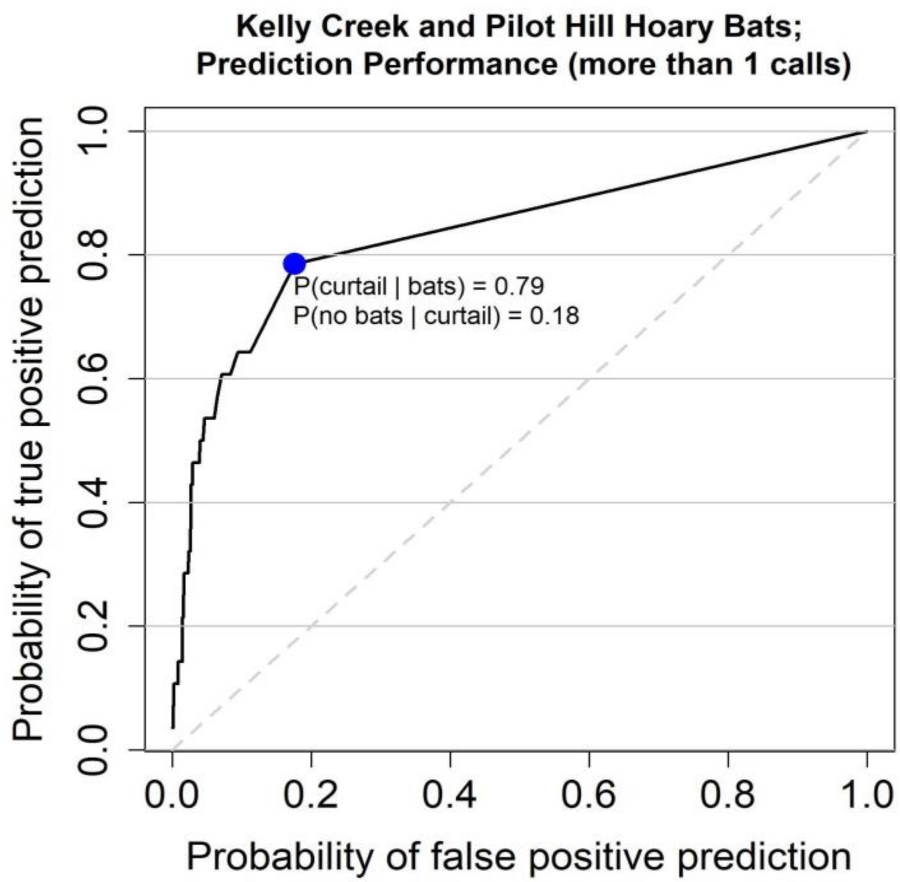

Figure 14. Model performance for the logistic regression model predicting the probability of a hoary bat call detection at both sites.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting a high activity bat period (on the y-axis) versus the probability of falsely predicting a high activity bat period (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts high bat activity periods with 79% fidelity, and generates 18% false positive predictions.

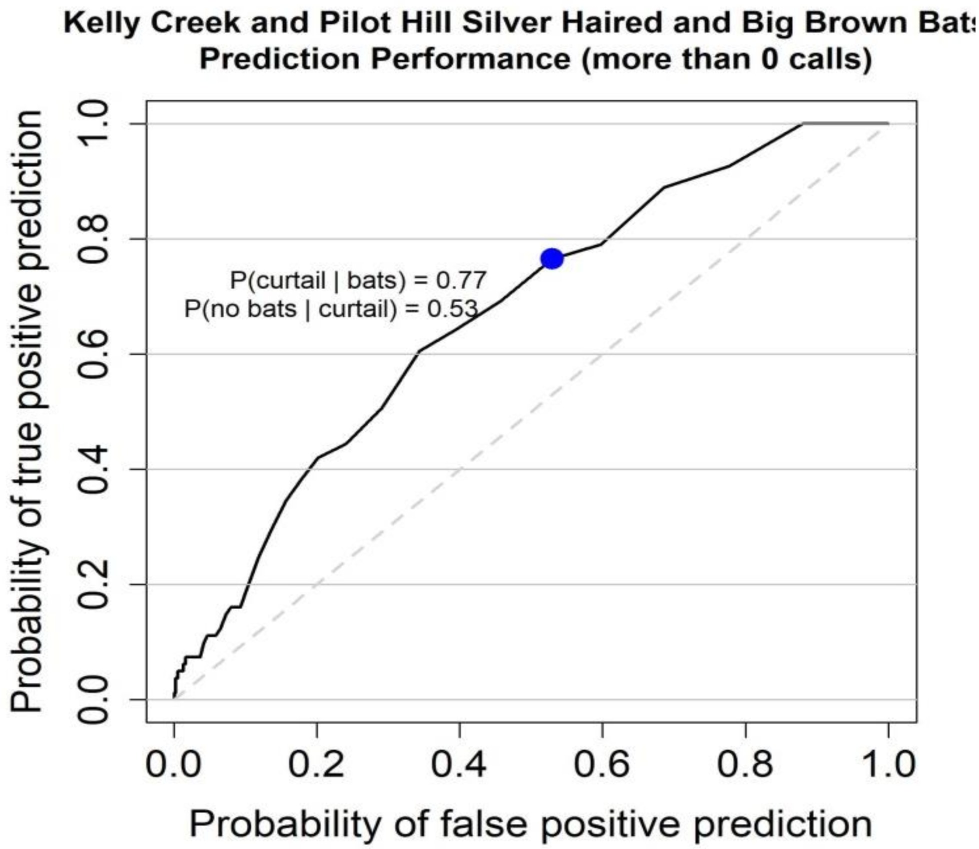

Figure 15. Model performance for the logistic regression model predicting the probability of a silver-haired or big brown bat call detection at both sites.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting a high activity bat period (on the y-axis) versus the probability of falsely predicting a high activity bat period (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts high bat activity periods with 77% fidelity, and generates 53% false positive predictions.

Airport Weather Analyses

Weather variables from surrounding airports showed a greater influence on predicted bat activity than weather variables from on-site met towers for all bats (Figure 16), eastern red bats (Figure 17), and silver-haired bats/big brown bats (Figure 19). Airport and on-site weather variables were influential for hoary bat activity (Figure 18).

The probability of a high all bat activity period was influenced by weather at airports to the south (Rantoul, 74.4 km [46.2 mi] from PHWF) and east (Stark County, 113.0 km [70.2 mi] from PHWF; Figure 20). Rising barometric pressure with wind from the east at Rantoul was associated with increased probability of a high bat activity period 12 hours later at the site, but rising barometric pressure with wind from the north, south, or especially the west at Rantoul was strongly negatively associated with high bat activity periods 12 hours later at the site. Periods of high bat activity at the site were slightly positively associated with winds from the north at the Stark County airport and negatively associated with winds from the west at the Stark County airport, compared to winds from the east or south (Figure 16).

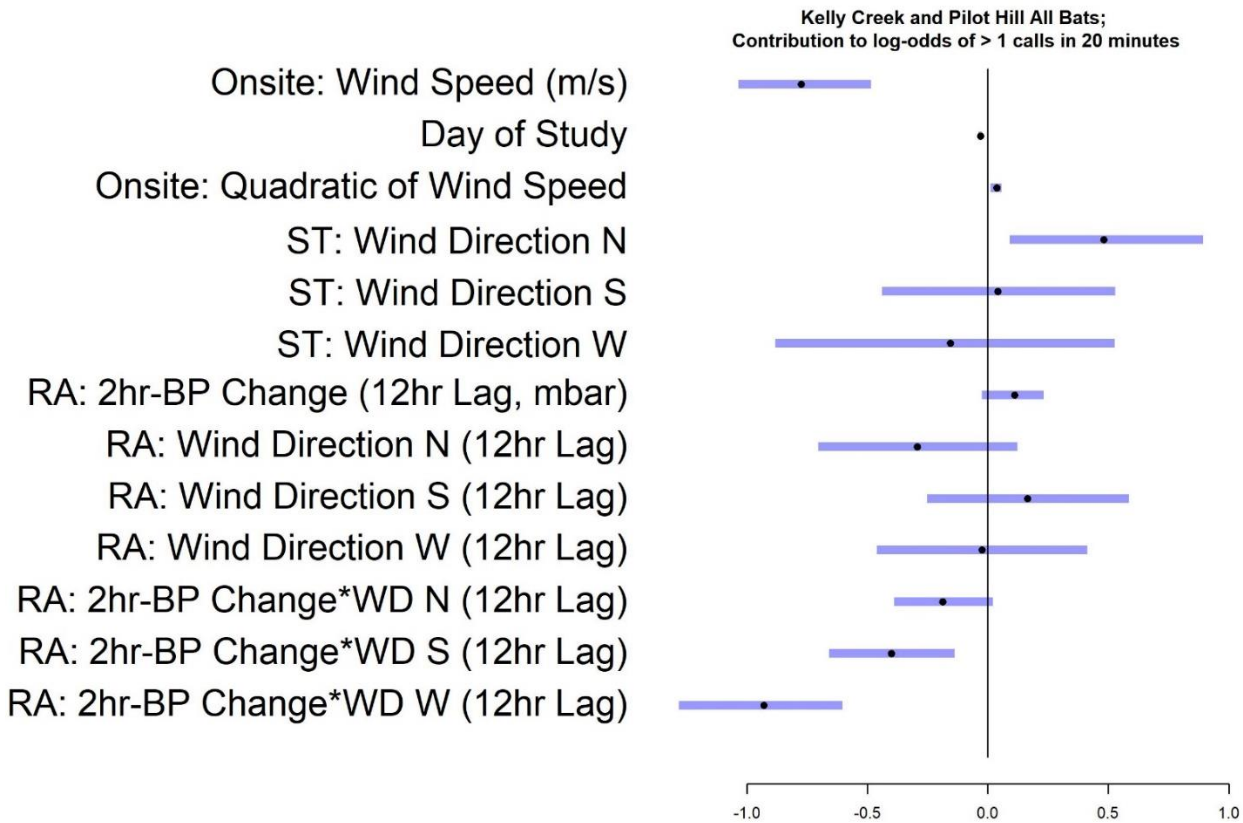

Figure 16. Model parameters for the logistic regression model predicting the probability of high all bat activity periods at both sites. Parameters are labeled as either collected on-site, or collected off-site at airports. Abbreviations for airport names are given in Figure 5 and are shown as the initial two letters.

Note, point estimates are indicated with dots, 90% confidence intervals on the model parameter values are indicated with lines. Parameter values are on a log-odds scale. Parameters with confidence intervals that cross the zero line have an uncertain association with the probability of a high activity bat period. The further the point is from the zero line, the greater the association between the covariate and the probability of a high-activity bat period. Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

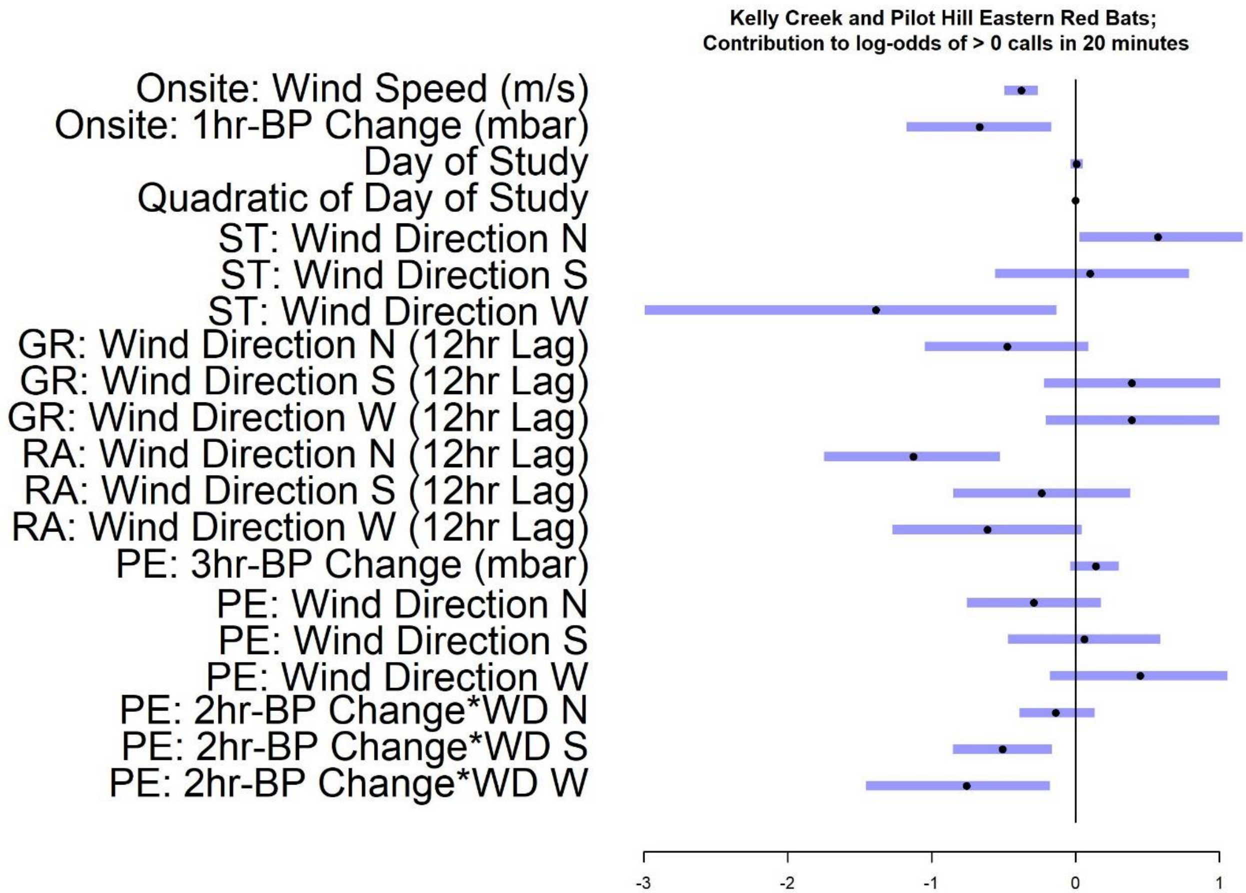

Figure 17. Model parameters for the logistic regression model predicting the probability of an eastern red bat call detection at both sites. Parameters are labeled as either collected on site, or collected off-site at airports. Abbreviations for airport names are given in Figure 5 and are shown as the initial two letters.

Note, point estimates are indicated with dots, 90% confidence intervals on the model parameter values are indicated with lines. Parameter values are on a log-odds scale. Parameters with confidence intervals that cross the zero line have an uncertain association with the probability of a high activity bat period. The further the point is from the zero line, the greater the association between the covariate and the probability of a high-activity bat period. Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

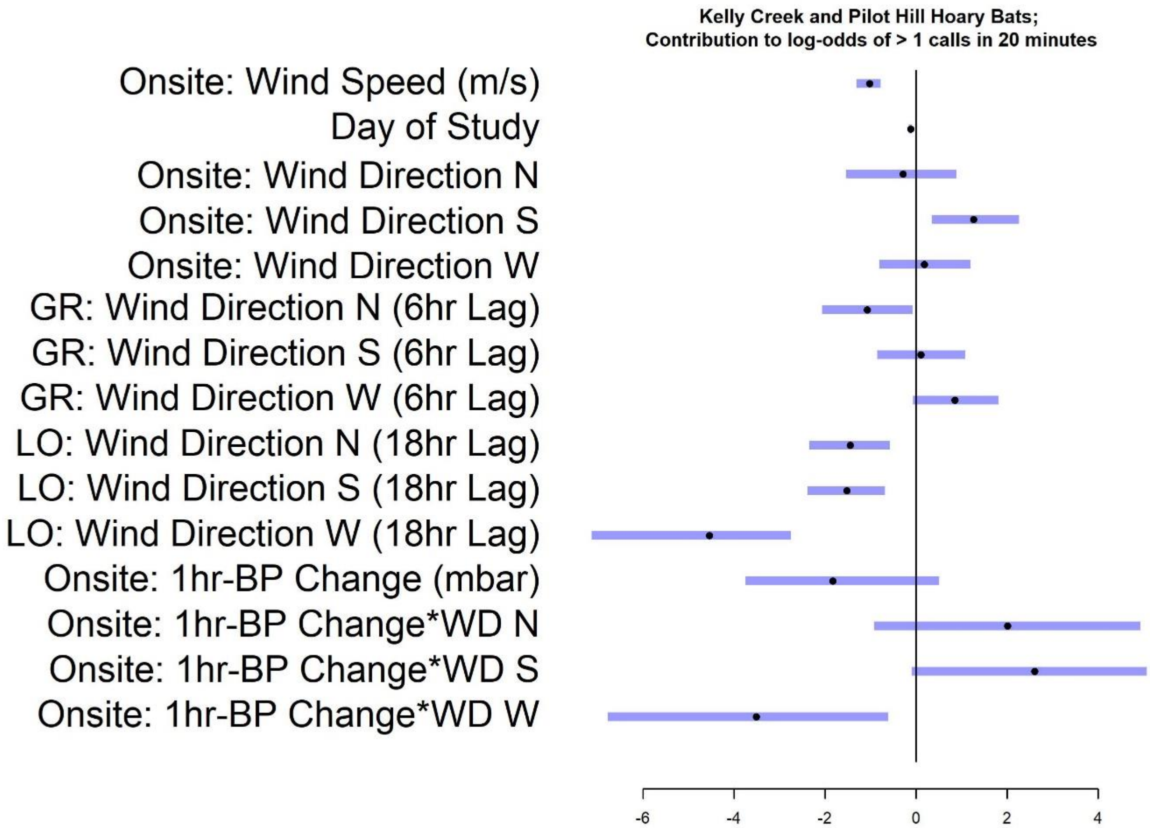

Figure 18. Model parameters for the logistic regression model predicting the probability of a hoary bat call detection at both sites. Parameters are labeled as either collected on-site, or collected off-site at airports. Abbreviations for airport names are given given in Figure 5 and are shown as the initial two letters.

Note, point estimates are indicated with dots, 90% confidence intervals on the model parameter values are indicated with lines. Parameter values are on a log-odds scale. Parameters with confidence intervals that cross the zero line have an uncertain association with the probability of a high activity bat period. The further the point is from the zero line, the greater the association between the covariate and the probability of a high-activity bat period. Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

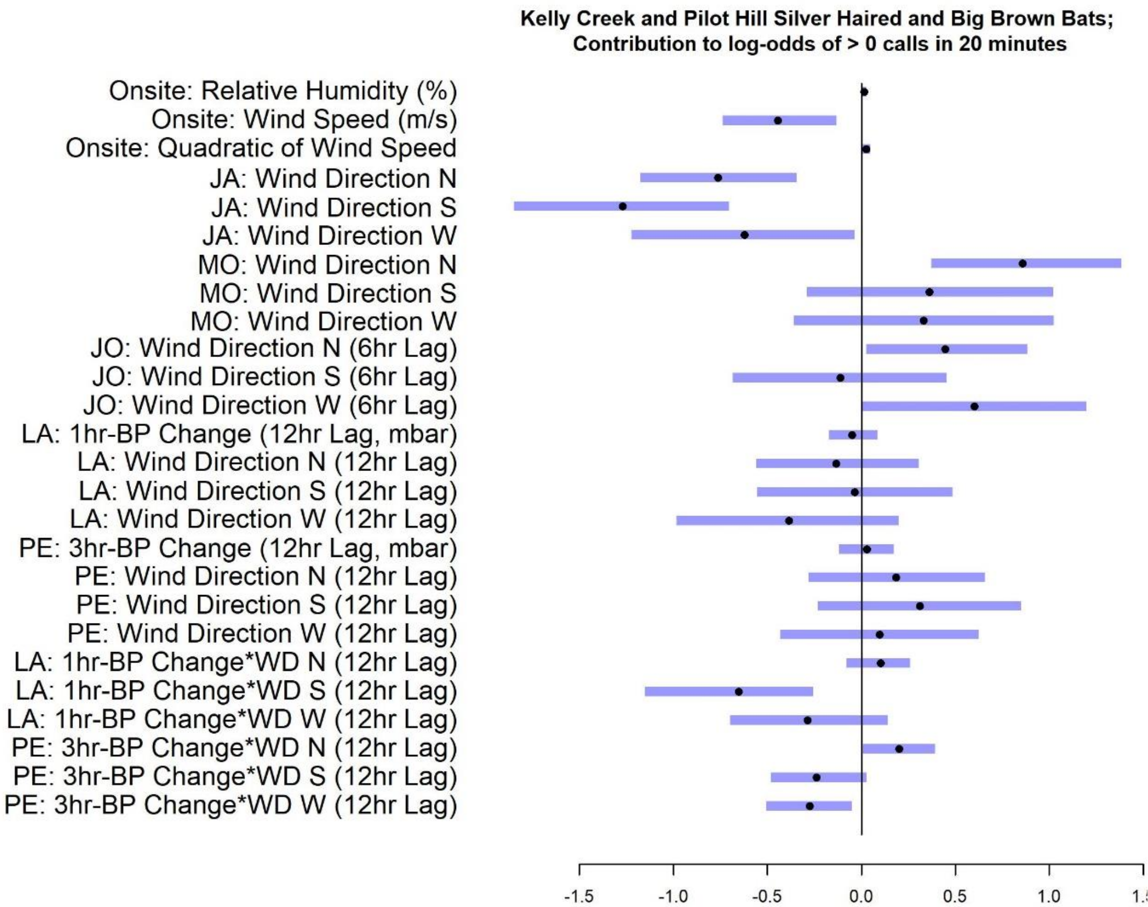

Figure 19. Model parameters for the logistic regression model predicting the probability of a silver-haired/big brown bat group call detection at both sites. Parameters are labeled as either collected on-site, or collected off-site at airports. Abbreviations for airport names are given in Figure 5 and are shown as the initial two letters.

Note, point estimates are indicated with dots, 90% confidence intervals on the model parameter values are indicated with lines. Parameter values are on a log-odds scale. Parameters with confidence intervals that cross the zero line have an uncertain association with the probability of a high activity bat period. The further the point is from the zero line, the greater the association between the covariate and the probability of a high-activity bat period. Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

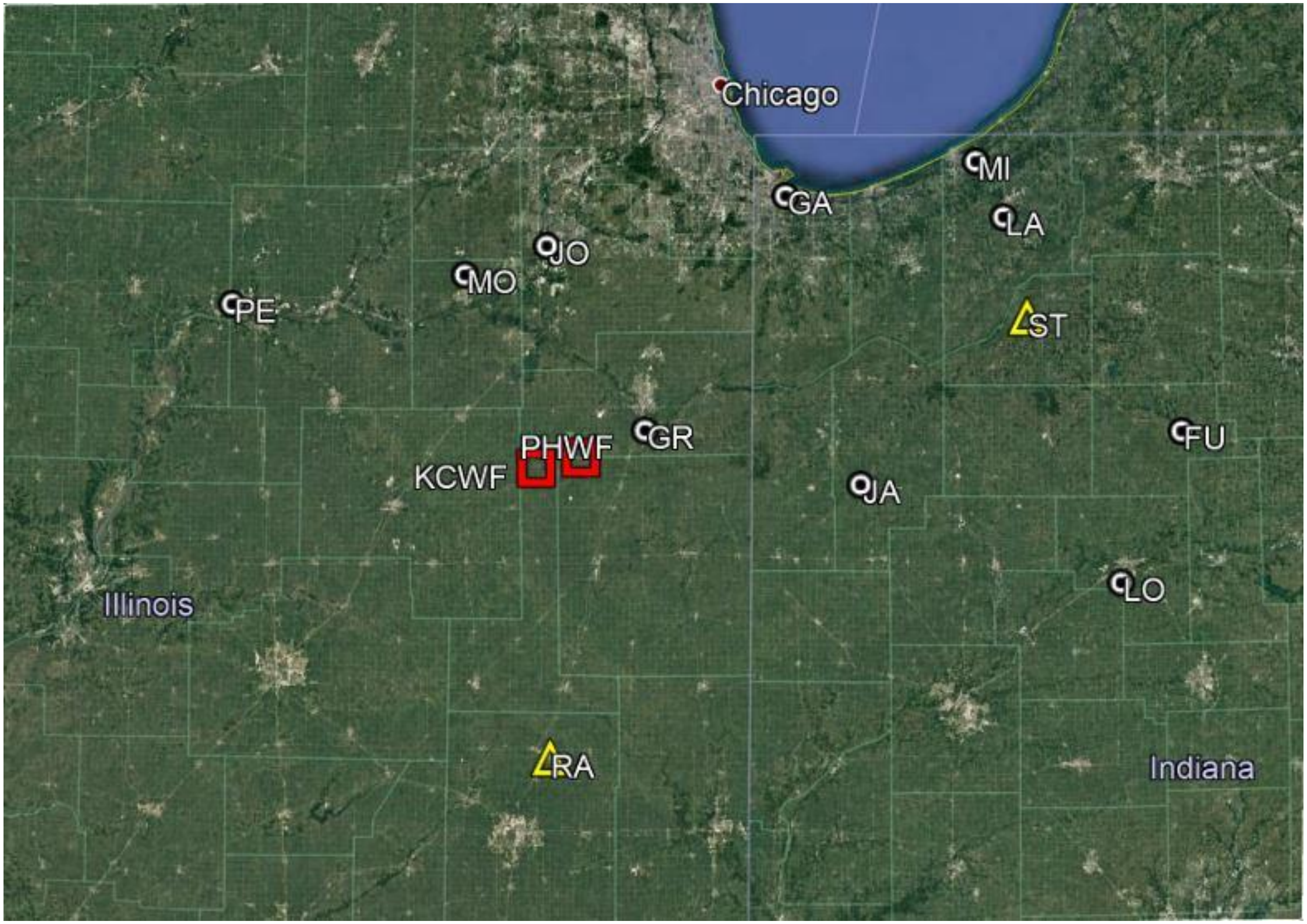

Figure 20. Map of airports that appeared in the all bat acoustic model in relationship to Pilot Hill and Kelly Creek Wind Farms. Airports with data included in the top model are represented by yellow triangles. Abbreviations for airport names are given in Figure 5.

Eastern red bat activity was most influenced by off-site weather recorded at the Peru airport, located to the west of the Projects and 94.4 km (58.7 mi) from PHWF (Figure 21). Variables from airports to the east (Stark, 113.1 km [70.3 mi] from PHWF, and Kankakee, 9.6 km (5.9 mi) from PHWF) and south (Rantoul, 74.4 km [46.2 mi] from PHWF) were included in the best model, but had less influence than Peru. Barometric pressure in combination with wind direction at the Peru airport was the most influential variable. Rising pressure and winds from the east at Peru were associated with higher probability of high bat activity periods, while rising barometric pressure and winds from the north, west and south were associated with lower probability of high bat activity periods (Figure 17).

Weather data from airports to the east of the Projects were selected as predictors of high hoary bat activity (Figure 22). Winds from the east from the Logansport airport, 137.7 km (85.5 mi) from PHWF, were positively associated with periods of high hoary bat activity, while winds from the north, south and west were negatively associated with periods of high hoary bat activity. Wind from the north at the Kankakee airport were negatively associated with high hoary bat activity periods, while winds from the south and west were positively associated with high hoary bat activity periods (Figure 18).

Weather data from four different airports to the north and one airport to the south were selected as predictors of silver-haired/big brown bat activity (Figure 23), with the most influential variables from airports to the northeast and northwest (Figure 19).

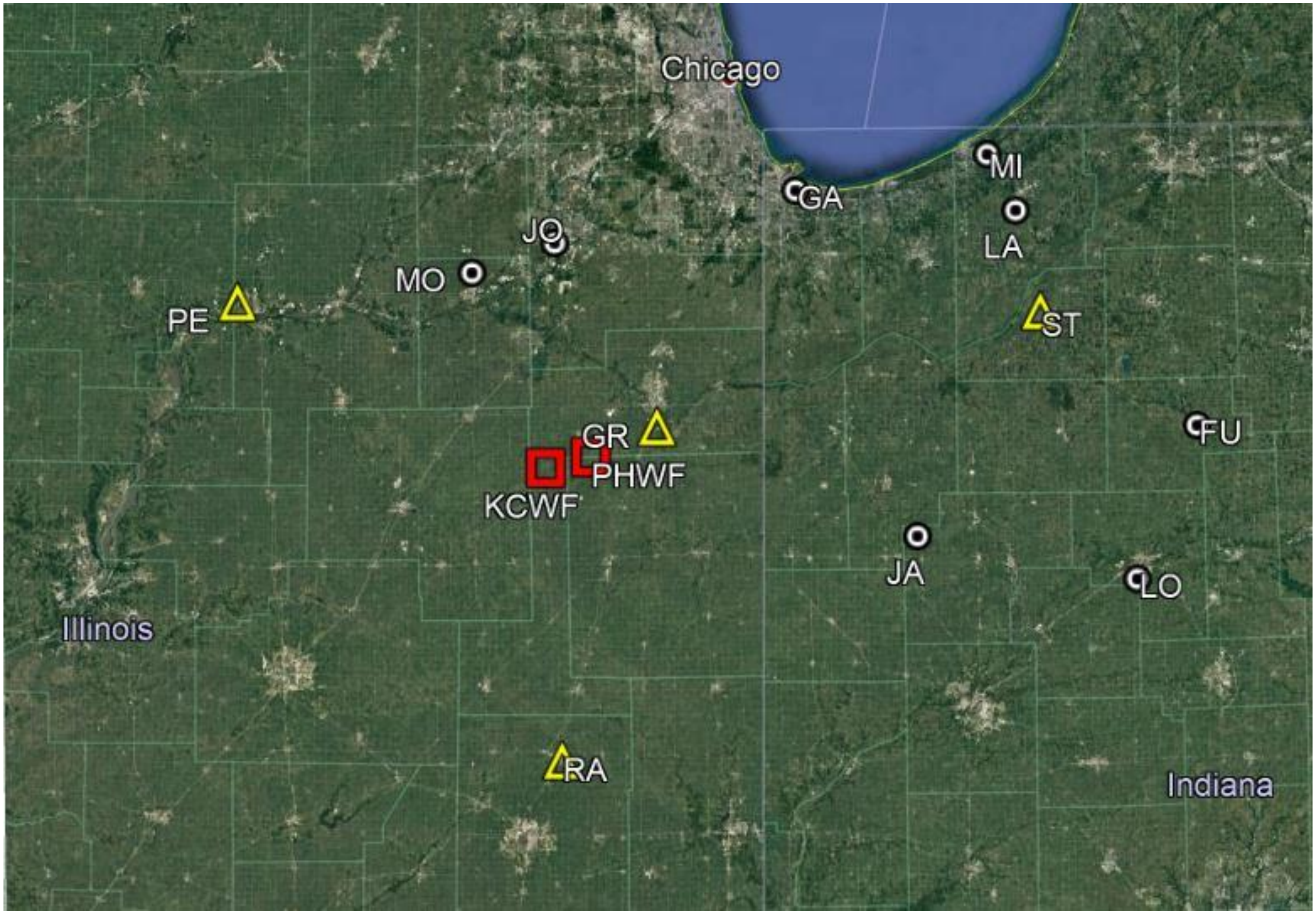

Figure 21. Map of airports that appeared in the eastern red bat acoustic model in relationship to Pilot Hill and Kelly Creek Wind Farms. Airports with data included in the top model are represented by yellow triangles. Abbreviations for airport names are given in Figure 5.

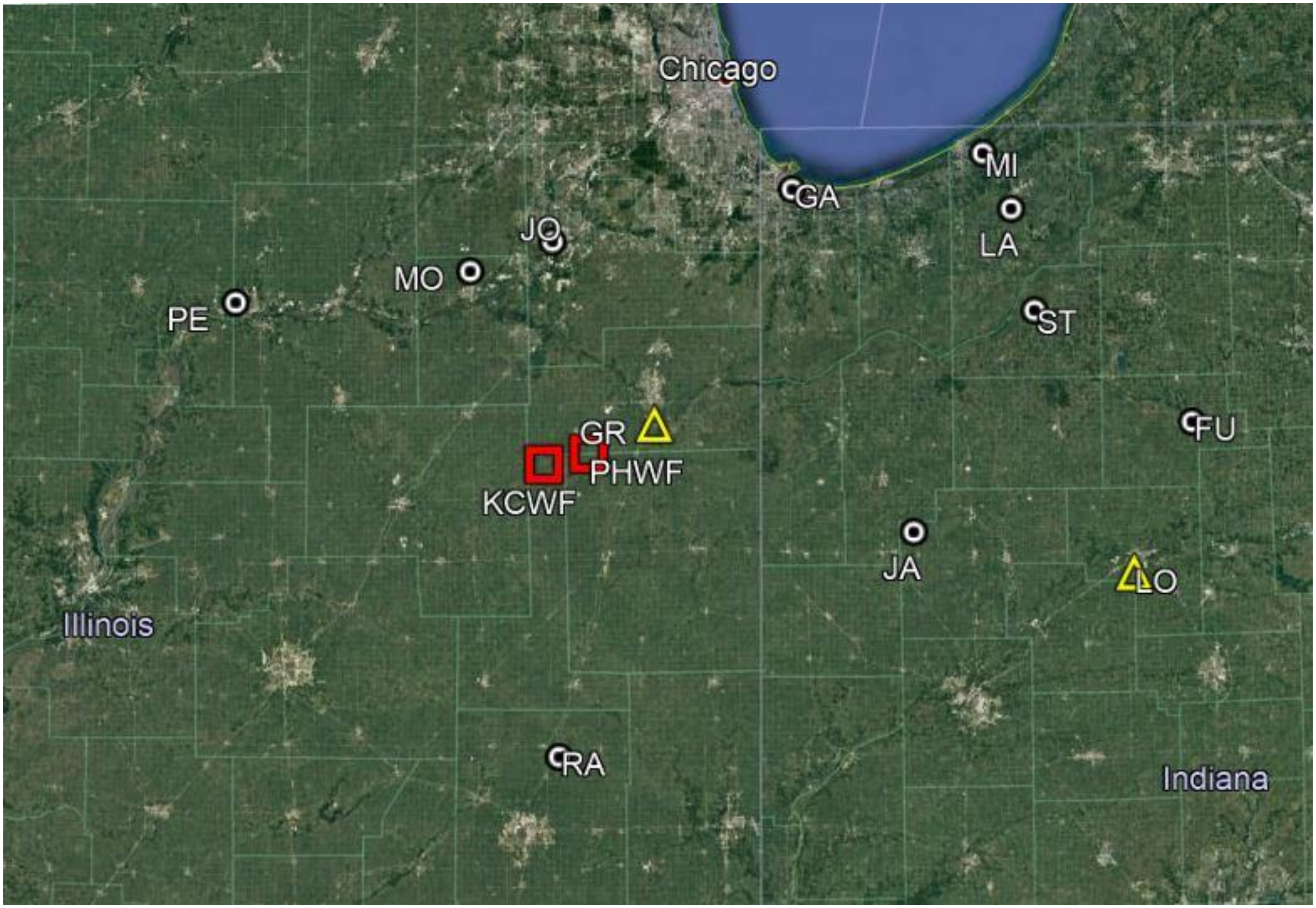

Figure 22. Map of airports that appeared in the hoary bat acoustic model in relationship to Pilot Hill and Kelly Creek Wind Farms. Airports with data included in the top model are represented by yellow triangles. Abbreviations for airport names are given in Figure 5.

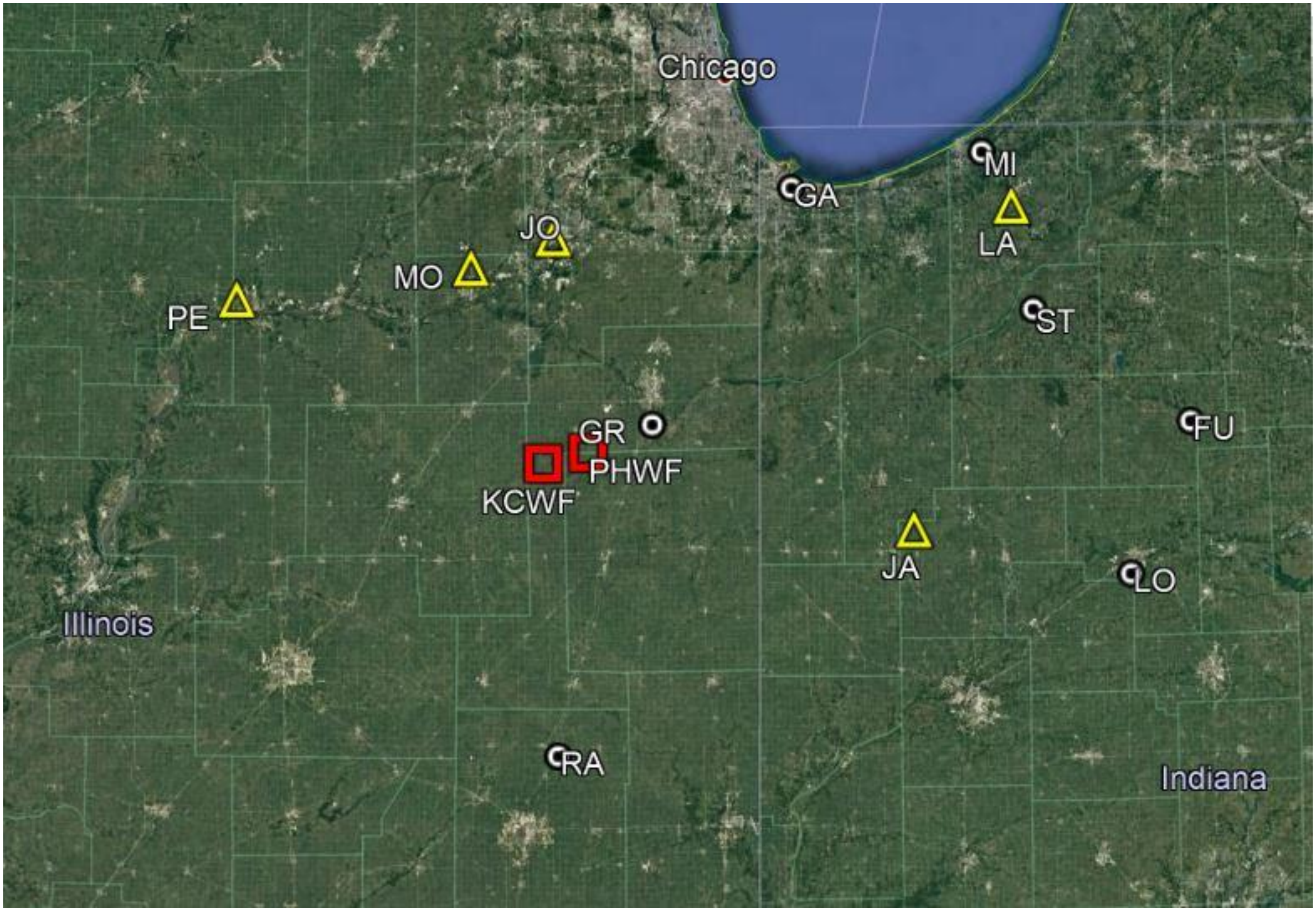

Figure 23. Map of airports that appeared in the silver-haired bat/big brown bat acoustic model in relationship to Pilot Hill and Kelly Creek Wind Farms. Airports with data included in the top model are represented by yellow triangles. Abbreviations for airport names are given in Figure 5.

Regression Analysis of Bat Carcass Counts on Previous Evening's Weather

Data collected during daily carcass searches from the PHWF were utilized to interpret patterns of bat fatalities and weather, which allowed for a broader range of potential weather conditions to be analyzed, compared to the KCWF, where searches only occurred twice per week. The eastern red bat fatality model correctly predicted 73% of nights with more than one carcass detected, but with a false positive rate of 45% (Figure 24). The hoary bat model correctly predicted 73% of days with at least one hoary bat carcass correctly predicted with a false positive rate of 17% (Figure 25). The silver-haired bat model correctly predicted when 89% of high-fatality nights occurred with a false positive rate of 75% (Figure 26).

On-Site Weather Analyses

In all cases, model selection resulted in off-site weather variables preferred over on-site weather variables. Only one non-airport variable was selected as a predictor of more than one eastern red bat fatality, day of study and its quadratic term (the quadratic term allows fatalities to have a peak in time rather than a linear increase or decrease through the season; Figure 27). Day of study was also positively related to higher numbers of fatalities for hoary bats (Figure 28), but not for silver-haired bats (Figure 29).

Airport Weather Analyses

Wind direction from airports to the northwest of the PHWF were the only variables chosen in the best models for hoary bat (Figure 30) and silver-haired bat fatalities (Figure 31); no weather variables from airports were included in the eastern red bat fatality model. Fewer high hoary bat fatality nights were associated with winds out of the west, south and north the night before the fatality was found (12 hours prior); winds from the east were associated with more high hoary bat fatality nights (Figure 28). Data from the Morris, IL airport located 53.2 km (33.1 mi) northwest of the PHWF near the Kankakee River was most influential for predicting hoary bat mortality (Figure 30).

The model predicting at least two silver-haired bat carcasses only included weather variables from the Joliet airport, located 52.2 km (32.5 mi) northwest of the PHWF (Figure 31). Winds from the west were positively associated with the detection of at least two carcasses, compared with winds from the north, south, or east (Figure 29).

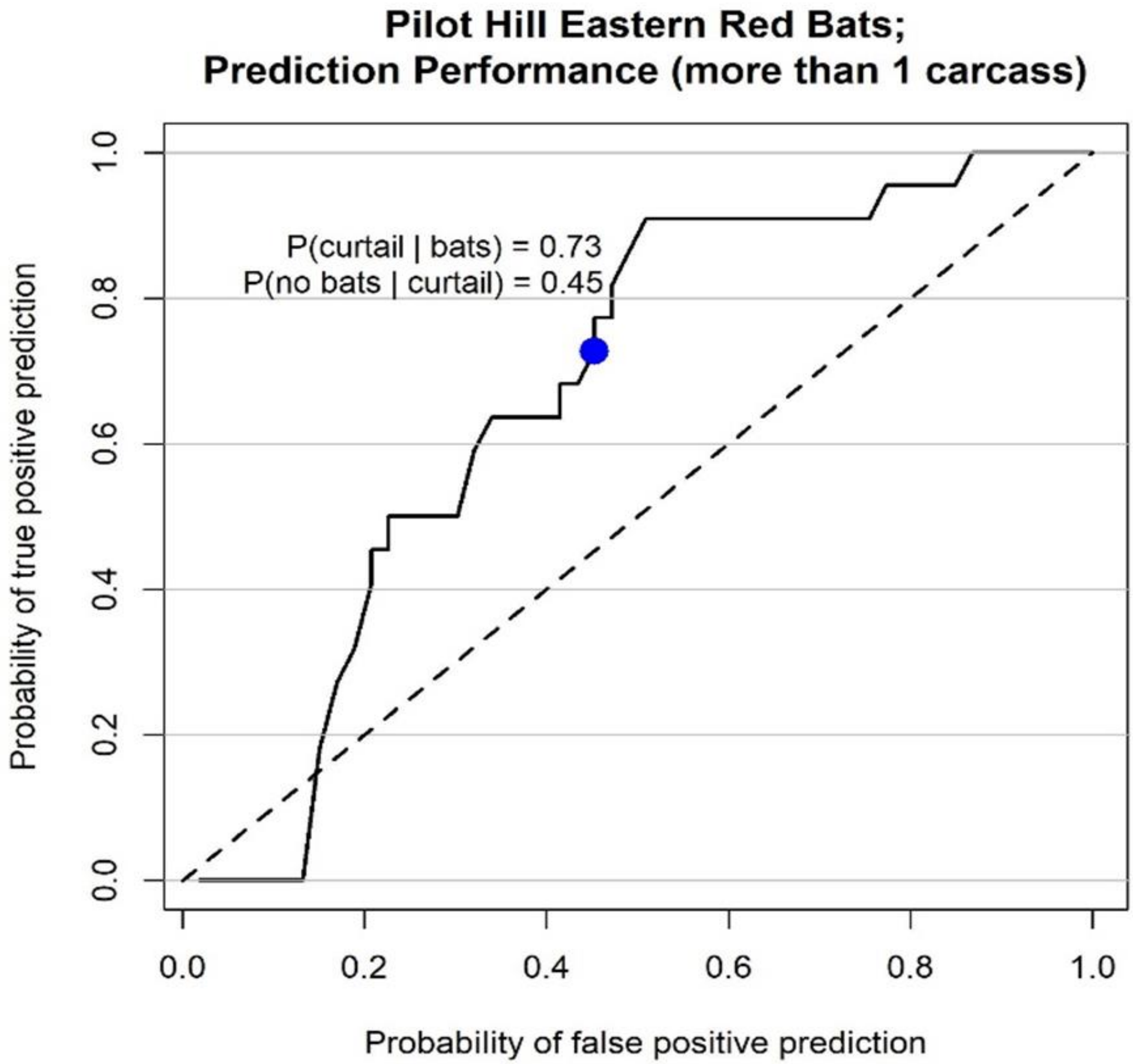

Figure 24. Model performance for the logistic regression model predicting the probability of at least two bat carcasses at Pilot Hill.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting at least two bat carcasses (on the y-axis) versus the probability of falsely predicting at least two bat carcasses (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts at least two bat carcasses with 73% fidelity, and generates 45% false positive predictions.

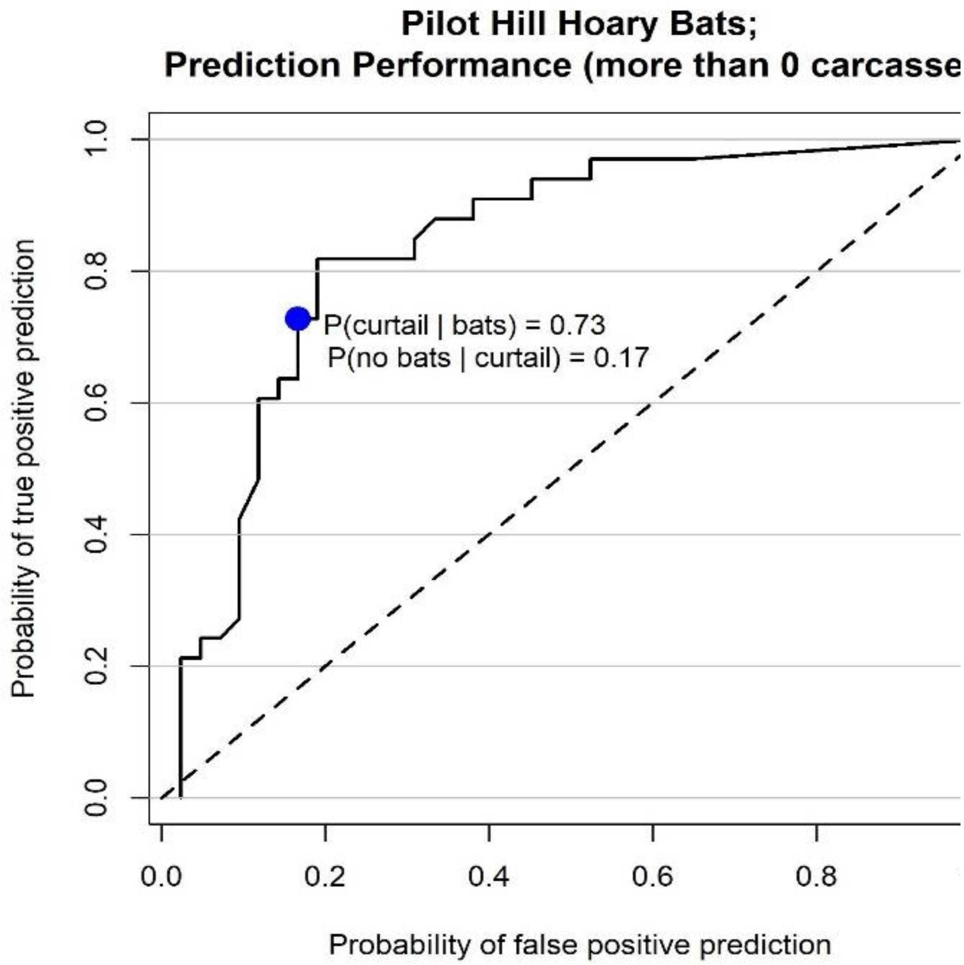

Figure 25. Fatality model performance for the logistic regression model predicting the probability at least one bat carcass at Pilot Hill.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting at least one bat carcass (on the y-axis) versus the probability of falsely predicting at least one bat carcass (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts at least two bat carcasses with 73% fidelity, and generates 17% false positive prediction.

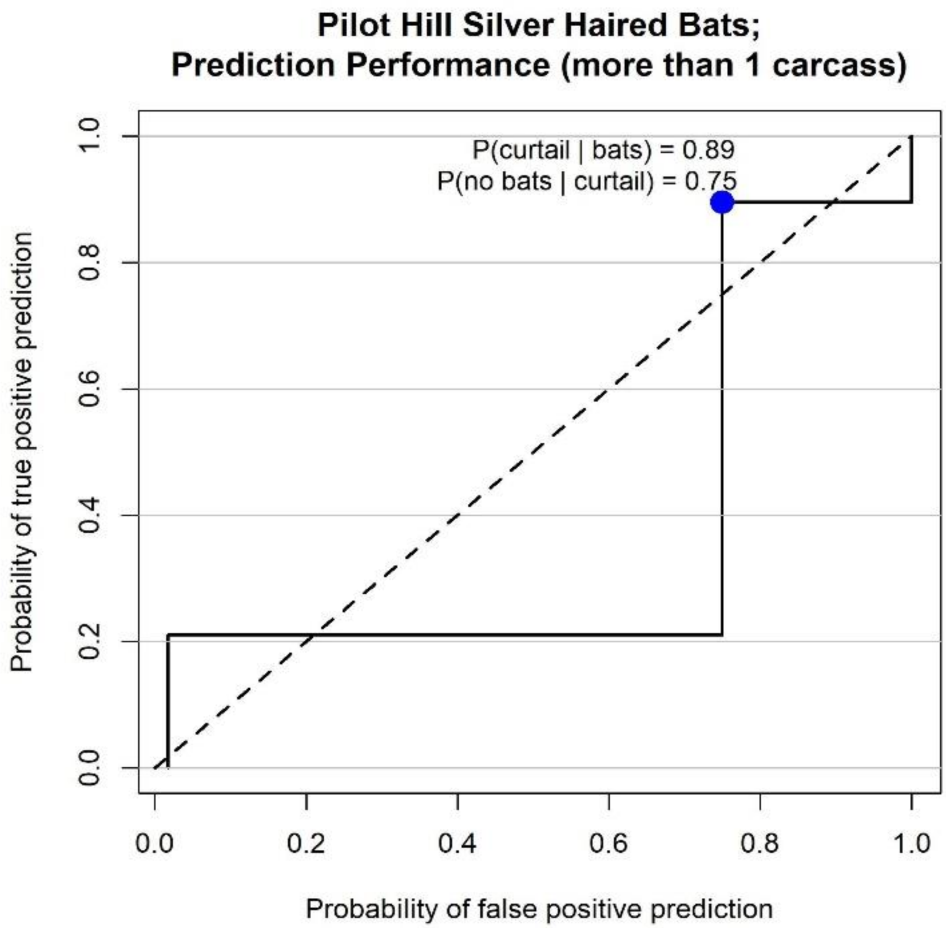

Figure 26. Fatality model performance for the logistic regression model predicting the probability at least two silver-haired bat carcasses at Pilot Hill.

Note, the solid line shows the range of prediction trade-offs available with the model, where the trade-off is expressed as the probability of correctly predicting at least two bat carcasses (on the y-axis) versus the probability of falsely predicting at least two bat carcasses (on the x-axis). The dashed grey 1:1 line indicates a model with no predictive power (i.e., no better at predicting than a coin flip). The blue point indicates an optimum for which the model correctly predicts at least two bat carcasses with 89% fidelity, and generates 75% false positive predictions.

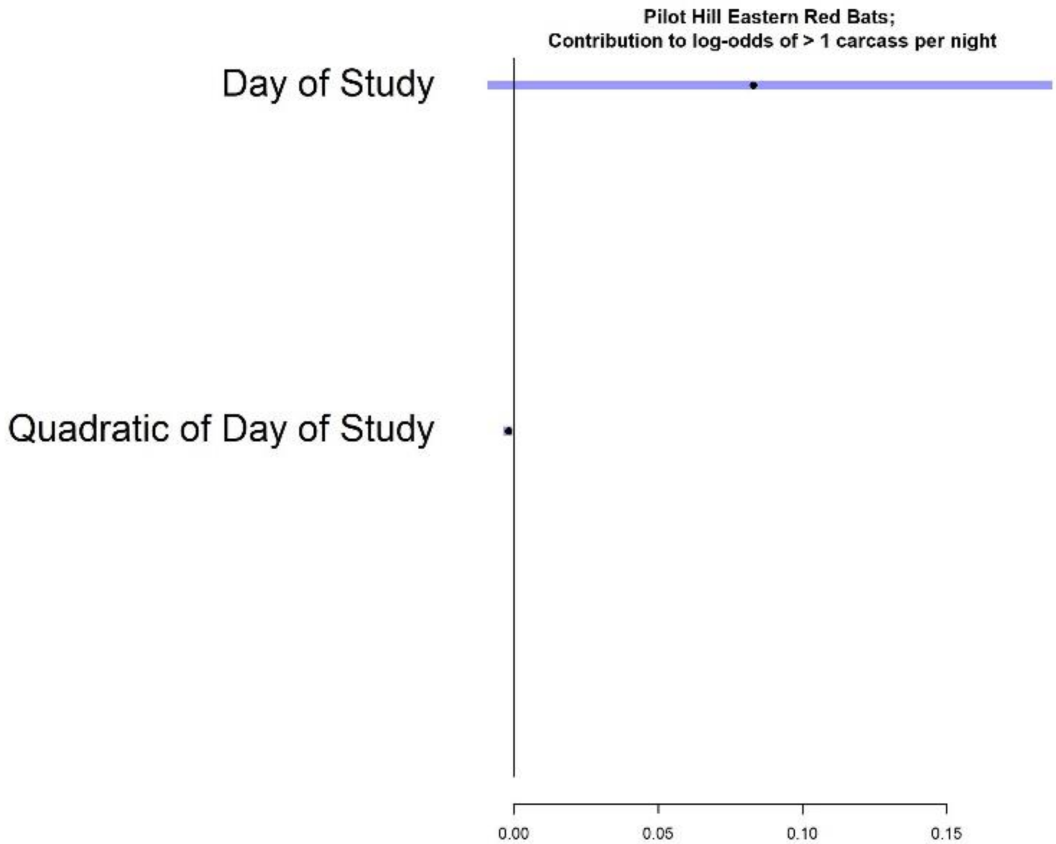

Figure 27. Parameters for the fatality model predicting probability of more than one eastern red bat carcass per turbine at the Pilot Hill Wind Farm.

Note, point estimates are indicated with dots, 90% confidence intervals (CI) on the model parameter values are indicated with lines. Parameter values are on a log-odds scale. Parameters with CIs that cross the zero line have an uncertain effect on the probability of carcass detection. CIs in blue are shown completely (see Appendix B for table showing CIs). Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

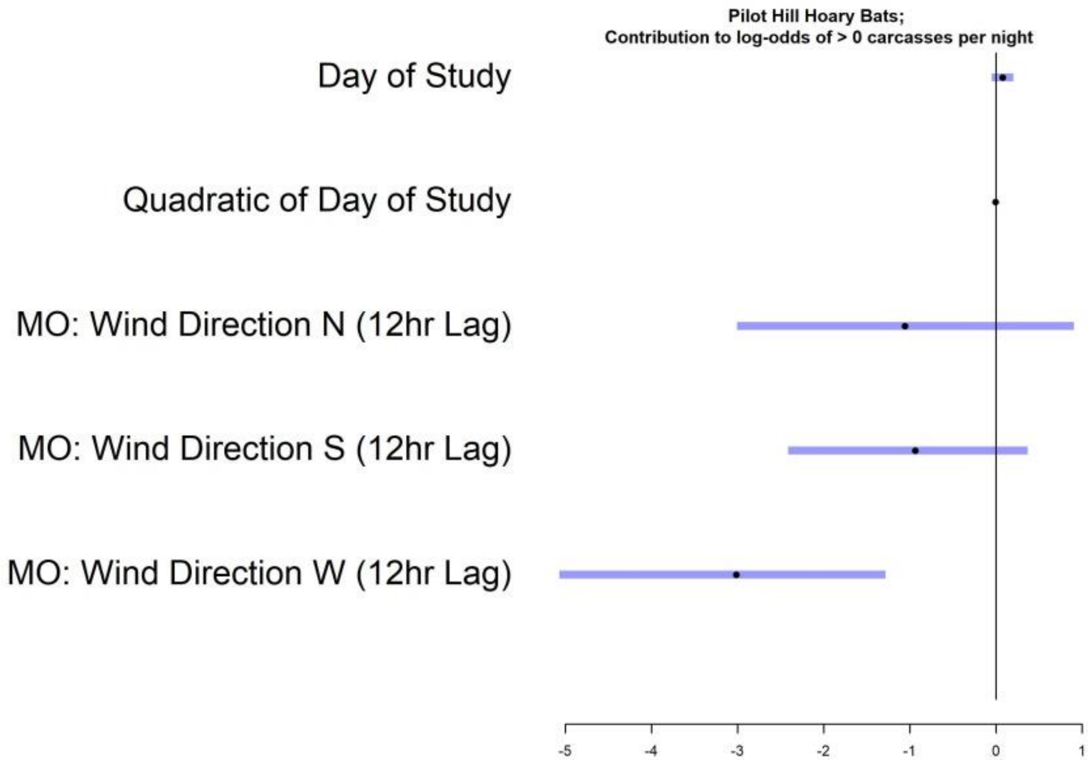

Figure 28. Parameters for the fatality model predicting probability of more than zero hoary bat carcasses per turbine at the Pilot Hill Wind Farm. Parameters are labeled as either collected on-site, or collected off-site at airports. Abbreviations for airport names are given in figure 5 and are shown as the initial two letters.

Note, point estimates are indicated with dots, 90% confidence intervals (CI) on the model parameter values are indicated with lines. Parameters with CIs that cross the zero line have an uncertain effect on the probability of carcass detection. CIs in blue are shown completely (see Appendix B for table showing CIs). Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

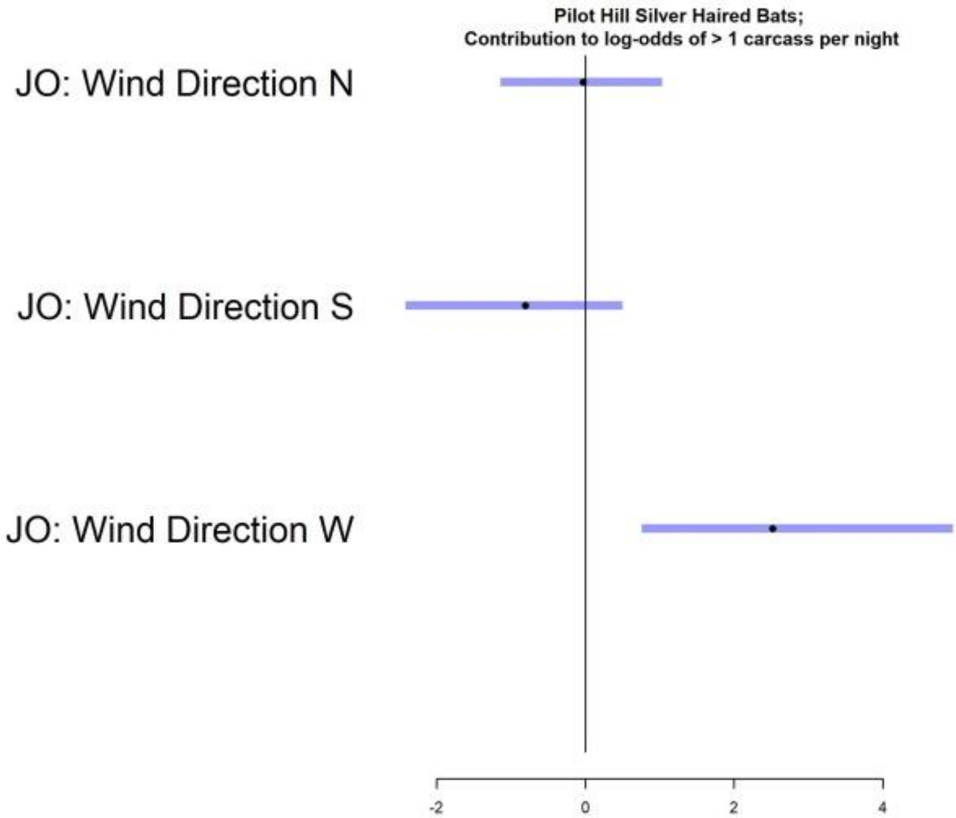

Figure 29. Parameters for the fatality model predicting probability of more than one silver-haired bat carcass per turbine at the Pilot Hill Wind Farm. Parameters are labeled as either collected on-site, or collected off-site at airports. Abbreviations for airport names are given in Figure 5 and are shown as the initial two letters.

Note, point estimates are indicated with dots, 90% confidence intervals (CI) on the model parameter values are indicated with lines. Parameter values are on a log-odds scale. Parameters with CIs that cross the zero line have an uncertain effect on the probability of carcass detection. CIs in blue are shown completely; (see Appendix B for table showing CIs). Parameters to the left of the vertical line indicate a decrease in the parameter was associated with increasing odds of greater than one call was recorded. Parameters to the right of the vertical line indicate an increase in the parameter was associated with increasing odds of greater than one call was recorded.

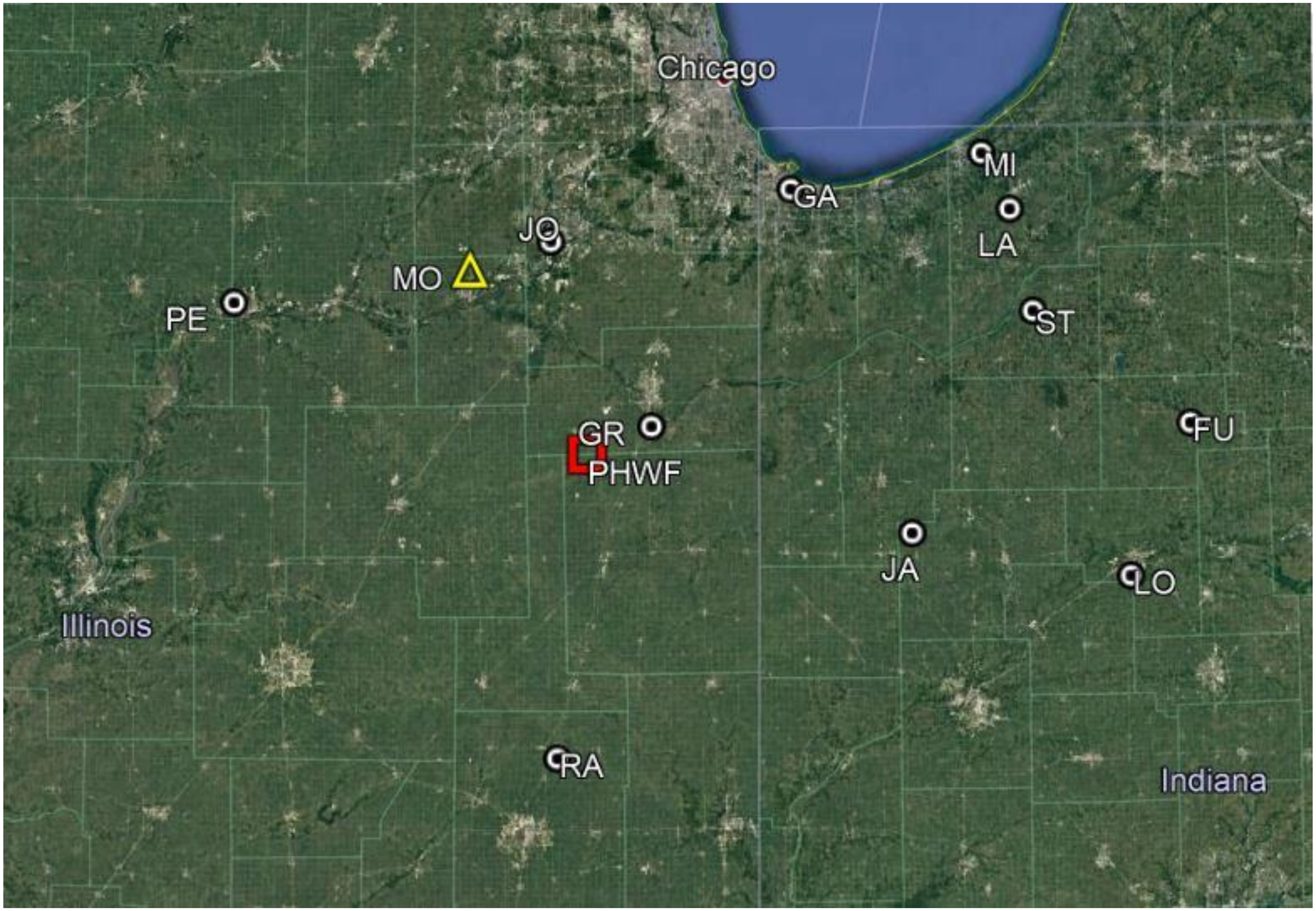

Figure 30. Map of airports that appeared in the hoary bat fatality model in relationship to the Pilot Hill Wind Farm. Airports with data included in the top model are represented by yellow triangles. Abbreviations for airport names are given in Figure 5.

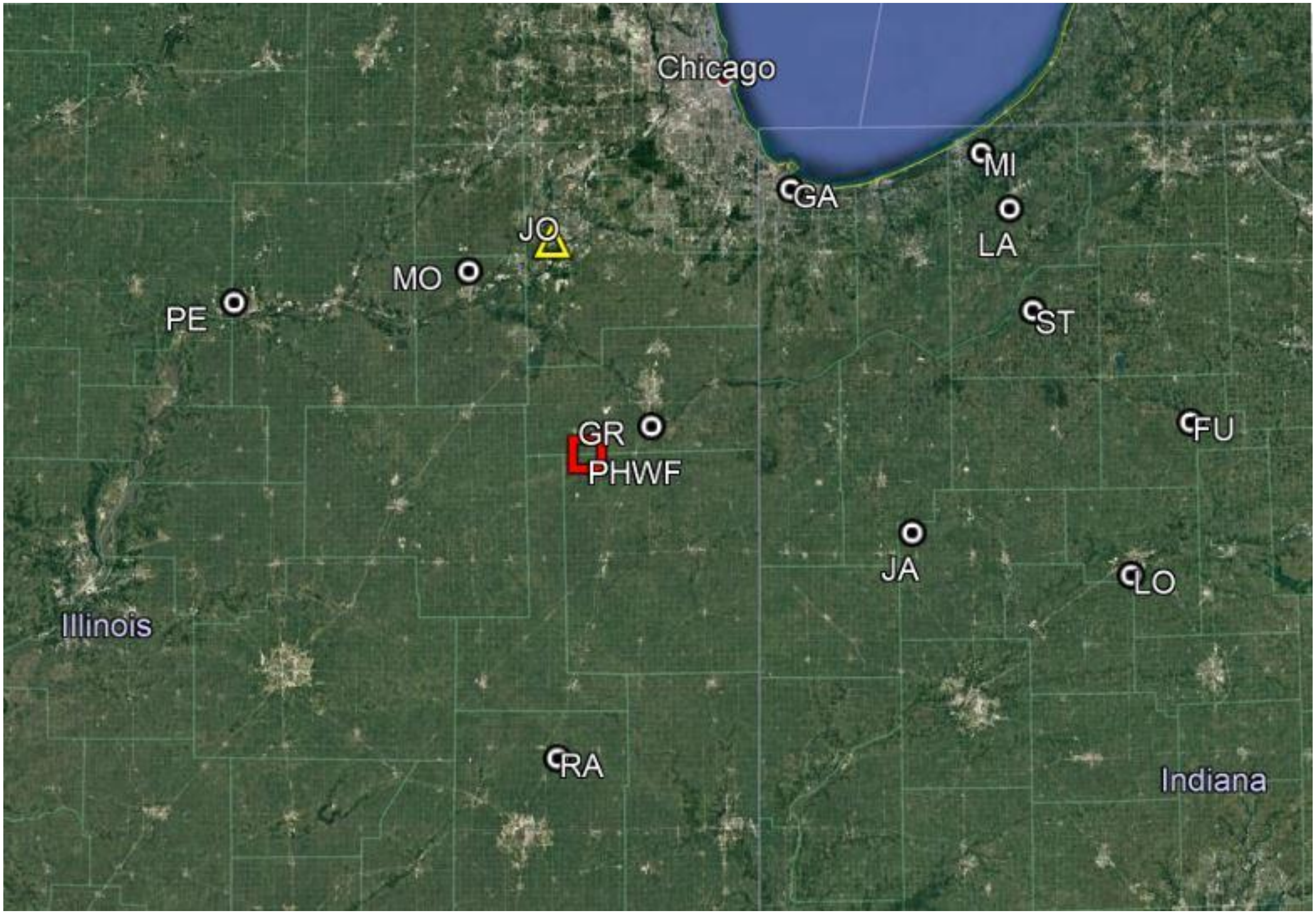

Figure 31. Map of airports that appeared in the silver-haired bat fatality model in relationship to the Pilot Hill Wind Farm. Airports with data included in the top model are represented by yellow triangles. Abbreviations for airport names are given in Figure 5.

Regression Analysis of Bat Carcasses Found on Bat Activity the Previous Night

We regressed the count of fatalities each day on the counts of acoustic calls from the previous evening to determine if acoustic activity was a strong predictor of bat mortality for all bats (Figure 32), eastern red bats (Figure 33), hoary bat (Figure 34), and silver-haired/big brown bats (Figure 35), but cross validation showed none of the models had good predictive power (Figures 36–39). A given percent increase in bat calls did not scale consistently with a similar percent increase in bat fatalities. However, a visual inspection of bat carcass and call counts suggested the presence of an increase in bat activity in a given night was potentially associated with an increase in bat fatalities. Models for bat carcass counts based on counts of bat calls were developed for PHWF site, but not for KCWF due to low carcass counts at turbines with detectors.

Some general patterns were observed from a visual inspection of fatalities compared to acoustic bat calls. Higher eastern red bat calls and fatalities were observed in mid-August to early September (Figure 32). Higher hoary bat activity and fatalities were observed in early August through early September (Figure 33).

There were only 24 calls that could be clearly identified as silver-haired bat, separate from big brown bat. The low number of calls precluded the use of a modeling approach to predict fatalities. Periods of time with more silver-haired bat calls were associated with higher silver-haired bat fatalities (Figure 40), and both activity and fatalities occurred later in the fall compared to eastern red bat and hoary bat.

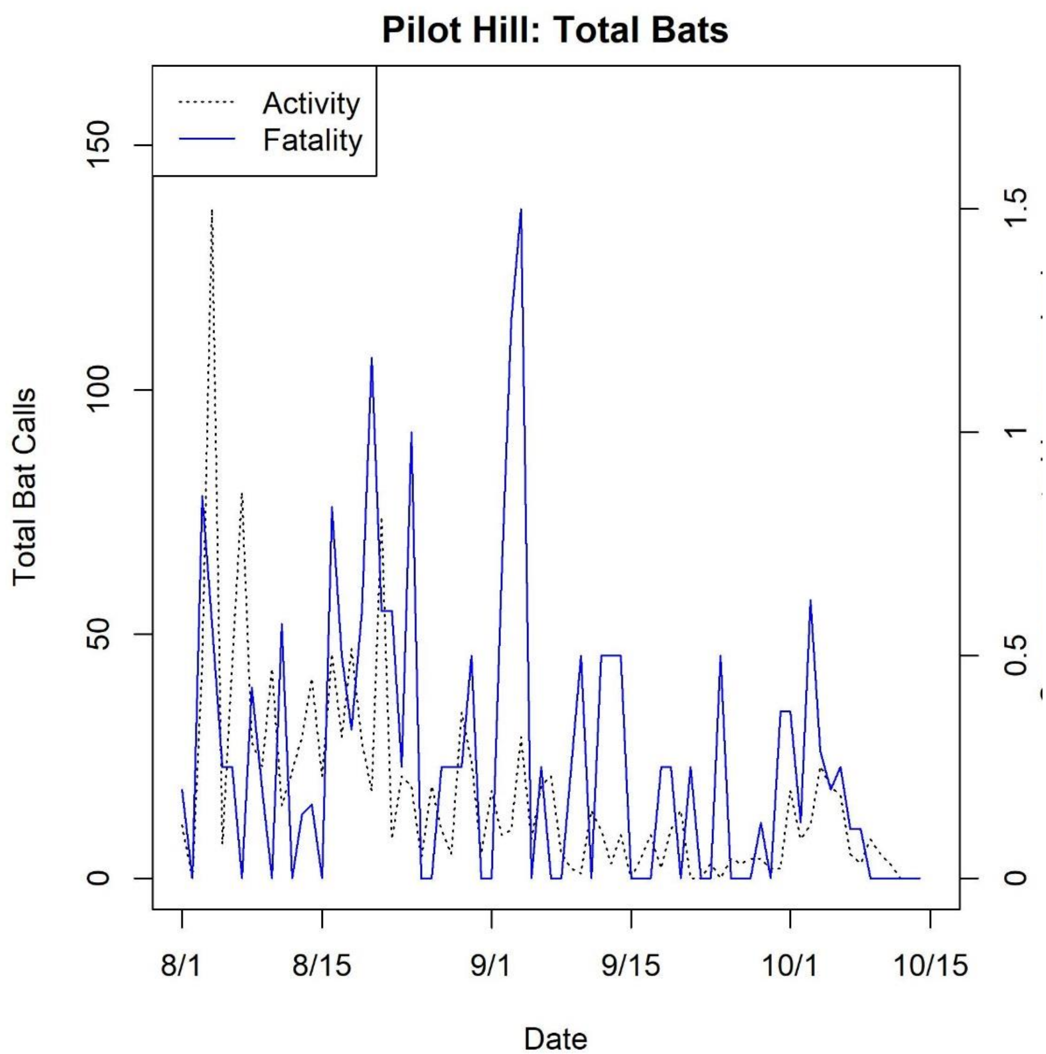

Figure 32. The number of all bat calls recorded from the previous evening relative to the number of bat carcasses per turbine searched at the Pilot Hill Wind Farm.

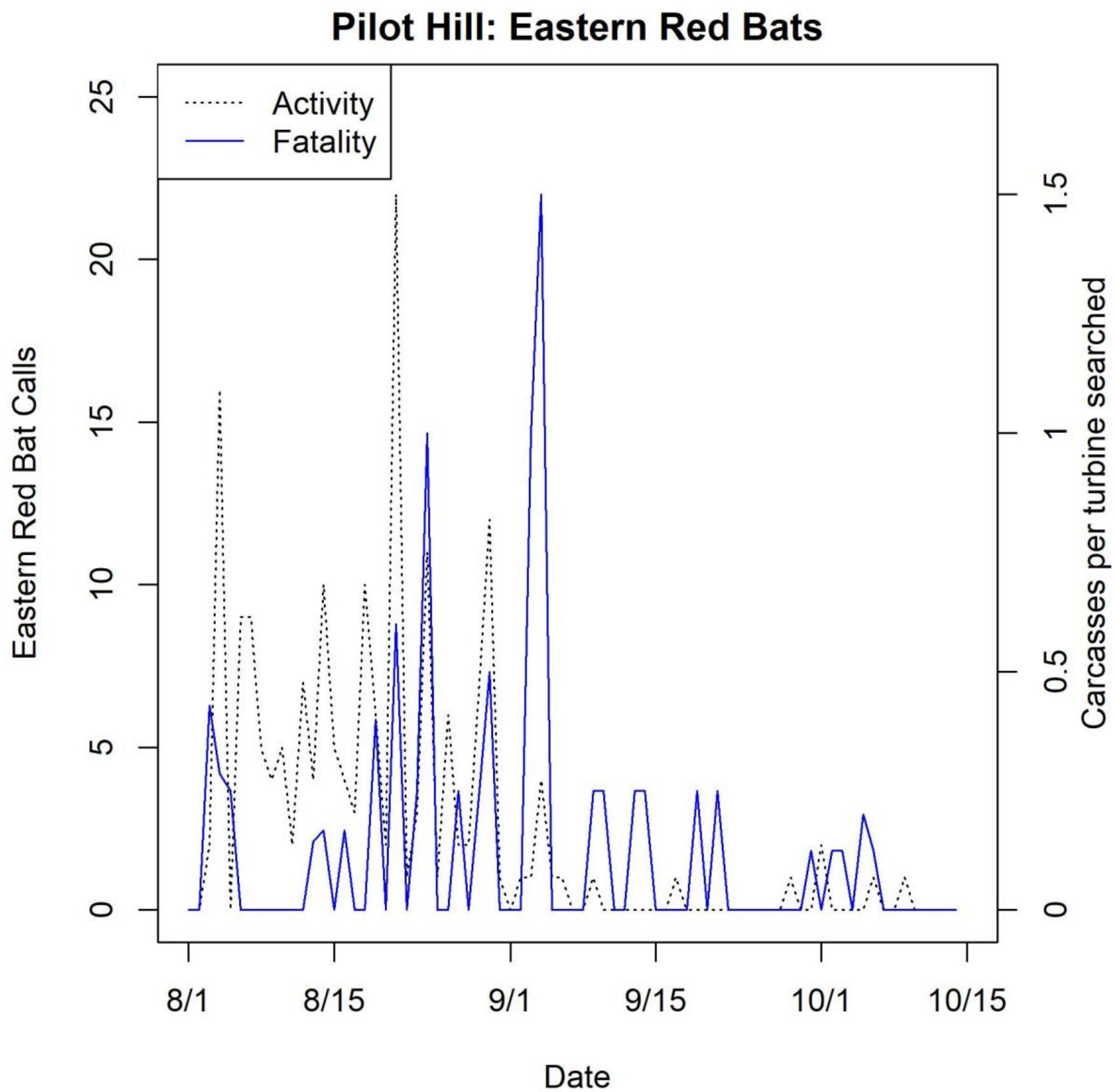

Figure 33. The number of eastern red bat calls recorded from the previous evening relative to the number of eastern red bat carcasses per turbine searched at the Pilot Hill Wind Farm.

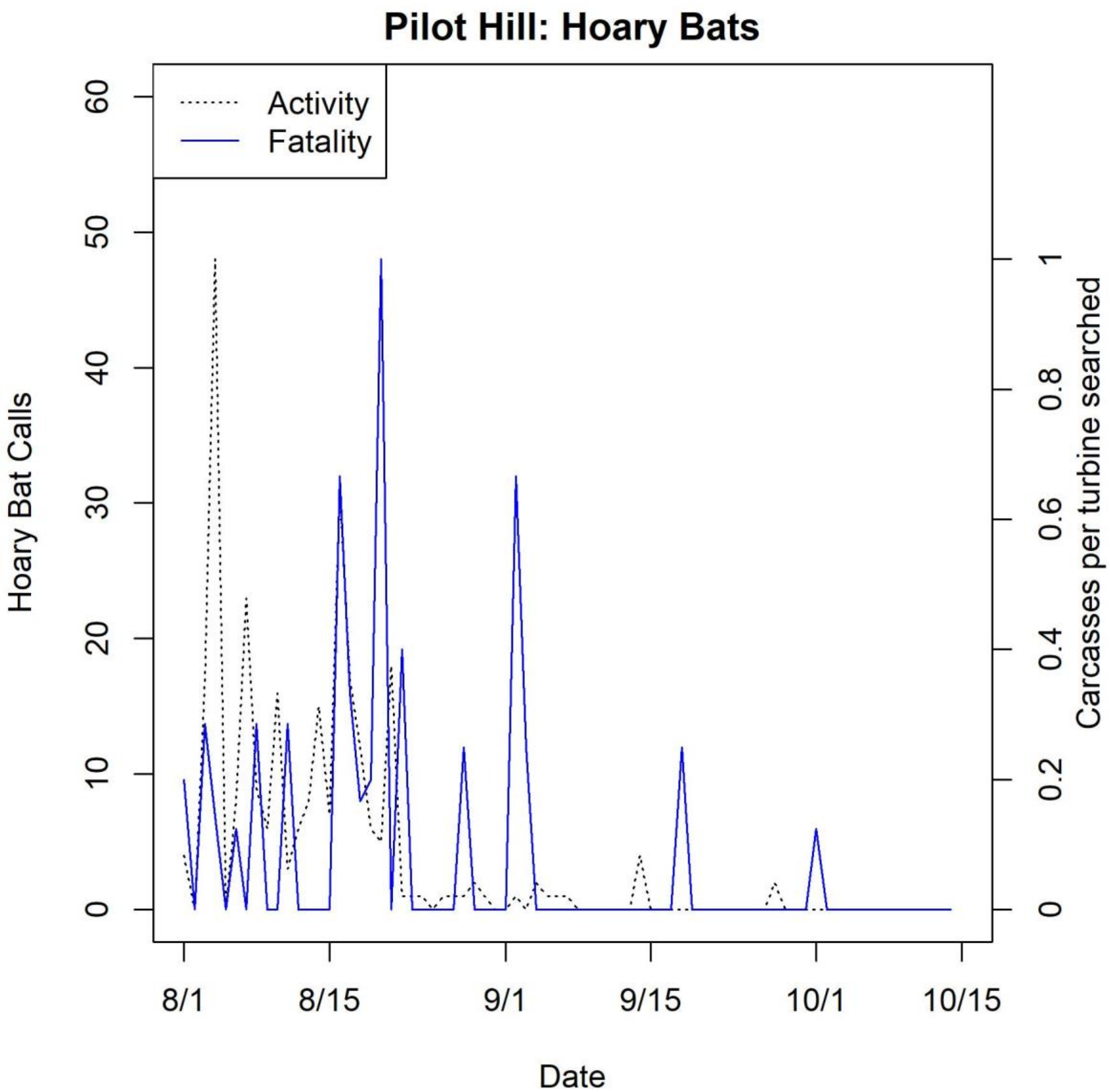

Figure 34. The number of hoary bat calls recorded from the previous evening relative to the number of hoary bat carcasses per turbine searched at the Pilot Hill Wind Farm.

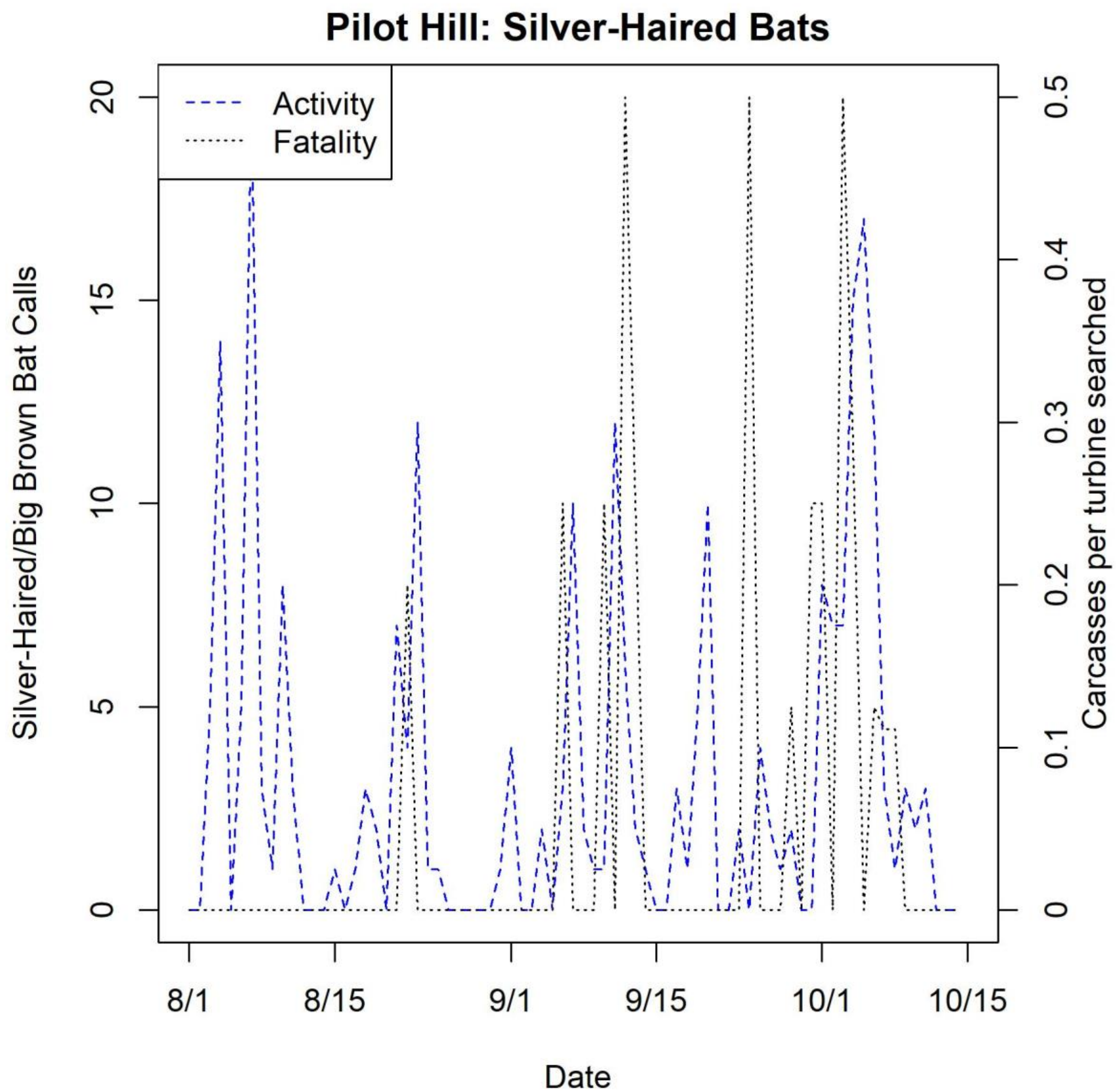

Figure 35. The number of silver-haired bat/big brown bat calls recorded from the previous evening relative to the number of silver-haired bat carcasses per turbine searched at the Pilot Hill Wind Farm.

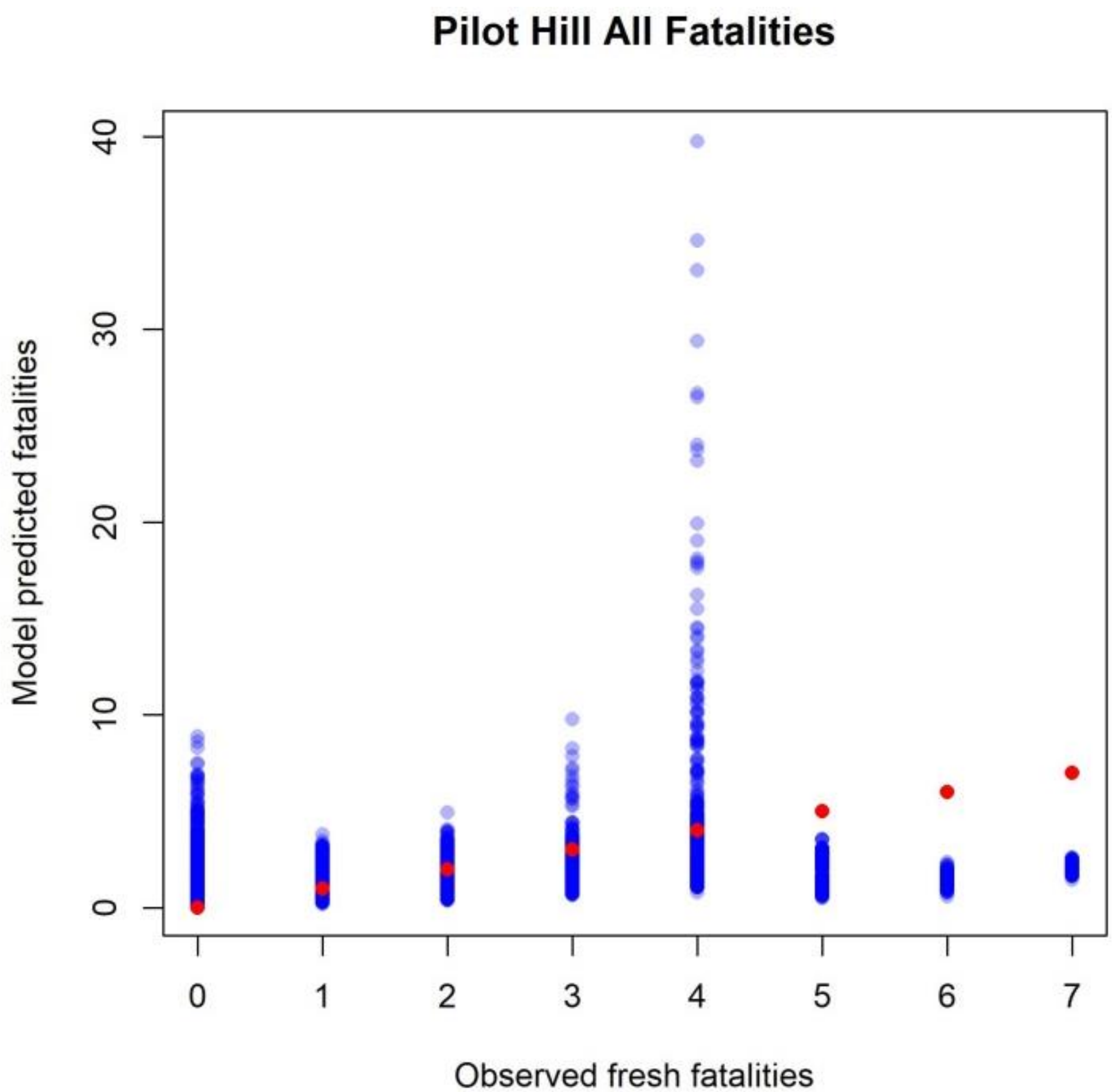

Figure 36. Summary of k-fold cross-validation results for the Poisson regression of 2018 all bat carcass counts on acoustic call counts from the previous evening at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis using blue dots. Perfect model performance would result in all points plotting on the red dots.

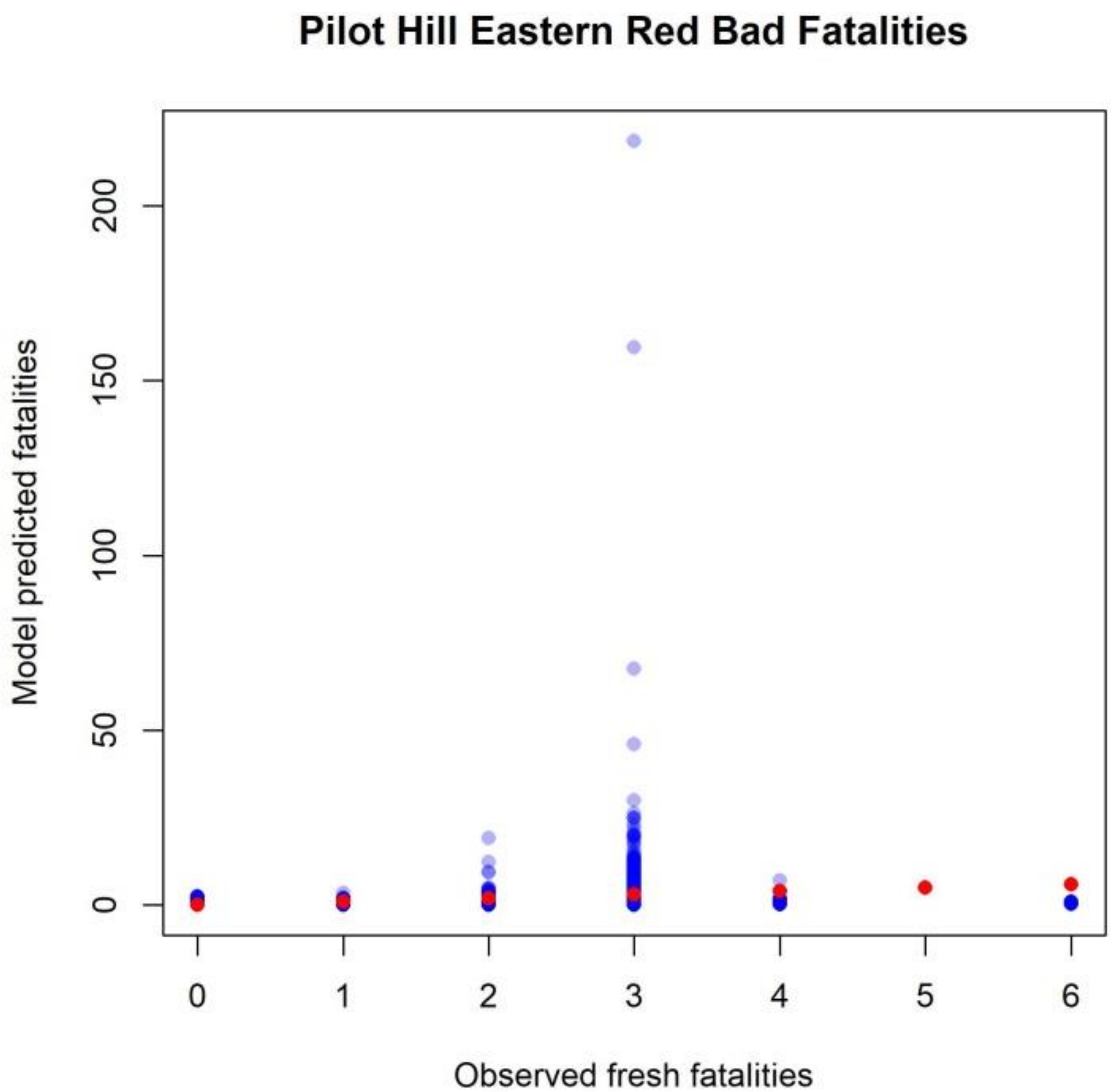

Figure 37. Summary of k-fold cross-validation results for the Poisson regression of 2018 eastern red bat carcass counts on acoustic call counts from the previous evening at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis in blue. Perfect model performance would result in all points plotting on the red dots.

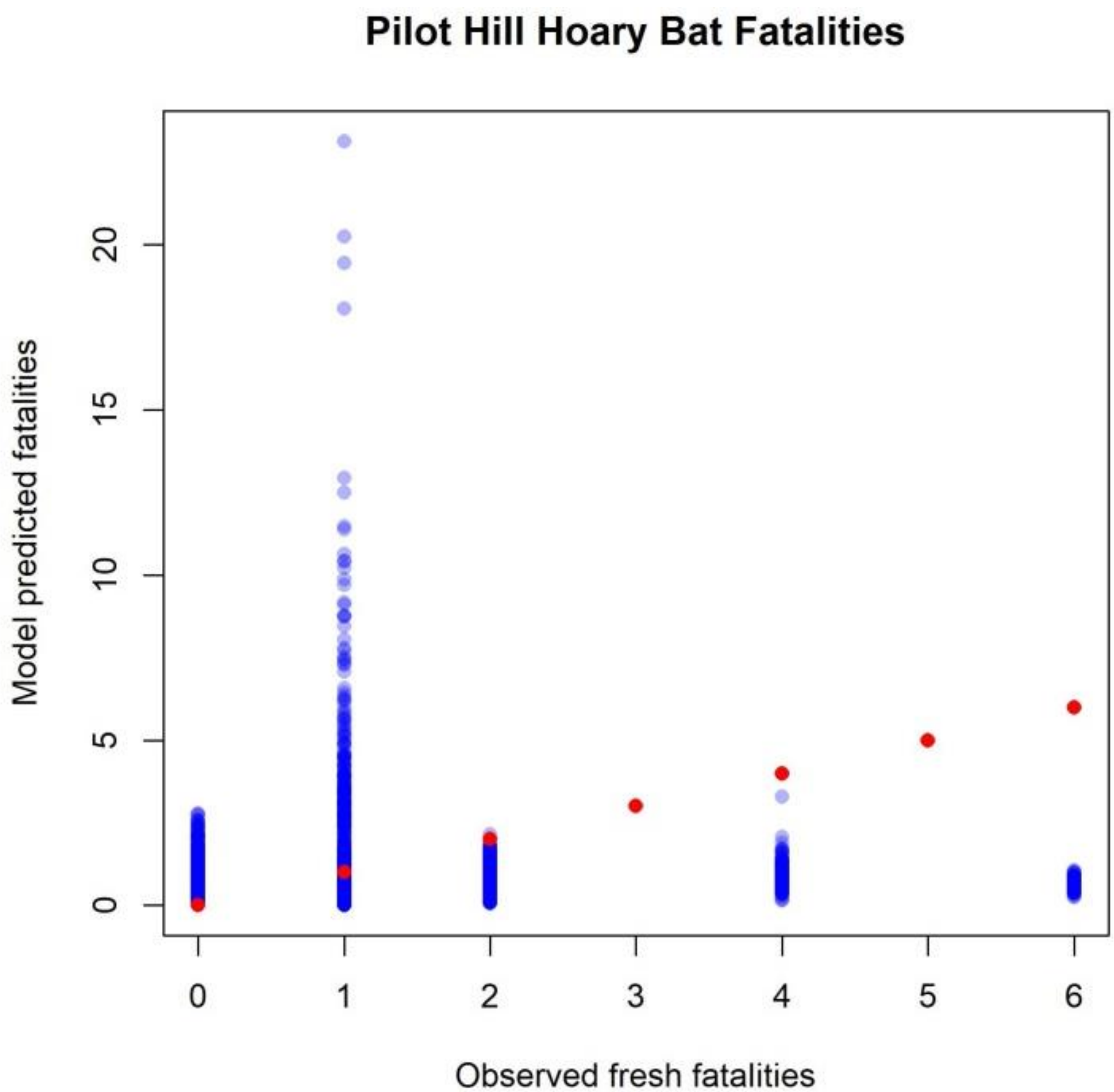

Figure 38. Summary of k-fold cross-validation results for the Poisson regression of 2018 hoary bat carcass counts on acoustic call counts from the previous evening at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis in blue. Perfect model performance would result in all points plotting on the red dots.

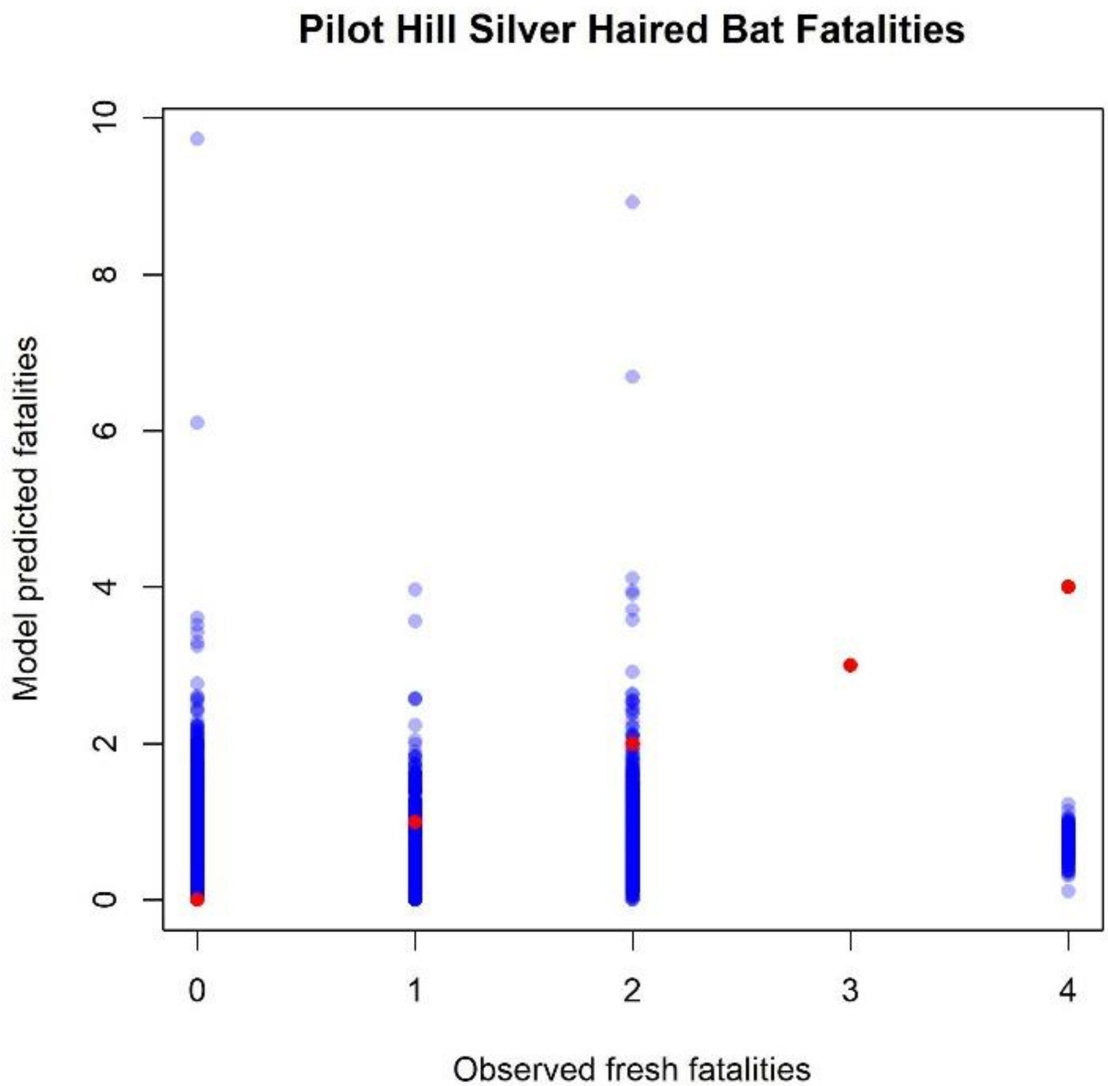

Figure 39. Summary of k-fold cross-validation results for the Poisson regression of 2018 silver-haired carcass counts on silver-haired/big brown bat acoustic call counts from the previous evening at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis in blue. Perfect model performance would result in all points plotting on the red dots.

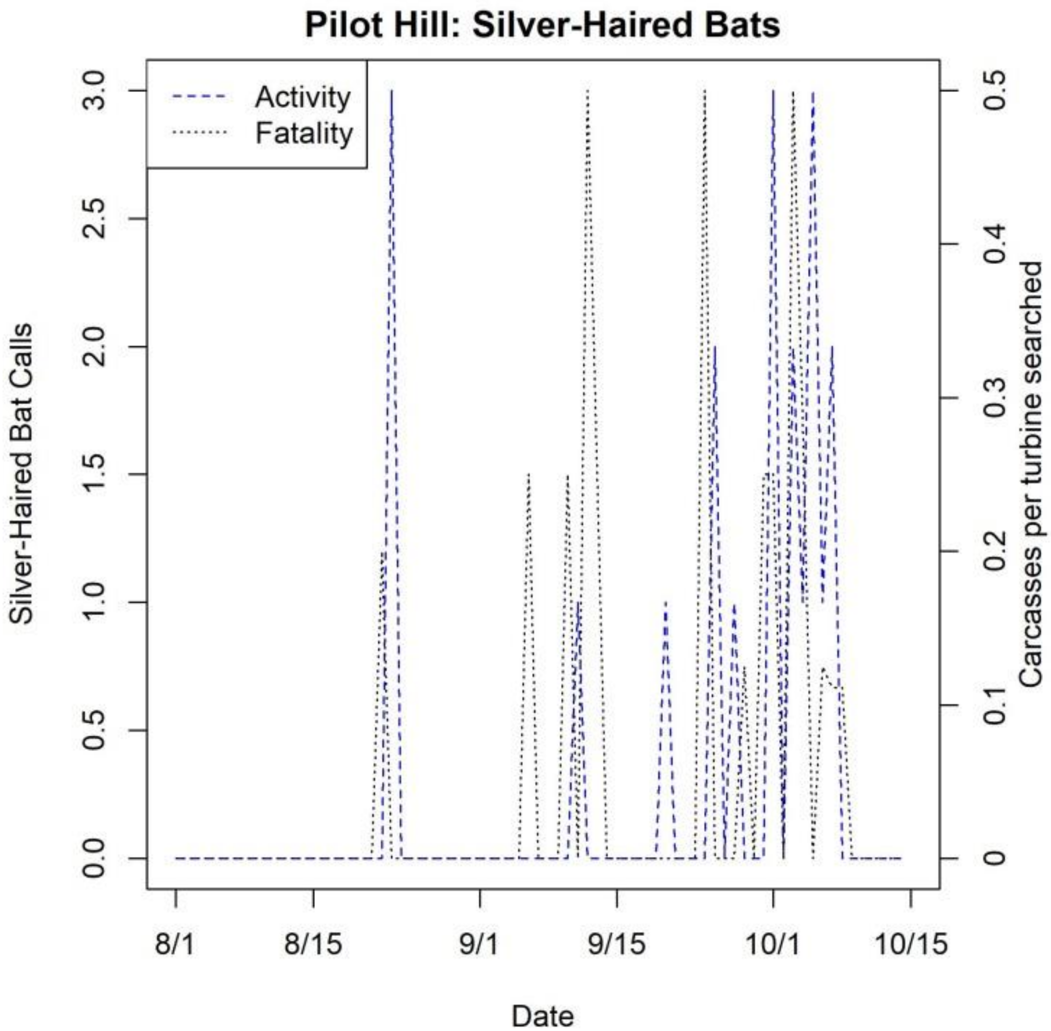

Figure 40. The number of silver-haired bat calls recorded from the previous evening relative to the number of silver-haired bat carcasses per turbine searched at the Pilot Hill Wind Farm.

We further divided the calls into three time periods (early night, midnight, and late night) to determine if the risk of bat fatalities was more closely related to activity in different portions of a night. We regressed the count of fatalities each day on the counts of acoustic calls from each of the three portions of the previous night. The best model for all bats included late night calls (Figure 41), early night calls for eastern red bats (Figure 42), and early to midnight calls for hoary bats (Figure 43), but cross validation showed none of the models had good predictive power (Figures 44–46); that is, a given percent increase in bat calls did not scale consistently with a similar percent increase in bat fatalities. Positive, but inconsistent relationships between acoustic bat activity during the late night period (2 AM–30 min before sunrise) and recent fatalities were observed at turbines with a detector (Figure 44). Counts of eastern red bat carcasses were positively but inconsistently associated with the number of bat calls in the early night (Figure 45). Counts of hoary bat carcasses were negatively and inconsistently associated with counts of early night bat calls and positively associated with midnight bat calls (Figure 46). Parameter estimates from partial night calls are provided within Appendix D. Silver-haired bat calls were not further analyzed due to low sample sizes.

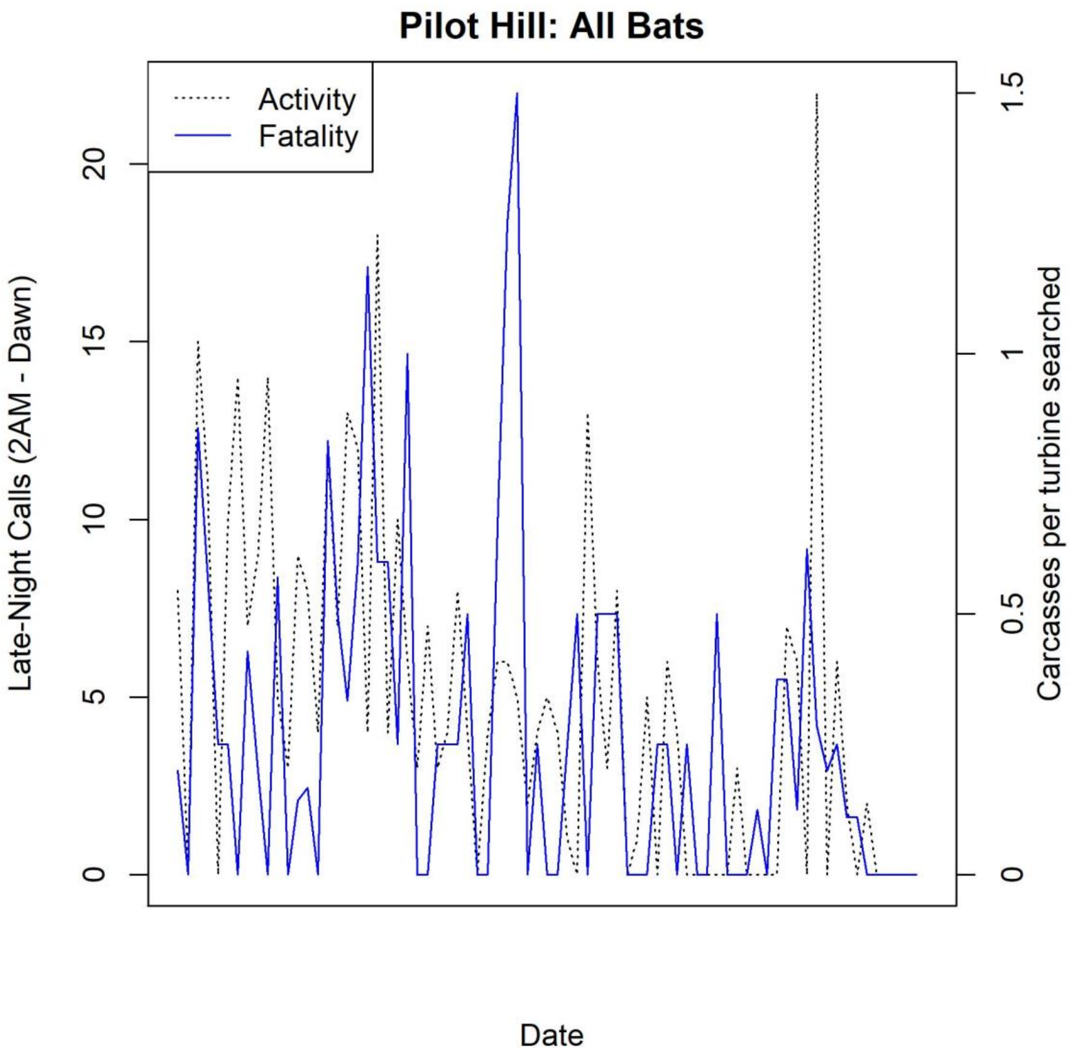

Figure 41. The number of all bat calls recorded from the late night relative to the number of bat carcasses per turbine searched at the Pilot Hill Wind Farm.

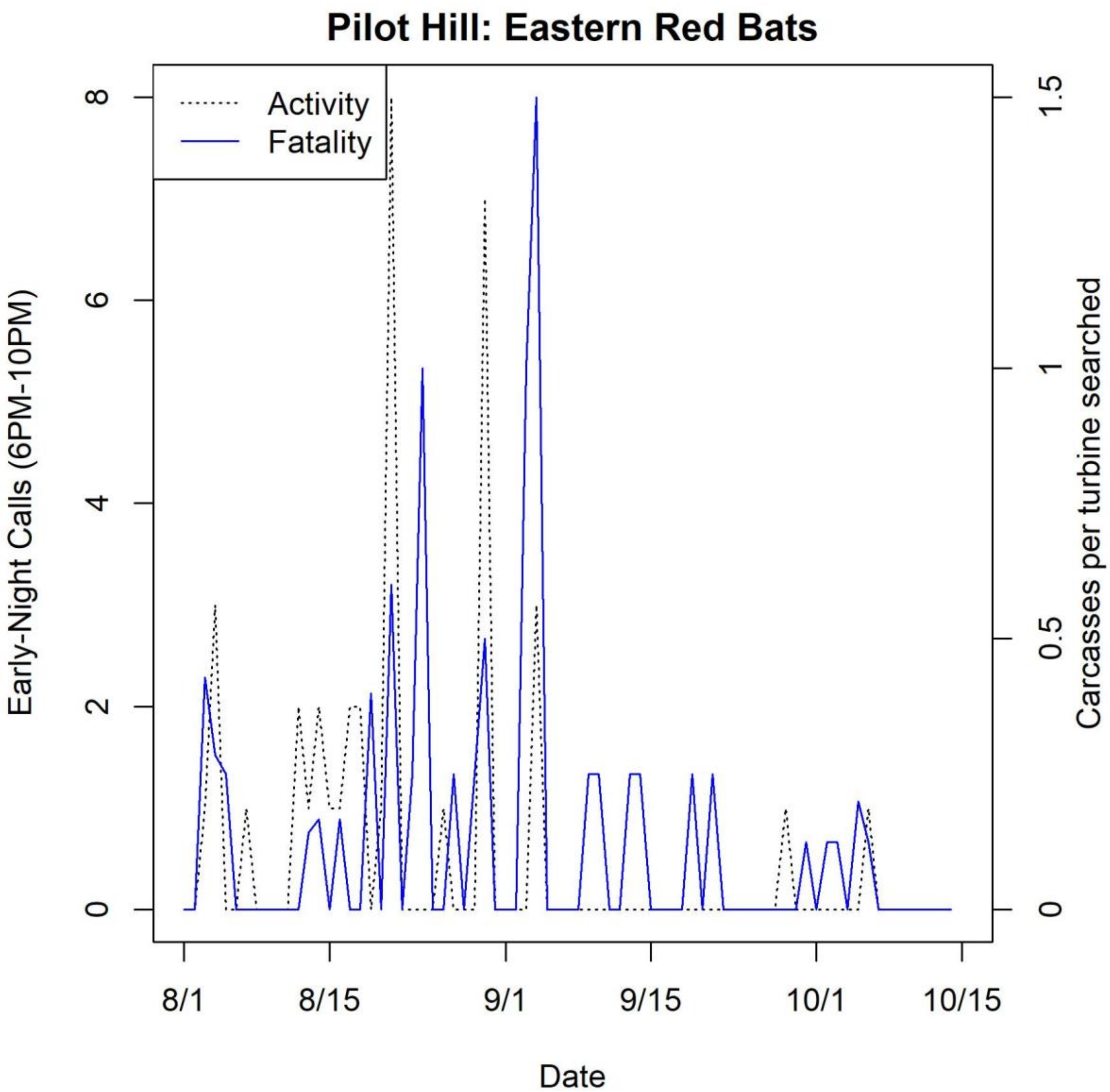

Figure 42. The number of eastern red bat calls recorded from the early night relative to the number of bat carcasses per turbine searched at the Pilot Hill Wind Farm.

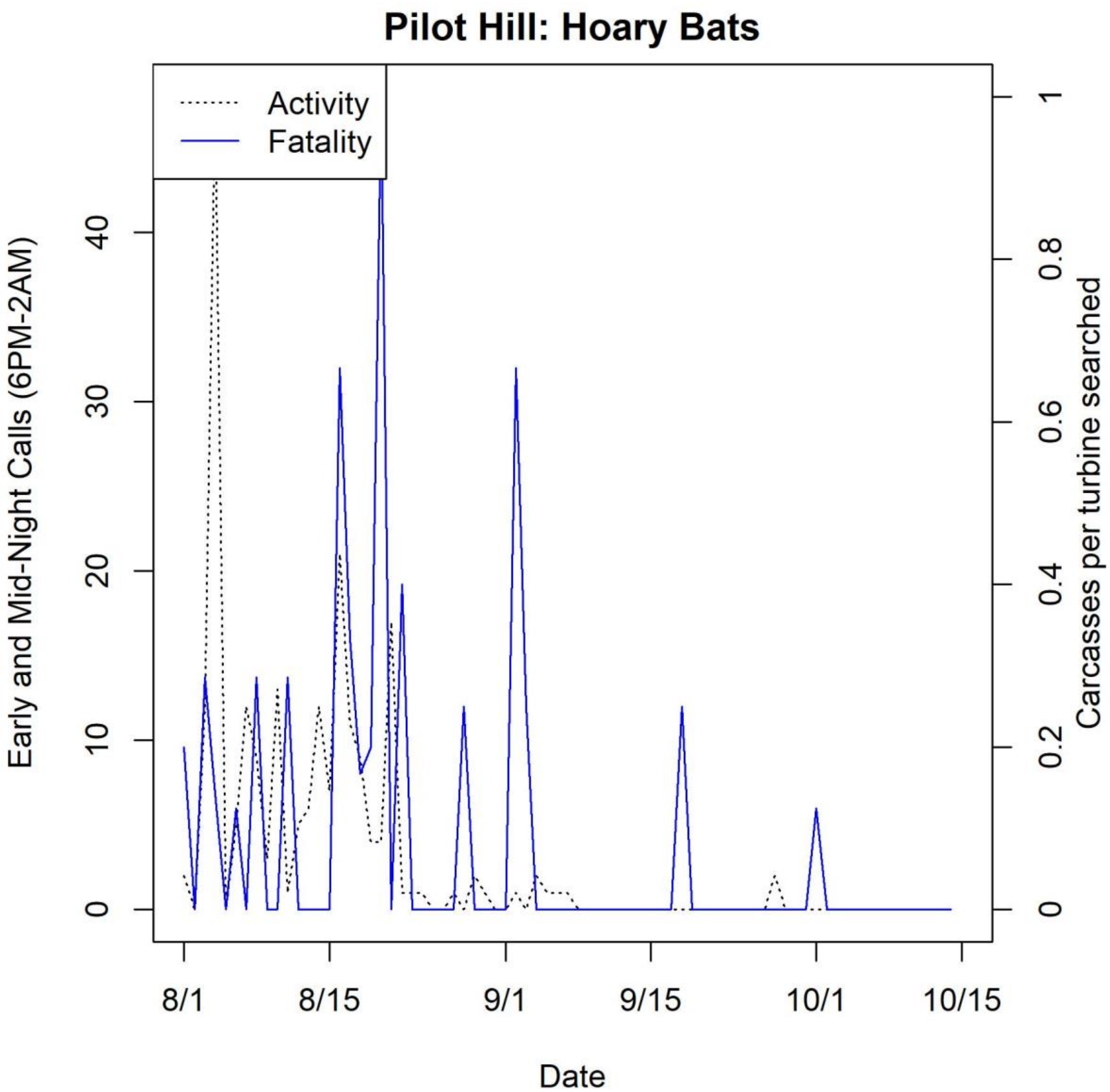

Figure 43. The number of early and mid night hoary bat calls recorded relative to the number of eastern hoary bat carcasses per turbine searched at the Pilot Hill Wind Farm.

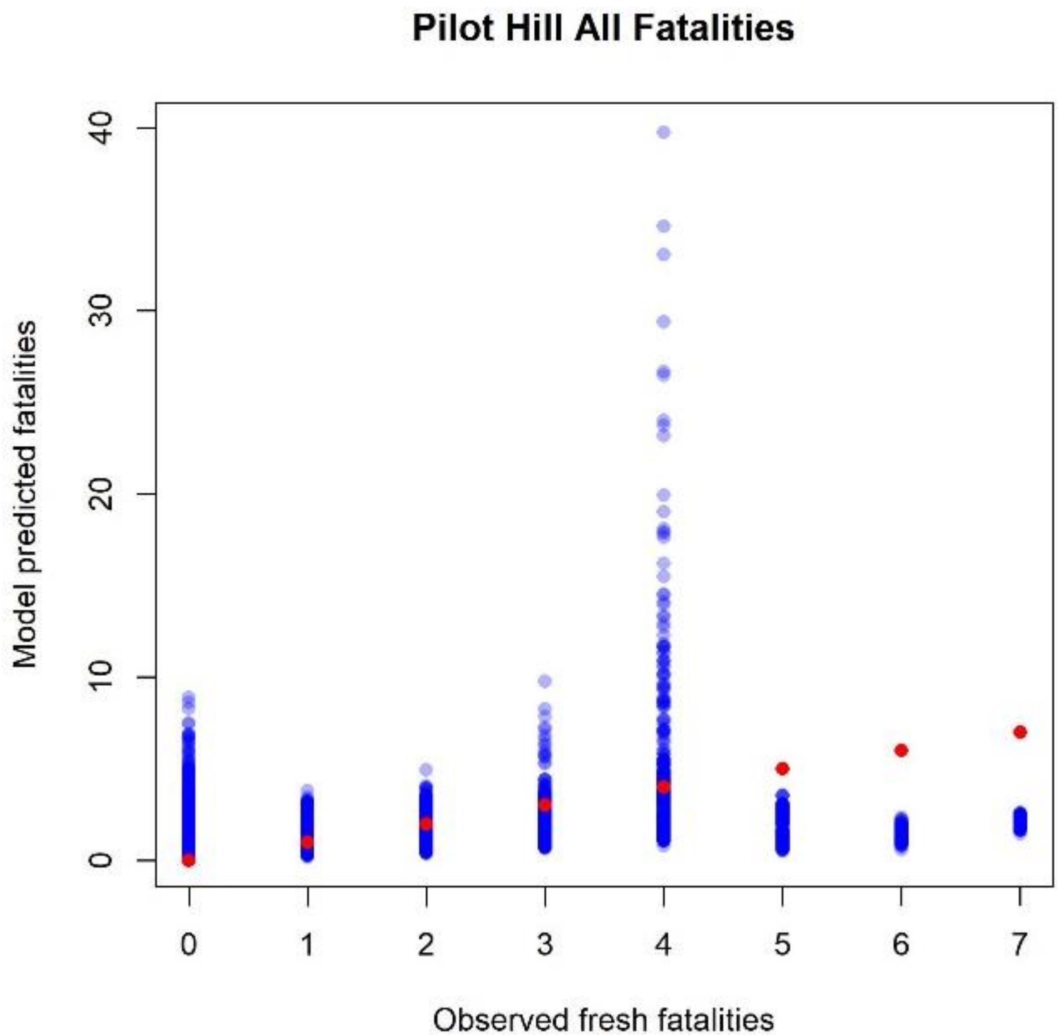

Figure 44. Summary of k-fold cross-validation results for the Poisson regression of all bat carcass counts on late night acoustic call counts from the previous night at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis in blue. Perfect model performance would result in all points plotting on the red dots.

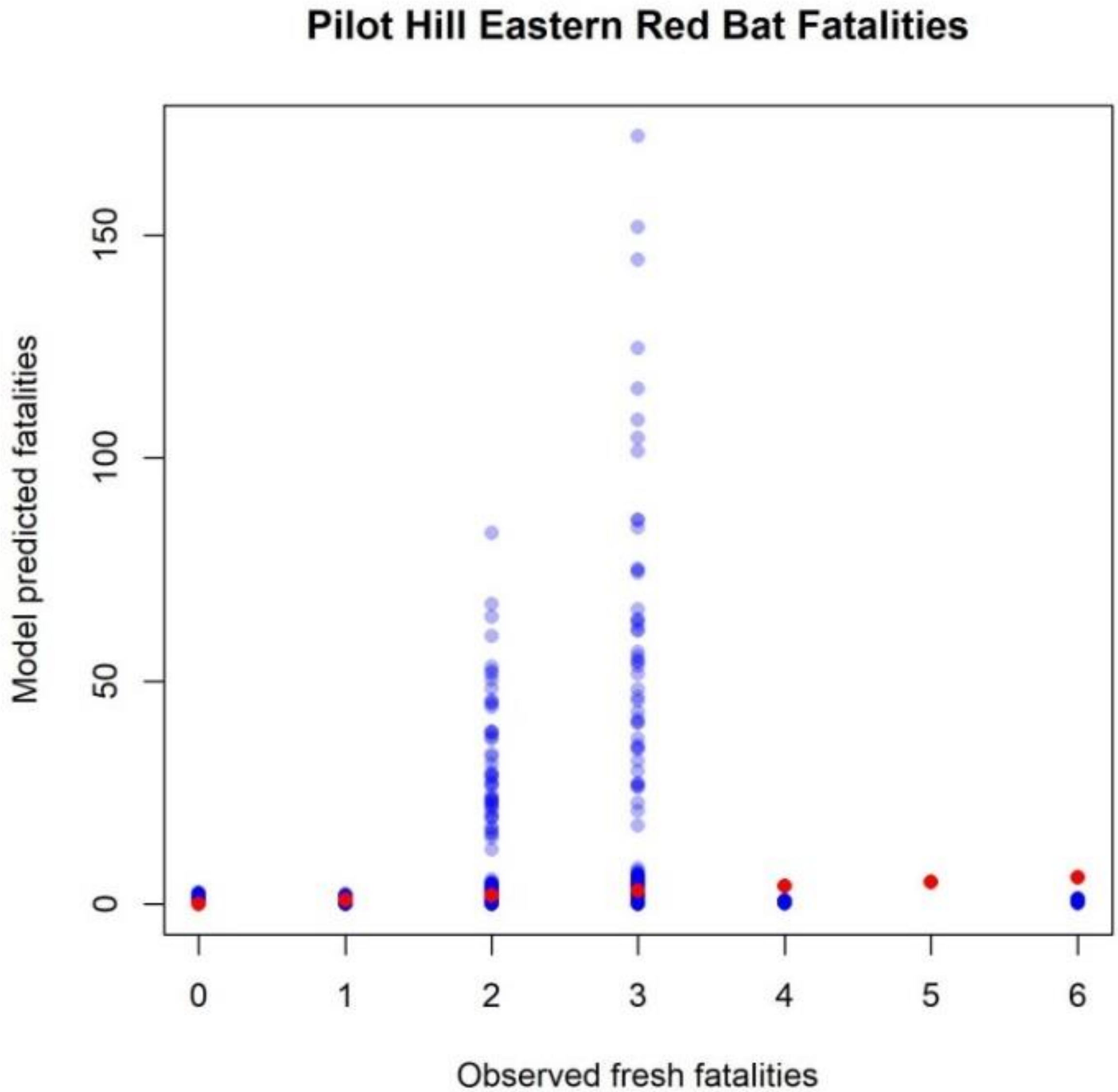

Figure 45. Summary of k-fold cross-validation results for the Poisson regression of 2018 eastern red bat carcass counts on early night eastern red bat acoustic call counts from the previous night at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis in blue. Perfect model performance would result in all points plotting on the red dots.

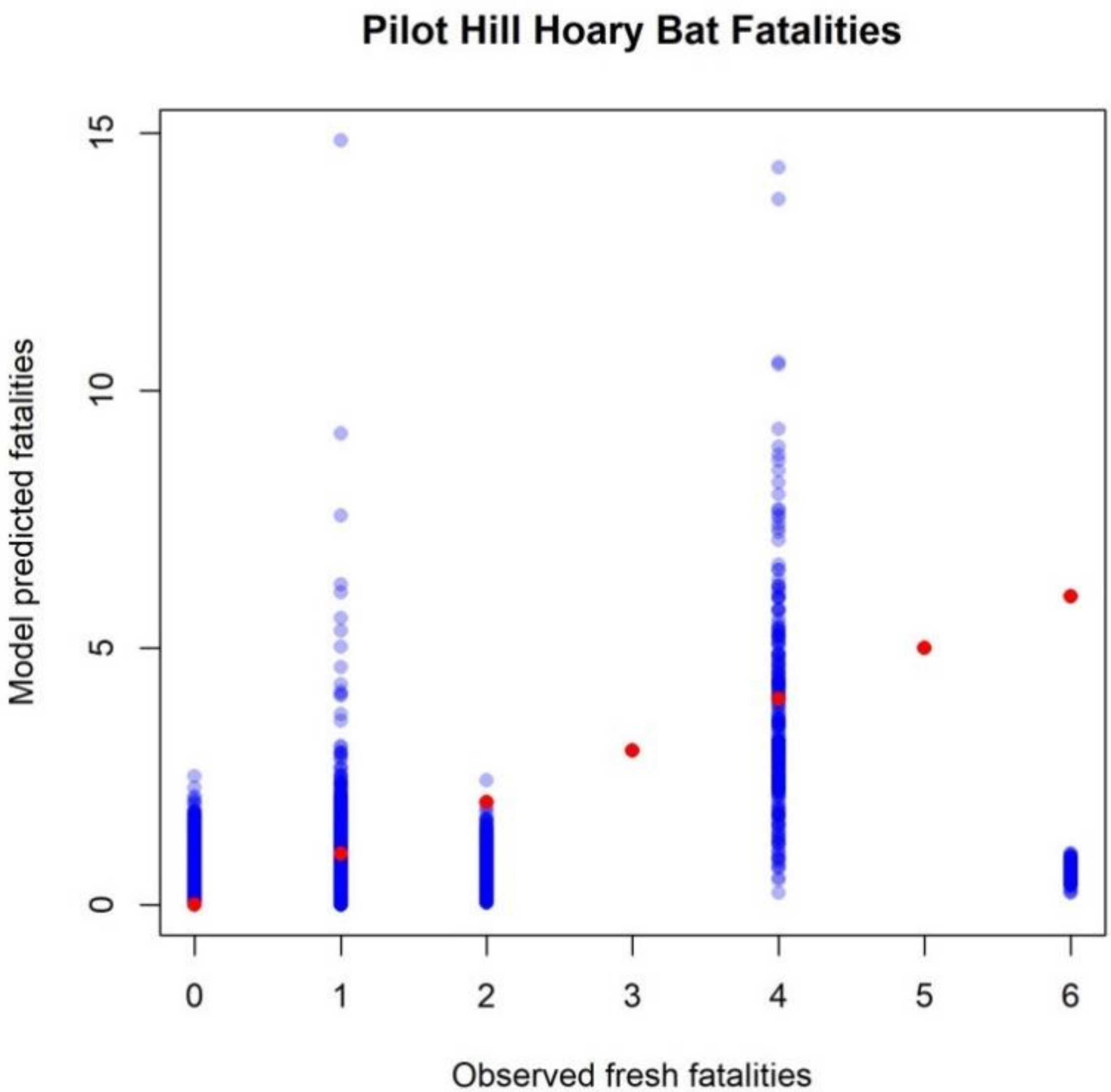

Figure 46. Summary of k-fold cross-validation results for the Poisson regression of 2018 hoary bat carcass counts on early and mid night hoary bat calls at the Pilot Hill Wind Farm.

Note, predicted counts from validation data sets are given on the y-axis, observations are given on the x-axis in blue. Perfect model performance would result in all points plotting on the red dots.

Data Summaries

Relationships between bat activity and time of night and wind speed, and bat fatalities and day of study were further explored to determine if curtailment could be refined.

The timing of bat passes recorded each night was similar between the two Projects and was combined into one figure (Figure 47). No bat activity was detected from sunset until two hours past sunset on most nights. The last call observed was typically near or shortly after sunrise. This general pattern was also observed in fall 2017 (Iskali et al. 2018).

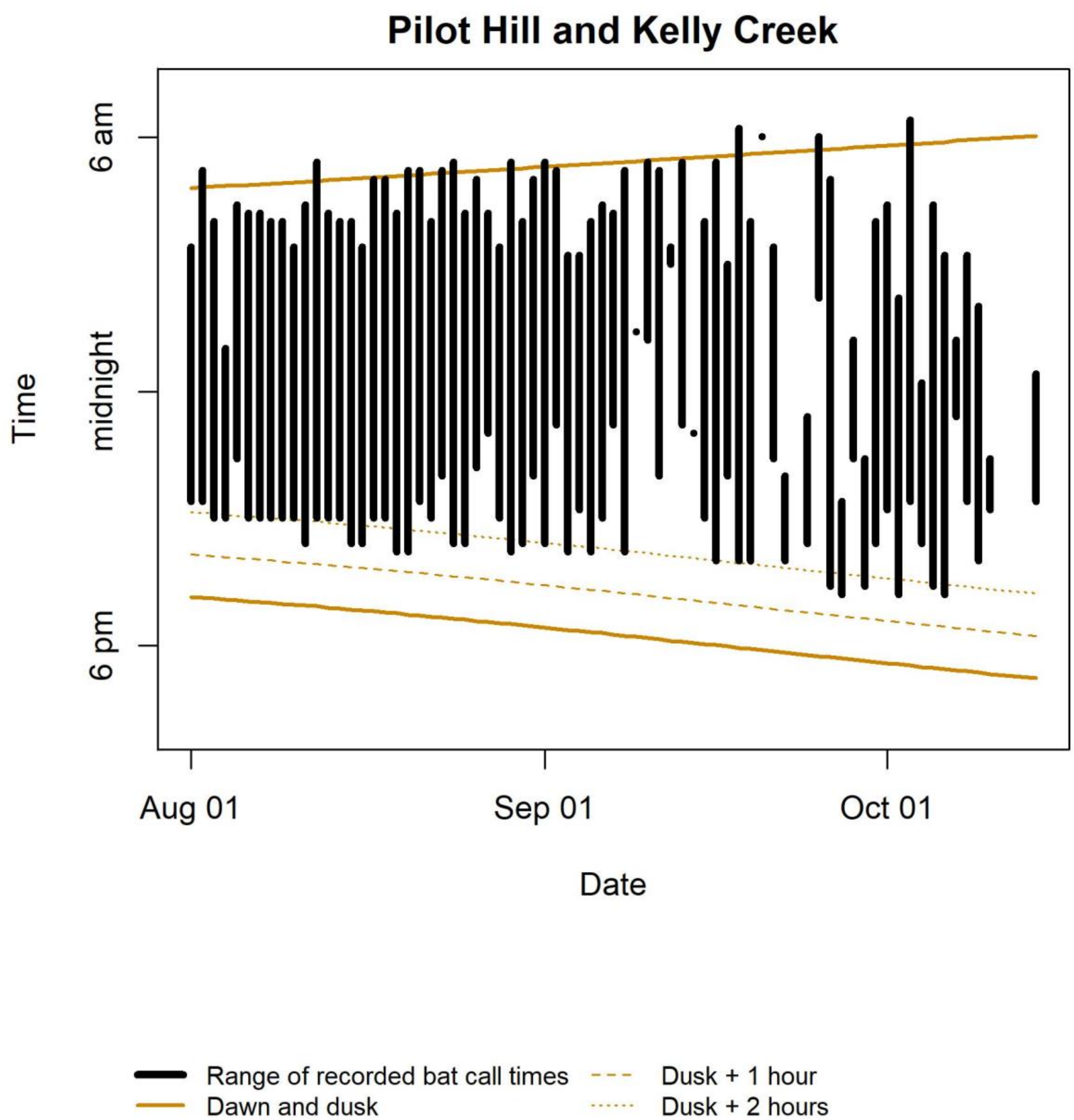

Figure 47. Range of times each night during which bat calls were recorded at all detectors at both sites. Dusk and dawn are shown with mustard-colored lines, and the times of the first and last calls recorded each night are joined by a vertical black bar.

Bat calls for all species decreased with increasing wind speeds, as this relationship was also observed in most models of bat activity based on weather, but the pattern of this response varied between species (Figure 48). Eastern red bat and hoary bat activity peaked at around 3.0 m/s, which was equivalent to the cut-in speed of turbines at both Projects. Very few silver-haired bat calls could be distinguished from big brown bat calls individually. However, when grouped, big brown bat/silver-haired bat calls also peaked below 3.0 m/s, but were occasionally recorded at wind speeds of 10.0–13.5 m/s (22.4–30.2 mph).

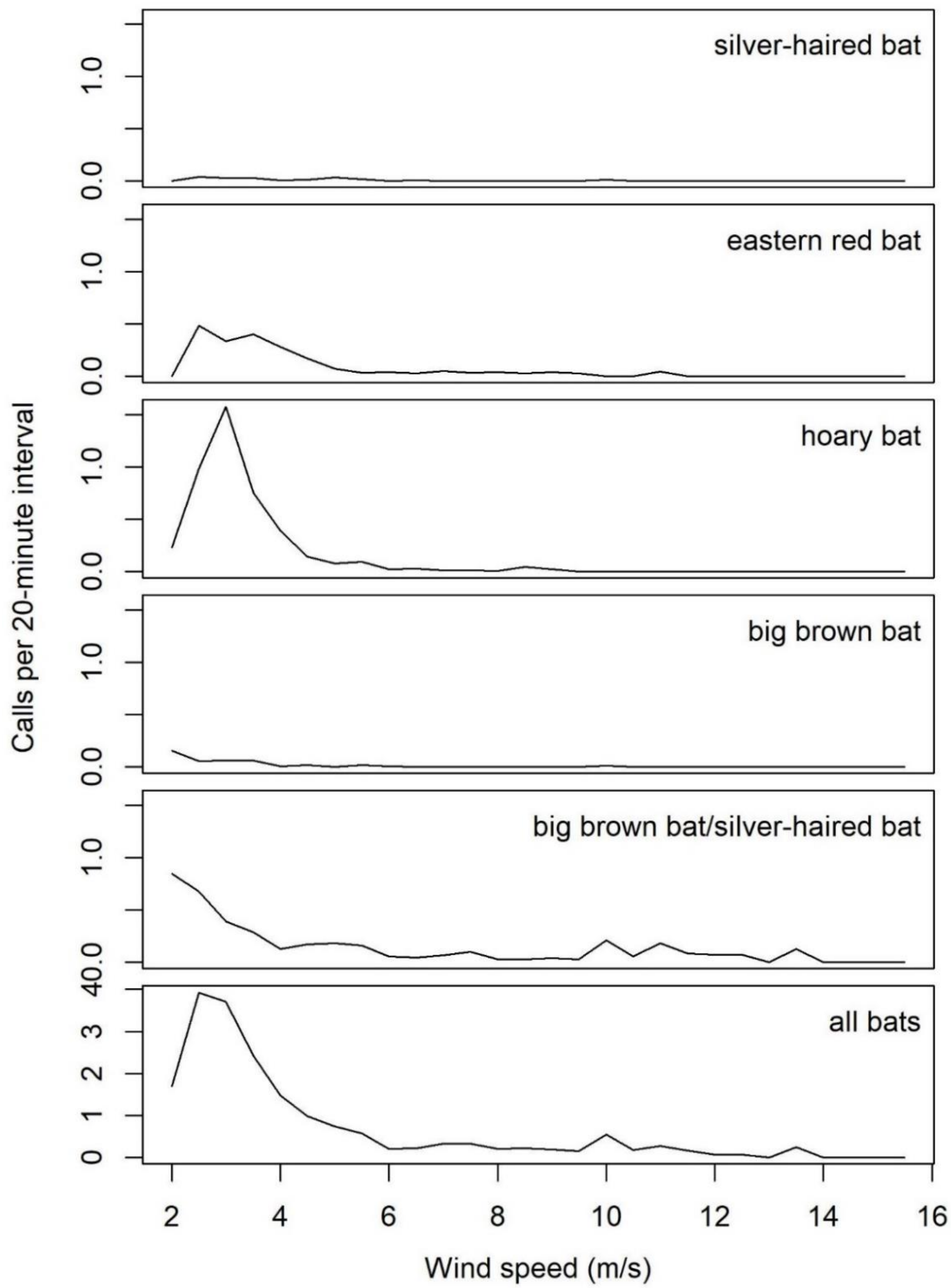

Figure 48. Bat activity (calls per 20-minute interval) according to wind speed for all bats, and for four species groups at Pilot Hill and Kelly Creek Wind Farms. Note, the y-axis is scaled differently for all bats than for the individual bat species groups.

The timing of bat fatalities from post-construction monitoring at the Projects showed some consistent patterns. Eastern red and hoary bat fatalities occurred more evenly throughout the fall, and had similar phenologies with higher numbers occurring from mid-August through mid-September. Silver-haired bat fatalities were more concentrated in time and occurred later in the season (Figure 49).

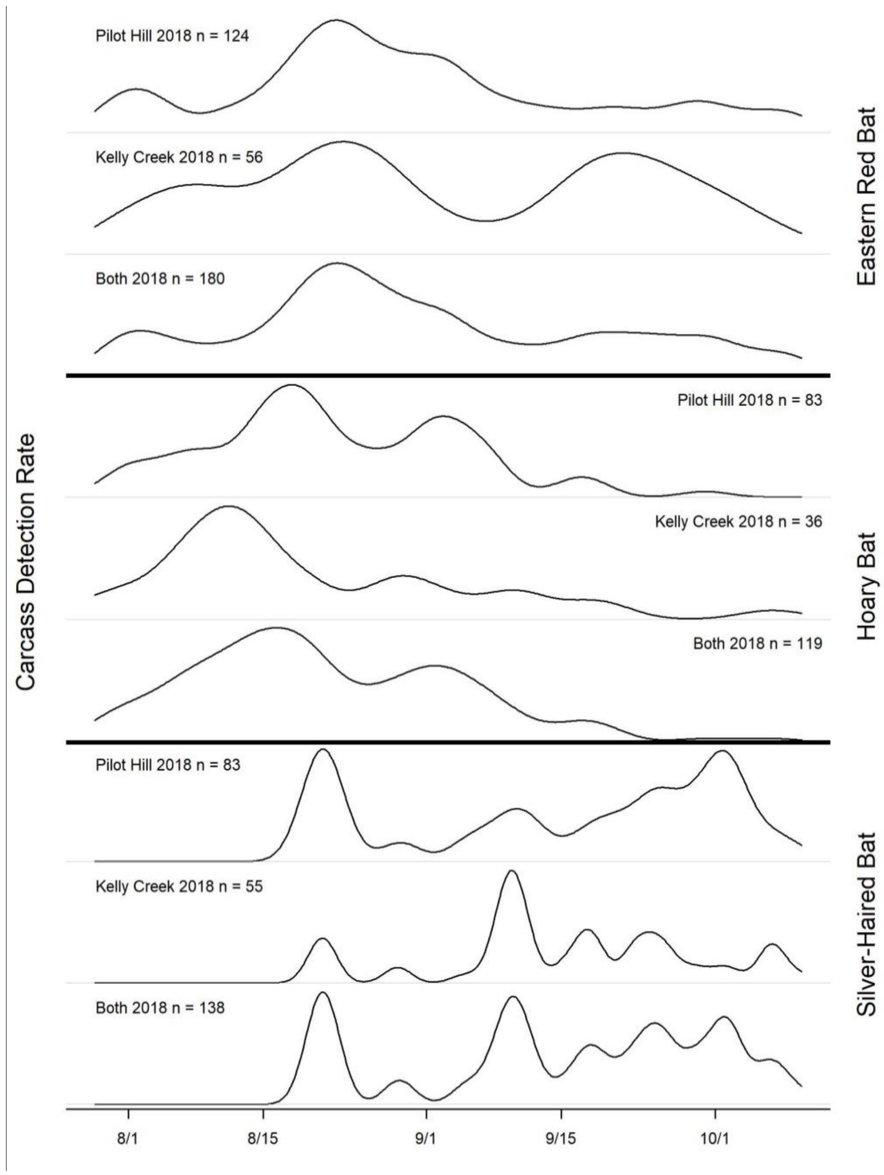

Figure 49. Timing of eastern red, hoary bat and silver-haired bat carcasses detected during post-construction monitoring searches at Pilot Hill and Kelly Creek Wind Farms in 2018.

Note, for each carcass, time of death was estimated as a range (e.g., less than 24 hours and 1–3 days, 3–7 days). Figures include only carcasses estimated to have died within seven or fewer days, due to increasing uncertainty in time since death for older carcasses. For plotting purposes, time of death was assumed to be the middle of the estimated interval (e.g., 12 hours or two days). Carcass detection rates are plotted on the y-axis, but the y-axis scale is variable from panel to panel, to maximize readability, and the absolute scale is not given because we are plotting uncorrected counts of carcasses. Total numbers of bats informing each panel (n) are given in the top left of the panels.

Discussion

Scientists have expressed concern over the potential impact of wind turbines on migratory tree bat populations (Frick et al. 2017); in response, several wind companies have sponsored research on cut-in speed curtailment for reducing bat collision fatalities. The most commonly implemented cut-in speed curtailment for reducing bat fatalities includes automatically feathering blades below a set wind speed, such as 5.0 or 6.0 m/s (11.2 or 13.4 mph), based only on date, sunset and sunrise times, wind speed, and perhaps air temperature to determine when turbines will be curtailed. This approach has been shown to be effective at reducing bat mortalities (Arnett et al. 2009, Good et al. 2012, Arnett et al. 2013, Martin et al. 2017). However, curtailment above 4.0 m/s (8.9 mph) clearly reduces energy production, and losses increase the higher the cut-in speed is raised and the greater the number of hours it is applied. The research completed at the PHWF and KCWF in 2018 was designed to examine patterns of bat activity and fatalities using various technologies to determine if periods of high bat activity and fatalities could be predicted from weather variables at and surrounding a project, so risk models could be developed to reduce unproductive curtailment while still reducing bat fatalities.

Are Bat Fatalities and Activity Better Predicted by On-Site or Off-Site Weather Variables?

Previous studies at the PHWF have shown positive relationships between silver-haired bat fatalities, on-site wind direction, and the presence of precipitation within the 48-hours preceding a fatality find (Iskali et al. 2018). Silver-haired bat fatalities occurred in pulses, and the PHWF has very little forest within 19 km (12 mi) of the Project, which suggested weather fronts farther from the Project were potentially triggering silver-haired migration. We were interested in analyzing weather data from the Project, as well as data from airports within 161 km (100 mi) of the PHWF to determine if on-site or off-site weather were better predictors of not only silver-haired bat activity and fatalities, but hoary and eastern red bats as well.

Past studies at the PHWF were unsuccessful in predicting when higher periods of bat activity or fatalities occurred using only weather data collected on-site (Iskali et al. 2018); models developed to predict activity and fatalities performed poorly. The inclusion of off-site weather variables from airports in 2018 resulted in models with much greater accuracy and power. The most influential variables in predicting the activity and fatalities of silver-haired and hoary bats were off-site variables, and other than wind speed, on-site weather was generally a poor predictor of bat activity and bat fatalities. When on-site variables were chosen and were relatively influential, they also suggested changing weather fronts affected activity; an interaction between changing barometric pressure and wind speed recorded on-site were influential variables in predicting hoary bat activity. The PHWF lacks any significant forest cover that would provide roosting habitat for tree bats; the nearest significant forested areas occur 10–19 km to the north along the Kankakee River and associated tributaries, and 8–11 km (5–7 mi) east along the Iroquois River and its tributaries. The selection of weather variables from airports located near the Kankakee River as the best predictors of silver-haired and hoary bat fatalities is consistent with the hypothesis that bats roosting along the Kankakee River and forested areas farther north of the Project migrate based on cues not measurable from on-site met towers.

Bat activity at the PHWF and KCWF was absent or very low until two hours after sunset, in contrast to many studies that have shown bat activity to be highest near or immediately after sunset (Johnson et al. 2013, Salvarina et al. 2018). The later start in bat activity at PHWF and KCWF are likely due to the lack of suitable roosting habitat for tree bats within 10–19 km of both Projects. The later start in bat activity at both Projects may also partially explain why off-site weather conditions were better predictors of bat activity and fatalities than most on-site variables, as hoary and silver-haired bat migration and activity appear to be triggered by weather conditions and fronts located away from both Projects.

What Variables Best Predicted Bat Activity and Fatalities?

One of the challenges associated with the use of weather data to predict bat activity and fatalities is the sheer number of ways weather data can be summarized. All variables could be summarized as the average, maximum, minimum, the variance, or a change metric, and any variable can be introduced into the model with a lagged effect. Our treatment of the data represents our best effort to meaningfully describe the weather, but in the interest of keeping our models computationally tractable, we eliminated some candidate variables that may yet prove to be meaningful.

Wind speed on-site has often been shown to be a consistent predictor of bat activity and bat fatalities; researchers have shown both variables are higher when wind speeds are lower (Arnett et al. 2009, Good et al. 2012, Arnett et al. 2013, Martin et al. 2017). The relationship between wind speed and bat activity was observed at both Projects, and the application of cut-in speed curtailment during lower wind speeds have consistently shown significant reductions in bat fatalities (Arnett et al. 2009, Good et al. 2012, Arnett et al. 2013, Martin et al. 2017). Our results are consistent with these findings. Wind speed and wind direction were the most influential on-site variables chosen in many models of bat activity; bat activity at both sites were lower when wind speeds increased. However, many nights with lower wind speeds happened with few or no bat fatalities, indicating cut-in speed curtailment based on wind speed would have been applied with no benefit.

The most influential variables for eastern red bat, hoary bat, and silver-haired bat activity included changing wind direction and barometric pressure changes recorded at off-site airports. Our results were strong and suggest variables that describe passing weather fronts, in combination with on-site measurements of wind speed, could potentially be used to develop smarter curtailment approaches that focus on the conditions in which to apply curtailment, and thereby reduce the amount of time curtailment is implemented.

The models predicting hoary bat activity and fatalities were particularly strong, and suggest incorporation of weather variables that are indicators of changing weather or broader weather patterns could be used to narrow curtailment windows and still significantly reduce hoary bat fatalities.

Models predicting eastern red bat activity were also strong, and included a mixture of variables from off-site airports and on-site changes in barometric pressure and wind speed. Interestingly, models were poor at predicting eastern red bat fatalities. The reasons for the poor model performance are not readily apparent, but suggest further research is needed before regional changes in weather are used to develop smarter curtailment approaches for eastern red bats.

Silver-haired fatality and activity models performed relatively poorly. Big brown bats and silver-haired bat call characteristics overlap significantly for most calls, and we grouped both species calls in our models of bat activity due to low sample sizes for calls conclusively identified as silver-haired bats. The few calls conclusively identified as silver-haired bats indicate a differing pattern in timing of activity than the combined call data, which suggests combining big brown and silver-haired bat calls likely reduced the model's performance. The poor performance of the silver-haired bat fatality model was surprising since the same issues in identification of calls were not present for differentiating big brown bat from silver-haired bat carcasses. McGuire et al. (2012) predicted silver-haired bats can migrate 250–300 km (155–186 mi) per night using migration simulations based on body composition; however, no field research has been completed to confirm their predictions. If McGuire's predictions are true, the poor performance of the silver-haired bat fatality model could be because our analysis was limited to weather data from airports within 161 km of Projects, and did not reach far enough to capture weather patterns that could trigger silver-haired bat migration movements.

The lack of on-site weather variables included in the best fatality prediction models may have also been due to the temporal scale of fatality data. Although we only used carcasses estimated to have been killed the night before, our review of the BAMM data show weather variables can vary considerably during the course of a night. We averaged most variables across the entire night, resulting in a loss of resolution in our data. The BAMM system did not function successfully, resulting in too few carcasses with an estimated time of death within a night to generate meaningful fatality models. Future analyses using the maximum or minimum values for variables may prove to be better predictors of fatalities.

Is Bat Activity a Good Indicator of Bat Fatalities?

Bat activity was positively related to bat fatalities for all of the species analyzed; however, the magnitude or level of bat fatalities did not scale consistently with the level of bat activity, which led to overall poor model performance for predictions of the numbers of bat carcasses. It is important to consider the study design was not optimized for associating acoustic activity with fatalities due to the relatively small portion of the rotor swept zone that was acoustically monitored, and the failure of BAMM to identify time of night on more than five bat fatalities. However, a visual inspection of bat activity compared to number of fresh carcasses found suggested increases in bat activity were often associated with increased number of fresh carcasses. This suggests curtailment systems such as Turbine-Integrated Mortality Reduction (TIMR), DTBat, and Natural Power’s acoustic activated curtailment system triggered by the detection of bat calls at wind projects have potential to be effective at sites with similar compositions of bat species to the PHWF and KCWF (Hayes et al. 2019).

Anabats have a detection range shorter than the rotor swept radius and the detectors used were only able to monitor a 90-degree cone-shaped area due to placement and enclosure noise shielding. Studies (Adams et al. 2012) show Anabat detectors have a maximum range of 30 m (98 ft) for the species in this study. In addition, only the lower portion of the rotor swept area was monitored, so it is likely only a small proportion of bats at risk in the rotor zone were detected. These factors likely contributed to the weak correlation between acoustic activity and fatalities, and may explain why bat activity did not scale with the number of fatalities.

Are Bat Activity or Fatalities Concentrated in Certain Periods of the Night?

Some researchers have suggested curtailment could be confined to portions of the night and still reduce bat fatalities while minimizing energy production loss. Nightly foraging activity by bats is related to changes in insect prey abundance, which directly affects bat nutritional intake and thereby can have implications for their fitness. Many researchers have shown bat foraging activity occurs within two hours of sunset, which is correlated with peak insect activity (Kunz 1973, Barclay 1982, Rydell et al. 1996). Very few bat calls were recorded during our study near sunset; activity generally did not begin until 90–120 min after sunset. Both Projects lack significant forest cover; the nearest significant forested areas are located 10–19 km from either Project, which suggest migrating or foraging bats within the Projects have to fly significant distances before they reach the Projects. Our results are likely applicable to other wind projects such as KCWF and PHWF located in areas that lack any significant forest cover within 10–19 km of turbines. The data collected during the study suggest this may be particularly true for hoary bat and silver-haired bats. The earliest time of death for the four hoary bats identified by the BAMM system was 0020 H, and increasing bat activity from 1000–0200 H was positively related to hoary bat and silver-haired bat fatalities. Eastern red bat fatalities were positively related to calls during the earlier portion of the evening.

Management Implications

As concerns over impacts to bat populations increase, the wind industry has increased efforts to research smarter curtailment strategies. The principle behind smart curtailment is periods of time exist when curtailment is in effect, yet bats are not present, so decreasing these ineffective curtailments could restore some lost energy production. Many efforts have focused on analyzing patterns of bat fatalities and activity relative to weather collected on-site at wind-energy projects to define smart curtailment regimes. The results of this study show management approaches are likely to vary significantly by species, and regional weather fronts have a large influence on bat fatalities and activity. Unfortunately, it is not so easy to utilize off-site weather for bat risk reduction because the monitoring locations could be many miles away from the project site, in multiple directions, and the data must be collected and curtailment decisions applied in real-time. Our research suggests changes in weather up to 161 km (100-mi) from a wind-energy facility, in combination with on-site weather variables such as wind speed and temperature, have potential to better predict when migratory tree bat activity and fatalities will be higher. If cost-effective methods to access and utilize these data can be developed, they could be used to focus curtailment when bat activity and fatalities are likely elevated. This could be especially true for projects like the PHWF and KCWF that lack significant bat roosting habitat within 10–19 km of wind turbines. Additional studies should be completed at other wind-energy facilities to determine if similar patterns exist. This does not require extensive new field work if ample carcass data has already been collected; rather, analyses could be conducted using fatality data from past studies and historical weather data from surrounding airports to verify if the patterns we observed hold true and could be applied to implement smarter curtailment. Our results were particularly encouraging for hoary bats, a migratory tree bat species scientists have expressed the most concern about to date (Frick et al. 2017).

Our results clearly show curtailment at PHWF and KCWF could be delayed until 90–120 min after sunset without significantly increasing bat fatalities. KCWF and PHWF are unique in the lack of significant forest cover within 10–19 km of either Project. Similar patterns in bat activity are likely to occur at other wind-energy projects where bats would have to travel several miles from roosting areas to encounter turbines; delaying curtailment until 90–120 min after sunset is a relatively safe and easy cost reduction measure that could be implemented at other sites located similar distances away from roosting habitat.

This was the first bat study that attempted to utilize an early proto-type of the BAMM system, which employs unattended image processing algorithms with night-vision cameras to attempt to identify the exact time of each bat fatality. Further development and improvements to BAMM are needed to increase its performance, reliability, and reduce false positives. Wind speed, air temperature, wind direction, barometric pressure, and other potentially important variables all vary considerably during a course of a night. Knowing when a fatality occurred would greatly improve our ability to model risk factors. The few carcasses for which we were able to identify a time of death using BAMM revealed some potential associations that could be used to further refine when curtailment should optimally be applied; however, we lacked sufficient sample size to draw strong conclusions based on time of death of bats. We believe additional investment and product development in systems designed to determine exact time of death are warranted; our ability to develop smart curtailment strategies using on-site weather data are likely to be improved if the exact time of death of a carcass is known. This pilot test showed BAMM or thermal cameras could be valuable in bat smart curtailment studies.

References

Adams, A. M., M. K. Jantzen, R. M. Hamilton, and M. B. Fenton. 2012. Do You Hear What I Hear? Implications of Detector Selection for Acoustic Monitoring of Bats. Methods in Ecology and Evolution 3(6): 992-998. doi: 10.1111/j.2041-210X.2012.00244.x.

Arnett, E. B., K. Brown, W. P. Erickson, J. Fiedler, B. L. Hamilton, T. H. Henry, A. Jain, G. D. Johnson, J. Kerns, R. R. Koford, C. P. Nicholson, T. O'Connell, M. Piorkowski, and R. Tankersley, Jr. 2008. Patterns of Bat Fatalities at Wind Energy Facilities in North America. Journal of Wildlife Management 72(1): 61-78.

Arnett, E. B., M. R. Schirmacher, M. M. P. Huso, and J. P. Hayes. 2009. Effectiveness of Changing Wind Turbine Cut-in Speed to Reduce Bat Fatalities at Wind Facilities: 2008 Annual Report. Prepared for the Bats and Wind Energy Cooperative (BWEC) and the Pennsylvania Game Commission. Bat Conservation International (BCI), Austin, Texas. April 2009. Available online: http://www.batsandwind.org/pdf/Curtailment_2008_Final_Report.pdf

Arnett, E. B., G. D. Johnson, W. P. Erickson, and C. D. Hein. 2013. A Synthesis of Operational Mitigation Studies to Reduce Bat Fatalities at Wind Energy Facilities in North America. A report submitted to the National Renewable Energy Laboratory (NREL), Golden Colorado. Bat Conservation International (BCI), Austin, Texas. March 2013. Available online: https://www.energy.gov/sites/prod/files/2015/03/f20/Operational-Mitigation-Synthesis-FINAL-REPORT-UPDATED.pdf

Arnold, T. W. 2010. Uninformative Parameters and Model Selection Using Akaike's Information Criterion. Journal of Wildlife Management 74(6): 1175-1178.

Barclay, R. M. R. 1982. Interindividual Use of Echolocation Calls: Eavesdropping by Bats. Behavioral Ecology and Sociobiology 10: 271-275.

Boyce, M. S., P. R. Vernier, S. E. Nielsen, and F. K. A. Schmiegelow. 2002. Evaluating Resource Selection Functions. Ecological Modelling 157(2-3): pp. 281-300. doi: 10.1016/S0304-3800(02)00200-4.

Castle, K. T., T. J. Weller, P. M. Cryan, C. Hein, D., and M. R. Schirmacher. 2015. Using Sutures to Attach Miniature Tracking Tags to Small Bats for Multimonth Movement and Behavioral Studies. Ecology and Evolution 5(14): 2980-2989. doi: 10.1002/ece3.1584. Available online: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4542000/pdf/ece30005-2980.pdf

Cryan, P. M. and A. C. Brown. 2007. Migration of Bats Past a Remote Island Offers Clues toward the Problem of Bat Fatalities at Wind Turbines. Biological Conservation 139: 1-11. doi: 10.1016/j.biocon.2007.05.019.

Efron, B. 2013. Estimation and Accuracy after Model Selection. Journal of the American Statisitcal Association 109(507): 991-1007. doi: 10.1080/01621459.2013.823775. Available online: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4207812/

ESRI. 2019. World Imagery and Aerial Photos. (World Topo). ArcGIS Resource Center. Environmental Systems Research Institute (ESRI), producers of ArcGIS software. Redlands, California. Information online: http://www.arcgis.com/home/webmap/viewer.html?useExisting=1

Feldhammer, G. A., J. E. Hofman, T. C. Carter, and J. A. Kath. 2015. Bats of Illinois. Indiana State University Center for Bat Research and Conservation, Terre Haute, Indiana.

Frick, W. F., E. F. Baerwald, J. F. Pollock, R. M. R. Barclay, J. A. Szymanski, T. J. Weller, A. L. Russell, S. C. Loeb, R. A. Medellin, and L. P. McGuire. 2017. Fatalities at Wind Turbines May Threaten Population Viability of a Migratory Bat. Biological Conservation 209: 172-177. doi: 10.1016/j.biocon.2017.02.023.

Good, R. E., A. Merrill, S. Simon, K. Murray, and K. Bay. 2012. Bat Monitoring Studies at the Fowler Ridge Wind Farm, Benton County, Indiana: April 1 - October 31, 2011. Prepared for the Fowler Ridge Wind Farm. Prepared by Western EcoSystems Technology, Inc. (WEST), Bloomington, Indiana. January 31, 2012. Available online: http://batsandwind.org/pdf/Good%20et%20al.%202012_Fowler%20Report.pdf

Good, R. E., G. Iskali, and J. L. Lombardi. 2018. Post-Construction Monitoring for the Pilot Hill Wind Farm, Kankakee County, Illinois. Final Report: August 1 – October 13, 2017. Prepared for EDF Renewable Energy, LLC., San Diego, California. Prepared by Western Ecosystems Technology, Inc. (WEST), Bloomington, Indiana.

Hastie, T. and J. Qian. 2014. Glmnet Vignette. Stanford Statistics Technical Report. June 26, 2014. Stanford University, Stanford, California. Available online: https://web.stanford.edu/~hastie/glmnet/ glmnet_alpha.html

Hayes, M. A., L. A. Hooton, K. L. Gilland, C. Grandgent, R. L. Smith, S. R. Lindsay, J. D. Collins, S. M. Schumacher, P. A. Rabie, J. C. Gruver, and J. Goodrich-Mahoney. 2019. A Smart Curtailment Approach for Reducing Bat Fatalities and Curtailment Time at Wind Energy Facilities. Ecological Applications: e01881. doi: 10.1002/eap.1881.

Iskali, G., J. Lombardi, R. Clark, and K. DuBridge. 2019a. Post-Construction Monitoring for the Kelly Creek Wind Farm, Kankakee and Ford Counties, Illinois. Final Report: August 1 – October 12, 2018. Prepared for Kelly Creek Wind, LLC, San Diego, California. Prepared by Western EcoSystems Technology, Inc. (WEST), Bloomington, Indiana. March 15, 2019.

Iskali, G., P. Rabie, and R. Good. 2018. Bat Activity, Weather, and Fatality Study for the Pilot Hill and Kelly Creek Wind Farms, Kankakee, Ford, and Iroquois Counties, Illinois. Draft Report: August 1 – October 15, 2017. Prepared for Pilot Hill Wind, LLC. and Kelly Creek Wind, LLC, San Diego, California. Prepared by Western Ecosystems Technology, Inc. (WEST), Bloomington, Indiana.

Iskali, G., J. Lombardi, R. Good, T. McDonald, and K. DuBridge. 2019b. Post-Construction Monitoring for the Pilot Hill Wind Farm, Kankaee and Iroquois Counties, Illinois. Final Report: July 23 – October 23, 2018. Prepared for Pilot Hill Wind, LLC, San Diego, California. Prepared by Western EcoSytems Technology, Inc., Bloomington, Indiana. May 7, 2019.

Johnson, J. B., J. L. Rodrigue, and W. M. Ford. 2013. Nightly and Yearly Bat Activity before and after White-Nose Syndrome on the Fernow Experimental Forest in West Virginia. Research Paper NRS-24. Northern Research Station, US Department of Agriculture (USDA) Forest Service. September 2013. Available online: https://www.fs.fed.us/nrs/pubs/rp/rp_nrs24.pdf

Khokan, M. R., W. Bari, and J. A. Khan. 2013. Weighted Maximum Likelihood Approach for Robust Estimation: Weibull Model. Dhaka University Journal of Science 61(2): 153-156.

Kunz, T. H. 1973. Resource Utilization: Temporal and Spatial Components of Bat Activity in Central Iowa. Journal of Mammalogy 54(1): 14-32.

Martin, C. M., E. B. Arnett, R. D. Stevens, and M. C. Wallace. 2017. Reducing Bat Fatalities at Wind Facilities While Improving the Economic Efficiency of Operational Mitigation. Journal of Mammalogy 98(2): 378-385. doi: 10.1093/jmammal/gyx005.

McGuire, L. P., C. G. Guglielmo, S. A. Mackenzi, and P. D. Taylor. 2012. Migratory Stopover in the Long-Distance Migrant Silver-Haired Bat, *Lasionycteris noctivagans*. Journal of Animal Ecology 81(2): 377-385. doi: 10.1111/j.1365-2656.2011.01912.x. Available online: https://besjournals.onlinelibrary.wiley.com/doi/full/10.1111/j.1365-2656.2011.01912.x

Multi-Resolution Land Characteristics (MRLC). 2019. National Land Cover Database (NLCD) 2011. Multi-Resolution Land Characteristics (MRLC) Consortium. US Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center, MRLC Project, Sioux Falls, South Dakota. May 10, 2019. Information online: https://www.mrlc.gov/data

National Geographic Society (National Geographic). 2018. World Maps. Digital topographic map. PDF topographic map quads. Accessed March 8, 2018. Available online: http://www.natgeomaps.com/trail-maps/pdf-quads

North American Datum (NAD). 1983. NAD83 Geodetic Datum.

R Development Core Team. 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Information online: https://www.R-project.org/

Rydell, J., A. Entwistle, and P. A. Racey. 1996. Timing of Foraging Flights of Three Species of Bats in Relation to Insect Activity and Predation Risk. OIKOS 76(2): 243-252. doi: 10.2307/3546196.

Salvarina, I., D. Gravier, and K. O. Rothhaupt. 2018. Seasonal Bat Activity Related to Insect Emergence at Three Temperate Lakes. Ecology and Evolution 8(7): 12 pp.

Tima and Date AS (Aksjeselskap). 2018. Moonrise, Moonset, and Phase Calendar for City of Kankakee, August 2018. Accessed December 2019. Information Online: https://www.timeanddate.com/moon/@7163963?month=8&year=2018

US Geological Survey (USGS). 2019. The National Map: USGS Imagery Only (Map Server). April 2019. Accessed May 2019. Available online: https://basemap.nationalmap.gov/arcgis/rest/services/USGSImageryOnly/MapServer

WeatherForYou.com. 2019. Weather Archives for Kankakee, IL. Weather Station MID_KIKK. Weather for August 2, 2018. Accessed December 2019. Information online: https://www.weatherforyou.com/reports/index.php?forecast=pass&pass=archive&zipcode=60901&pands=KIKK&place=kankakee&state=il&icao=KIKK&country=us&month=08&day=02&year=2018&

Weller, T. J., K. T. Castle, F. Liechti, C. Hein, M. R. Schirmacher, and P. M. Cryan. 2016. First Direct Evidence of Long-Distance Seasonal Movements and Hibernation in a Migratory Bat. Nature 6: 34585. doi: 10.1038/srep34585.

Yang, L., S. Jin, P. Danielson, C. Homer, L. Gass, S. M. Bender, A. Case, C. Costello, J. Dewitz, J. Fry, M. Funk, B. Granneman, G. C. Liknes, M. Rigge, and G. Xian. 2018. A New Generation of the United States National Land Cover Database: Requirements, Research Priorities, Design, and Implementation Strategies. ISPRS Journal of Photogrammetry and Remote Sensing 146: 108-123. doi: 10.1016/j.isprsjprs.2018.09.006.

Appendix A. Carcasses with an Estimated Time of Death of the Previous Night Used in the Analyses for the Pilot Hill and Kelly Creek Wind Farms.

Date	Common Name	Site	Turbine
8/2/2018	Hoary bat	Pilot Hill	D5
8/4/2018	Hoary bat	Pilot Hill	A5
8/4/2018	Eastern red bat	Pilot Hill	B1
8/4/2018	Big brown bat	Pilot Hill	D5
8/4/2018	Hoary bat	Pilot Hill	D5
8/4/2018	Eastern red bat	Pilot Hill	D5
8/4/2018	Eastern red bat	Pilot Hill	D5
8/5/2018	Big brown bat	Pilot Hill	A5
8/5/2018	Hoary bat	Pilot Hill	A5
8/5/2018	Eastern red bat	Pilot Hill	D5
8/5/2018	Eastern red bat	Pilot Hill	D5
8/6/2018	Eastern red bat	Pilot Hill	B1
8/6/2018	Eastern red bat	Pilot Hill	A9
8/7/2018	Big brown bat	Pilot Hill	A15
8/7/2018	Big brown bat	Pilot Hill	D5
8/7/2018	Hoary bat	Pilot Hill	D5
8/8/2018	Hoary bat	Kelly Creek	H18
8/9/2018	Eastern red bat	Kelly Creek	I1
8/9/2018	Hoary bat	Kelly Creek	I1
8/9/2018	Hoary bat	Pilot Hill	B14

Date	Common Name	Site	Turbine
8/9/2018	Big brown bat	Pilot Hill	B14
8/9/2018	Hoary bat	Pilot Hill	D3
8/9/2018	Hoary bat	Pilot Hill	B30
8/10/2018	Big brown bat	Pilot Hill	B14
8/11/2018	Hoary bat	Pilot Hill	A3
8/11/2018	Big brown bat	Pilot Hill	B8
8/12/2018	Big brown bat	Pilot Hill	B14
8/12/2018	Eastern red bat	Pilot Hill	A3
8/12/2018	Hoary bat	Pilot Hill	B4
8/12/2018	Big brown bat	Pilot Hill	B14
8/12/2018	Eastern red bat	Pilot Hill	A3
8/12/2018	Hoary bat	Pilot Hill	B14
8/13/2018	Hoary bat	Kelly Creek	G5
8/13/2018	Hoary bat	Pilot Hill	B20
8/13/2018	Hoary bat	Pilot Hill	B30
8/13/2018	Big brown bat	Pilot Hill	A5
8/14/2018	Hoary bat	Kelly Creek	H18
8/14/2018	Eastern red bat	Pilot Hill	B8
8/14/2018	Eastern red bat	Pilot Hill	D3
8/15/2018	Hoary bat	Pilot Hill	A3
8/15/2018	Eastern red bat	Pilot Hill	B14
8/16/2018	Big brown bat	Pilot Hill	B8
8/16/2018	Hoary bat	Pilot Hill	A9
8/16/2018	Hoary bat	Pilot Hill	B8

Date	Common Name	Site	Turbine
8/17/2018	Hoary bat	Pilot Hill	A15
8/17/2018	Eastern red bat	Pilot Hill	A15
8/17/2018	Hoary bat	Pilot Hill	D5
8/17/2018	Hoary bat	Pilot Hill	D5
8/17/2018	Eastern red bat	Pilot Hill	D5
8/17/2018	Eastern red bat	Pilot Hill	A9
8/17/2018	Hoary bat	Pilot Hill	B1
8/17/2018	Hoary bat	Pilot Hill	B1
8/17/2018	Hoary bat	Pilot Hill	A9
8/18/2018	Big brown bat	Pilot Hill	B14
8/18/2018	Hoary bat	Pilot Hill	B1
8/18/2018	Hoary bat	Pilot Hill	D5
8/19/2018	Hoary bat	Pilot Hill	B14
8/19/2018	Hoary bat	Pilot Hill	A3
8/19/2018	Eastern red bat	Pilot Hill	A5
8/19/2018	Big brown bat	Pilot Hill	D3
8/20/2018	Hoary bat	Pilot Hill	D5
8/20/2018	Eastern red bat	Pilot Hill	D3
8/20/2018	Eastern red bat	Pilot Hill	B1
8/20/2018	Eastern red bat	Pilot Hill	A3
8/21/2018	Big brown bat	Kelly Creek	F10
8/21/2018	Hoary bat	Pilot Hill	B1
8/21/2018	Hoary bat	Pilot Hill	B4
8/21/2018	Big brown bat	Pilot Hill	B14

Date	Common Name	Site	Turbine
8/21/2018	Eastern red bat	Pilot Hill	A9
8/21/2018	Hoary bat	Pilot Hill	A9
8/21/2018	Hoary bat	Pilot Hill	A3
8/21/2018	Hoary bat	Pilot Hill	B1
8/21/2018	Hoary bat	Pilot Hill	B14
8/21/2018	Hoary bat	Pilot Hill	D5
8/21/2018	Hoary bat	Pilot Hill	D5
8/21/2018	Hoary bat	Pilot Hill	B11
8/22/2018	Silver-haired bat	Pilot Hill	A9
8/22/2018	Silver-haired bat	Pilot Hill	A3
8/22/2018	Silver-haired bat	Pilot Hill	A9
8/22/2018	Eastern red bat	Pilot Hill	B4
8/22/2018	Eastern red bat	Pilot Hill	D3
8/22/2018	Eastern red bat	Pilot Hill	D5
8/23/2018	Silver-haired bat	Kelly Creek	I1
8/23/2018	Hoary bat	Pilot Hill	D5
8/23/2018	Silver-haired bat	Pilot Hill	A9
8/23/2018	Hoary bat	Pilot Hill	A3
8/23/2018	Silver-haired bat	Pilot Hill	B14
8/23/2018	Hoary bat	Pilot Hill	B14
8/23/2018	Silver-haired bat	Pilot Hill	A3
8/23/2018	Silver-haired bat	Pilot Hill	A3
8/24/2018	Eastern red bat	Kelly Creek	K19
8/24/2018	Eastern red bat	Pilot Hill	B4

Date	Common Name	Site	Turbine
8/24/2018	Silver-haired bat	Pilot Hill	A7
8/24/2018	Eastern red bat	Pilot Hill	A15
8/24/2018	Silver-haired bat	Pilot Hill	A7
8/24/2018	Eastern red bat	Pilot Hill	A3
8/24/2018	Eastern red bat	Pilot Hill	A5
8/24/2018	Eastern red bat	Pilot Hill	B8
8/24/2018	Hoary bat	Pilot Hill	B37
8/24/2018	Silver-haired bat	Pilot Hill	B8
8/24/2018	Silver-haired bat	Pilot Hill	B8
8/24/2018	Eastern red bat	Pilot Hill	B8
8/25/2018	Eastern red bat	Pilot Hill	B1
8/25/2018	Silver-haired bat	Pilot Hill	B8
8/25/2018	Eastern red bat	Pilot Hill	D5
8/25/2018	Eastern red bat	Pilot Hill	D5
8/25/2018	Eastern red bat	Pilot Hill	D5
8/25/2018	Eastern red bat	Pilot Hill	D3
8/26/2018	Hoary bat	Pilot Hill	B8
8/26/2018	Eastern red bat	Pilot Hill	A9
8/26/2018	Eastern red bat	Pilot Hill	B8
8/27/2018	Eastern red bat	Pilot Hill	B37
8/27/2018	Eastern red bat	Pilot Hill	B37
8/27/2018	Hoary bat	Pilot Hill	A5
8/28/2018	Eastern red bat	Kelly Creek	F5
8/28/2018	Eastern red bat	Pilot Hill	B14

Date	Common Name	Site	Turbine
8/28/2018	Eastern red bat	Pilot Hill	B1
8/29/2018	Hoary bat	Pilot Hill	B14
8/29/2018	Eastern red bat	Pilot Hill	B1
8/29/2018	Hoary bat	Pilot Hill	B1
8/30/2018	Hoary bat	Kelly Creek	I1
8/30/2018	Eastern red bat	Kelly Creek	I1
8/30/2018	Eastern red bat	Kelly Creek	K3
8/30/2018	Eastern red bat	Pilot Hill	A5
8/30/2018	Eastern red bat	Pilot Hill	A9
8/30/2018	Big brown bat	Pilot Hill	B1
8/30/2018	Hoary bat	Pilot Hill	B1
8/30/2018	Eastern red bat	Pilot Hill	D5
8/30/2018	Hoary bat	Pilot Hill	B20
8/31/2018	Eastern red bat	Kelly Creek	K13
8/31/2018	Hoary bat	Kelly Creek	K13
8/31/2018	Hoary bat	Kelly Creek	K19
8/31/2018	Hoary bat	Kelly Creek	K19
8/31/2018	Silver-haired bat	Kelly Creek	J9
8/31/2018	Silver-haired bat	Kelly Creek	K13
8/31/2018	Silver-haired bat	Pilot Hill	A15
8/31/2018	Eastern red bat	Pilot Hill	B14
8/31/2018	Eastern red bat	Pilot Hill	B14
8/31/2018	Hoary bat	Pilot Hill	A5
8/31/2018	Eastern red bat	Pilot Hill	A9

Date	Common Name	Site	Turbine
8/31/2018	Eastern red bat	Pilot Hill	A3
8/31/2018	Silver-haired bat	Pilot Hill	A3
9/1/2018	Silver-haired bat	Pilot Hill	B1
9/2/2018	Eastern red bat	Pilot Hill	A9
9/2/2018	Hoary bat	Pilot Hill	A3
9/3/2018	Hoary bat	Pilot Hill	B8
9/3/2018	Hoary bat	Pilot Hill	D5
9/3/2018	Hoary bat	Pilot Hill	D3
9/4/2018	Hoary bat	Kelly Creek	F5
9/4/2018	Eastern red bat	Pilot Hill	B4
9/4/2018	Hoary bat	Pilot Hill	D5
9/4/2018	Eastern red bat	Pilot Hill	D3
9/4/2018	Eastern red bat	Pilot Hill	B14
9/4/2018	Eastern red bat	Pilot Hill	B14
9/5/2018	Eastern red bat	Pilot Hill	B4
9/5/2018	Hoary bat	Pilot Hill	A9
9/5/2018	Eastern red bat	Pilot Hill	B4
9/5/2018	Eastern red bat	Pilot Hill	B4
9/5/2018	Eastern red bat	Pilot Hill	B4
9/5/2018	Silver-haired bat	Pilot Hill	A9
9/5/2018	Eastern red bat	Pilot Hill	D3
9/5/2018	Eastern red bat	Pilot Hill	D5
9/6/2018	Eastern red bat	Pilot Hill	A5
9/7/2018	Silver-haired bat	Kelly Creek	K19

Date	Common Name	Site	Turbine
9/7/2018	Hoary bat	Pilot Hill	A9
9/7/2018	Silver-haired bat	Pilot Hill	D5
9/7/2018	Silver-haired bat	Pilot Hill	B11
9/7/2018	Eastern red bat	Pilot Hill	B11
9/8/2018	Eastern red bat	Pilot Hill	A9
9/8/2018	Silver-haired bat	Pilot Hill	A3
9/8/2018	Hoary bat	Pilot Hill	A5
9/9/2018	Hoary bat	Pilot Hill	A5
9/10/2018	Hoary bat	Pilot Hill	A9
9/10/2018	Eastern red bat	Pilot Hill	A7
9/10/2018	Seminole bat	Pilot Hill	A5
9/10/2018	Big brown bat	Pilot Hill	A3
9/10/2018	Eastern red bat	Pilot Hill	B4
9/11/2018	Silver-haired bat	Pilot Hill	B37
9/11/2018	Silver-haired bat	Pilot Hill	A3
9/11/2018	Eastern red bat	Pilot Hill	B11
9/11/2018	Eastern red bat	Pilot Hill	D5
9/11/2018	Silver-haired bat	Pilot Hill	D5
9/12/2018	Eastern red bat	Kelly Creek	J2
9/12/2018	Hoary bat	Kelly Creek	I8
9/12/2018	Silver-haired bat	Kelly Creek	H18
9/12/2018	Silver-haired bat	Kelly Creek	J2
9/13/2018	Eastern red bat	Kelly Creek	K19
9/13/2018	Silver-haired bat	Kelly Creek	K13

Date	Common Name	Site	Turbine
9/13/2018	Silver-haired bat	Kelly Creek	K19
9/13/2018	Silver-haired bat	Pilot Hill	D5
9/13/2018	Silver-haired bat	Pilot Hill	B14
9/14/2018	Eastern red bat	Pilot Hill	D5
9/14/2018	Silver-haired bat	Pilot Hill	A9
9/14/2018	Eastern red bat	Pilot Hill	B8
9/14/2018	Silver-haired bat	Pilot Hill	D5
9/15/2018	Eastern red bat	Pilot Hill	B14
9/15/2018	Big brown bat	Pilot Hill	B14
9/16/2018	Eastern red bat	Pilot Hill	A3
9/17/2018	Hoary bat	Pilot Hill	B8
9/18/2018	Eastern red bat	Kelly Creek	H18
9/19/2018	Silver-haired bat	Pilot Hill	A5
9/19/2018	Hoary bat	Pilot Hill	B14
9/20/2018	Silver-haired bat	Kelly Creek	K3
9/20/2018	Big brown bat	Pilot Hill	A5
9/20/2018	Silver-haired bat	Pilot Hill	B8
9/20/2018	Eastern red bat	Pilot Hill	D5
9/21/2018	Eastern red bat	Kelly Creek	K19
9/21/2018	Eastern red bat	Kelly Creek	K19
9/21/2018	Silver-haired bat	Pilot Hill	A7
9/21/2018	Eastern red bat	Pilot Hill	A15
9/22/2018	Eastern red bat	Pilot Hill	B14
9/22/2018	Silver-haired bat	Pilot Hill	B8

Date	Common Name	Site	Turbine
9/22/2018	Silver-haired bat	Pilot Hill	B8
9/24/2018	Eastern red bat	Pilot Hill	B8
9/24/2018	Silver-haired bat	Pilot Hill	A3
9/24/2018	Silver-haired bat	Pilot Hill	A5
9/25/2018	Silver-haired bat	Kelly Creek	G5
9/25/2018	Silver-haired bat	Pilot Hill	D5
9/25/2018	Silver-haired bat	Pilot Hill	B14
9/26/2018	Eastern red bat	Kelly Creek	H18
9/26/2018	Eastern red bat	Kelly Creek	H7
9/26/2018	Silver-haired bat	Kelly Creek	H18
9/26/2018	Silver-haired bat	Pilot Hill	B1
9/26/2018	Eastern red bat	Pilot Hill	B8
9/26/2018	Silver-haired bat	Pilot Hill	B8
9/27/2018	Silver-haired bat	Pilot Hill	B30
9/27/2018	Silver-haired bat	Pilot Hill	A3
9/27/2018	Silver-haired bat	Pilot Hill	A3
9/28/2018	Eastern red bat	Kelly Creek	K19
9/28/2018	Eastern red bat	Pilot Hill	B8
9/28/2018	Silver-haired bat	Pilot Hill	A7
9/28/2018	Eastern red bat	Pilot Hill	A7
9/29/2018	Silver-haired bat	Pilot Hill	B14
10/1/2018	Silver-haired bat	Pilot Hill	A5
10/1/2018	Eastern red bat	Pilot Hill	B1
10/1/2018	Silver-haired bat	Pilot Hill	B14

Date	Common Name	Site	Turbine
10/1/2018	Eastern red bat	Pilot Hill	B8
10/1/2018	Eastern red bat	Pilot Hill	B8
10/1/2018	Silver-haired bat	Pilot Hill	B8
10/1/2018	Silver-haired bat	Pilot Hill	D3
10/2/2018	Silver-haired bat	Pilot Hill	A5
10/2/2018	Silver-haired bat	Pilot Hill	B1
10/2/2018	Hoary bat	Pilot Hill	B14
10/3/2018	Eastern red bat	Kelly Creek	H18
10/3/2018	Eastern red bat	Kelly Creek	H18
10/3/2018	Eastern red bat	Pilot Hill	A9
10/4/2018	Silver-haired bat	Pilot Hill	B20
10/4/2018	Silver-haired bat	Pilot Hill	B14
10/4/2018	Silver-haired bat	Pilot Hill	B14
10/4/2018	Eastern red bat	Pilot Hill	B4
10/4/2018	Silver-haired bat	Pilot Hill	A9
10/4/2018	Silver-haired bat	Pilot Hill	B4
10/5/2018	Silver-haired bat	Pilot Hill	B37
10/5/2018	Silver-haired bat	Pilot Hill	B4
10/6/2018	Eastern red bat	Pilot Hill	B1
10/7/2018	Silver-haired bat	Pilot Hill	A3
10/7/2018	Silver-haired bat	Pilot Hill	B8
10/7/2018	Eastern red bat	Pilot Hill	A3
10/8/2018	Eastern red bat	Pilot Hill	A7
10/8/2018	Silver-haired bat	Pilot Hill	B37

Date	Common Name	Site	Turbine
10/9/2018	Hoary bat	Kelly Creek	F10
10/9/2018	Silver-haired bat	Kelly Creek	F10
10/9/2018	Silver-haired bat	Kelly Creek	F10
10/9/2018	Silver-haired bat	Kelly Creek	H18
10/9/2018	Silver-haired bat	Pilot Hill	B8
10/9/2018	Silver-haired bat	Pilot Hill	B1
10/12/2018	Silver-haired bat	Kelly Creek	J9
10/12/2018	Silver-haired bat	Pilot Hill	B8
8/2/2018	Hoary bat	Pilot Hill	D5
8/4/2018	Hoary bat	Pilot Hill	A5
8/4/2018	Eastern red bat	Pilot Hill	B1
8/4/2018	Big brown bat	Pilot Hill	D5
8/4/2018	Hoary bat	Pilot Hill	D5
8/4/2018	Eastern red bat	Pilot Hill	D5
8/4/2018	Eastern red bat	Pilot Hill	D5
8/5/2018	Big brown bat	Pilot Hill	A5
8/5/2018	Hoary bat	Pilot Hill	A5
8/5/2018	Eastern red bat	Pilot Hill	D5
8/5/2018	Eastern red bat	Pilot Hill	D5
8/6/2018	Eastern red bat	Pilot Hill	B1
8/6/2018	Eastern red bat	Pilot Hill	A9
8/7/2018	Big brown bat	Pilot Hill	A15
8/7/2018	Big brown bat	Pilot Hill	D5
8/7/2018	Hoary bat	Pilot Hill	D5

Date	Common Name	Site	Turbine
8/8/2018	Hoary bat	Kelly Creek	H18
8/9/2018	Eastern red bat	Kelly Creek	I1
8/9/2018	Hoary bat	Kelly Creek	I1
8/9/2018	Hoary bat	Pilot Hill	B14
8/9/2018	Big brown bat	Pilot Hill	B14

Appendix B. Activity and Weather Model Parameters

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Both	All bats	0.798	Intercept	1.810	0.876	2.714
Both	All bats	0.798	Wind Speed (m/s)	-0.774	-1.035	-0.485
Both	All bats	0.798	Day of Study	-0.031	-0.038	-0.025
Both	All bats	0.798	Quadratic of Wind Speed	0.037	0.012	0.058
Both	All bats	0.798	ST: Wind Direction North (N)	0.482	0.090	0.893
Both	All bats	0.798	ST: Wind Direction South (S)	0.041	-0.439	0.530
Both	All bats	0.798	ST: Wind Direction West (W)	-0.155	-0.882	0.527
Both	All bats	0.798	RA: 2hr-BP Change (12hr Lag, mbar)	0.112	-0.025	0.233
Both	All bats	0.798	RA: Wind Direction N (12hr Lag)	-0.293	-0.703	0.123
Both	All bats	0.798	RA: Wind Direction S (12hr Lag)	0.165	-0.251	0.587
Both	All bats	0.798	RA: Wind Direction W (12hr Lag)	-0.025	-0.461	0.413
Both	All bats	0.798	RA: 2hr-BP Change*WD N (12hr Lag)	-0.187	-0.389	0.021
Both	All bats	0.798	RA: 2hr-BP Change*WD S (12hr Lag)	-0.401	-0.659	-0.138
Both	All bats	0.798	RA: 2hr-BP Change*WD W (12hr Lag)	-0.929	-1.282	-0.603
Both	Eastern red bats	0.832	Intercept	0.406	-0.543	1.338
Both	Eastern red bats	0.832	Wind Speed (m/s)	-0.375	-0.492	-0.262

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Both	Eastern red bats	0.832	1hr-BP Change (mbar)	-0.667	-1.175	-0.168
Both	Eastern red bats	0.832	Day of Study	0.008	-0.031	0.049
Both	Eastern red bats	0.832	Quadratic of Day of Study	-0.001	-0.002	0
Both	Eastern red bats	0.832	ST: Wind Direction N	0.573	0.030	1.162
Both	Eastern red bats	0.832	ST: Wind Direction S	0.103	-0.557	0.791
Both	Eastern red bats	0.832	ST: Wind Direction W	-1.387	-2.992	-0.132
Both	Eastern red bats	0.832	GR: Wind Direction N (12hr Lag)	-0.475	-1.046	0.092
Both	Eastern red bats	0.832	GR: Wind Direction S (12hr Lag)	0.390	-0.216	1.006
Both	Eastern red bats	0.832	GR: Wind Direction W (12hr Lag)	0.392	-0.206	1.002
Both	Eastern red bats	0.832	RA: Wind Direction N (12hr Lag)	-1.128	-1.746	-0.524
Both	Eastern red bats	0.832	RA: Wind Direction S (12hr Lag)	-0.234	-0.847	0.382
Both	Eastern red bats	0.832	RA: Wind Direction W (12hr Lag)	-0.613	-1.271	0.042
Both	Eastern red bats	0.832	PE: 3hr-BP Change (mbar)	0.140	-0.038	0.299
Both	Eastern red bats	0.832	PE: Wind Direction N	-0.290	-0.752	0.177
Both	Eastern red bats	0.832	PE: Wind Direction S	0.062	-0.467	0.591
Both	Eastern red bats	0.832	PE: Wind Direction W	0.450	-0.179	1.059
Both	Eastern red bats	0.832	PE: 2hr-BP Change*WD N	-0.137	-0.386	0.134

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Both	Eastern red bats	0.832	PE: 2hr-BP Change*WD S	-0.509	-0.851	-0.162
Both	Eastern red bats	0.832	PE: 2hr-BP Change*WD W	-0.758	-1.457	-0.179
Both	Hoary bats	0.873	Intercept	4.110	2.454	5.840
Both	Hoary bats	0.873	Wind Speed (m/s)	-1.019	-1.302	-0.769
Both	Hoary bats	0.873	Day of Study	-0.110	-0.151	-0.077
Both	Hoary bats	0.873	Wind Direction N	-0.282	-1.527	0.900
Both	Hoary bats	0.873	Wind Direction S	1.268	0.352	2.266
Both	Hoary bats	0.873	Wind Direction W	0.185	-0.806	1.207
Both	Hoary bats	0.873	GR: Wind Direction N (6hr Lag)	-1.069	-2.062	-0.072
Both	Hoary bats	0.873	GR: Wind Direction S (6hr Lag)	0.105	-0.847	1.087
Both	Hoary bats	0.873	GR: Wind Direction W (6hr Lag)	0.852	-0.062	1.823
Both	Hoary bats	0.873	LO: Wind Direction N (18hr Lag)	-1.448	-2.332	-0.572
Both	Hoary bats	0.873	LO: Wind Direction S (18hr Lag)	-1.521	-2.375	-0.674
Both	Hoary bats	0.873	LO: Wind Direction W (18hr Lag)	-4.540	-7.123	-2.745
Both	Hoary bats	0.873	1hr-BP Change (mbar)	-1.823	-3.742	0.516
Both	Hoary bats	0.873	1hr-BP Change*WD N	2.018	-0.914	4.938
Both	Hoary bats	0.873	1hr-BP Change*WD S	2.606	-0.093	5.076

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Both	Hoary bats	0.873	1hr-BP Change*WD W	-3.508	-6.776	-0.599
Both	Big brown & silver-haired bats	0.671	Intercept	-2.462	-3.838	-1.139
Both	Big brown & silver-haired bats	0.671	Relative Humidity (%)	0.016	0.005	0.027
Both	Big brown & silver-haired bats	0.671	Wind Speed (m/s)	-0.444	-0.736	-0.131
Both	Big brown & silver-haired bats	0.671	Quadratic of Wind Speed	0.025	0.001	0.048
Both	Big brown & silver-haired bats	0.671	JA: Wind Direction N	-0.762	-1.173	-0.342
Both	Big brown & silver-haired bats	0.671	JA: Wind Direction S	-1.270	-1.848	-0.704
Both	Big brown & silver-haired bats	0.671	JA: Wind Direction W	-0.622	-1.221	-0.035
Both	Big brown & silver-haired bats	0.671	MO: Wind Direction N	0.858	0.372	1.384
Both	Big brown & silver-haired bats	0.671	MO: Wind Direction S	0.362	-0.290	1.022
Both	Big brown & silver-haired bats	0.671	MO: Wind Direction W	0.332	-0.359	1.025
Both	Big brown & silver-haired bats	0.671	JO: Wind Direction N (6hr Lag)	0.446	0.026	0.883
Both	Big brown & silver-haired bats	0.671	JO: Wind Direction S (6hr Lag)	-0.111	-0.685	0.456
Both	Big brown & silver-haired bats	0.671	JO: Wind Direction W (6hr Lag)	0.602	-0.002	1.199
Both	Big brown & silver-haired bats	0.671	LA: 1hr-BP Change (12hr Lag, mbar)	-0.050	-0.170	0.085
Both	Big brown & silver-haired bats	0.671	LA: Wind Direction N (12hr Lag)	-0.133	-0.561	0.306
Both	Big brown & silver-haired bats	0.671	LA: Wind Direction S (12hr Lag)	-0.035	-0.555	0.486

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Both	Big brown & silver-haired bats	0.671	LA: Wind Direction W (12hr Lag)	-0.386	-0.983	0.198
Both	Big brown & silver-haired bats	0.671	PE: 3hr-BP Change (12hr Lag, mbar)	0.028	-0.119	0.174
Both	Big brown & silver-haired bats	0.671	PE: Wind Direction N (12hr Lag)	0.185	-0.281	0.657
Both	Big brown & silver-haired bats	0.671	PE: Wind Direction S (12hr Lag)	0.310	-0.229	0.848
Both	Big brown & silver-haired bats	0.671	PE: Wind Direction W (12hr Lag)	0.096	-0.431	0.625
Both	Big brown & silver-haired bats	0.671	LA: 1hr-BP Change*WD N (12hr Lag)	0.102	-0.077	0.261
Both	Big brown & silver-haired bats	0.671	LA: 1hr-BP Change*WD S (12hr Lag)	-0.652	-1.153	-0.255
Both	Big brown & silver-haired bats	0.671	LA: 1hr-BP Change*WD W (12hr Lag)	-0.287	-0.697	0.143
Both	Big brown & silver-haired bats	0.671	PE: 3hr-BP Change*WD N (12hr Lag)	0.200	0.011	0.392
Both	Big brown & silver-haired bats	0.671	PE: 3hr-BP Change*WD S (12hr Lag)	-0.237	-0.481	0.028
Both	Big brown & silver-haired bats	0.671	PE: 3hr-BP Change*WD W (12hr Lag)	-0.274	-0.508	-0.050
Pilot Hill	All bats	0.776	Intercept	0.372	-0.625	1.359
Pilot Hill	All bats	0.776	Relative humidity (%)	0.017	0.009	0.025
Pilot Hill	All bats	0.776	Wind Speed (m/s)	-0.673	-0.902	-0.437
Pilot Hill	All bats	0.776	Day of Study	-0.024	-0.029	-0.018
Pilot Hill	All bats	0.776	Quadratic of Wind Speed	0.033	0.015	0.051
Pilot Hill	All bats	0.776	MO: Wind Direction N	0.523	0.188	0.871

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Pilot Hill	All bats	0.776	MO: Wind Direction S	0.392	-0.017	0.808
Pilot Hill	All bats	0.776	MO: Wind Direction W	0.482	0.026	0.938
Pilot Hill	All bats	0.776	LA: 2hr-BP Change (6hr Lag, mbar)	-0.024	-0.127	0.079
Pilot Hill	All bats	0.776	LA: Wind Direction N (6hr Lag)	-0.165	-0.492	0.165
Pilot Hill	All bats	0.776	LA: Wind Direction S (6hr Lag)	-0.326	-0.704	0.053
Pilot Hill	All bats	0.776	LA: Wind Direction W (6hr Lag)	-1.138	-1.679	-0.622
Pilot Hill	All bats	0.776	PE: 3hr-BP Change (12hr Lag, mbar)	0.048	-0.064	0.162
Pilot Hill	All bats	0.776	PE: Wind Direction N (12hr Lag)	0.133	-0.219	0.487
Pilot Hill	All bats	0.776	PE: Wind Direction S (12hr Lag)	0.341	-0.053	0.738
Pilot Hill	All bats	0.776	PE: Wind Direction W (12hr Lag)	0.275	-0.112	0.665
Pilot Hill	All bats	0.776	RA: 2hr-BP Change (12hr Lag, mbar)	-0.005	-0.113	0.104
Pilot Hill	All bats	0.776	RA: Wind Direction N (12hr Lag)	-0.278	-0.651	0.096
Pilot Hill	All bats	0.776	RA: Wind Direction S (12hr Lag)	0.321	-0.082	0.728
Pilot Hill	All bats	0.776	RA: Wind Direction W (12hr Lag)	0.162	-0.242	0.569
Pilot Hill	All bats	0.776	LA: 2hr-BP Change*WD N (6hr Lag)	-0.010	-0.152	0.130
Pilot Hill	All bats	0.776	LA: 2hr-BP Change*WD S (6hr Lag)	0.490	0.238	0.747
Pilot Hill	All bats	0.776	LA: 2hr-BP Change*WD W (6hr Lag)	0.332	0.046	0.635

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Pilot Hill	All bats	0.776	PE: 3hr-BP Change*WD N (12hr Lag)	-0.099	-0.251	0.053
Pilot Hill	All bats	0.776	PE: 3hr-BP Change*WD S (12hr Lag)	-0.233	-0.423	-0.043
Pilot Hill	All bats	0.776	PE: 3hr-BP Change*WD W (12hr Lag)	-0.263	-0.449	-0.081
Pilot Hill	All bats	0.776	RA: 2hr-BP Change*WD N (12hr Lag)	-0.088	-0.253	0.077
Pilot Hill	All bats	0.776	RA: 2hr-BP Change*WD S (12hr Lag)	-0.127	-0.338	0.083
Pilot Hill	All bats	0.776	RA: 2hr-BP Change*WD W (12hr Lag)	-0.250	-0.536	0.018
Pilot Hill	Eastern red bats	0.812	Intercept	0.904	-0.045	1.849
Pilot Hill	Eastern red bats	0.812	Wind Speed (m/s)	-0.435	-0.554	-0.322
Pilot Hill	Eastern red bats	0.812	Day of Study	0.010	-0.035	0.058
Pilot Hill	Eastern red bats	0.812	Quadratic of Day of Study	-0.001	-0.002	0
Pilot Hill	Eastern red bats	0.812	ST: Wind Direction N (12hr Lag)	-1.588	-2.229	-0.950
Pilot Hill	Eastern red bats	0.812	ST: Wind Direction S (12hr Lag)	-1.203	-1.887	-0.521
Pilot Hill	Eastern red bats	0.812	ST: Wind Direction W (12hr Lag)	-0.535	-1.228	0.160
Pilot Hill	Eastern red bats	0.812	3hr-BP Change (mbar)	0.357	-0.073	0.783
Pilot Hill	Eastern red bats	0.812	Wind Direction N	-0.392	-1.173	0.336
Pilot Hill	Eastern red bats	0.812	Wind Direction S	0.011	-0.531	0.562
Pilot Hill	Eastern red bats	0.812	Wind Direction W	-0.345	-1.002	0.292

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Pilot Hill	Eastern red bats	0.812	GR: 2hr-BP Change (12hr Lag, mbar)	-0.023	-0.261	0.184
Pilot Hill	Eastern red bats	0.812	GR: Wind Direction N (12hr Lag)	-0.077	-0.758	0.613
Pilot Hill	Eastern red bats	0.812	GR: Wind Direction S (12hr Lag)	1.012	0.297	1.740
Pilot Hill	Eastern red bats	0.812	GR: Wind Direction W (12hr Lag)	0.585	-0.145	1.329
Pilot Hill	Eastern red bats	0.812	3hr-BP Change*WD N	-0.624	-1.461	0.171
Pilot Hill	Eastern red bats	0.812	3hr-BP Change*WD S	-0.956	-1.605	-0.320
Pilot Hill	Eastern red bats	0.812	3hr-BP Change*WD W	-2.269	-3.262	-1.356
Pilot Hill	Eastern red bats	0.812	GR: 2hr-BP Change*WD N (12hr Lag)	-0.119	-0.480	0.299
Pilot Hill	Eastern red bats	0.812	GR: 2hr-BP Change*WD S (12hr Lag)	0.091	-0.374	0.599
Pilot Hill	Eastern red bats	0.812	GR: 2hr-BP Change*WD W (12hr Lag)	-0.471	-0.814	-0.130
Pilot Hill	Hoary bats	0.875	Intercept	-8.427	-20.505	1.220
Pilot Hill	Hoary bats	0.875	Temperature (F)	-0.126	-0.200	-0.053
Pilot Hill	Hoary bats	0.875	Wind Speed (m/s)	-1.257	-1.827	-0.651
Pilot Hill	Hoary bats	0.875	Cum. prop. of 2 nights w/o rain	13.492	4.316	25.267
Pilot Hill	Hoary bats	0.875	Day of Study	0.023	-0.032	0.082
Pilot Hill	Hoary bats	0.875	Quadratic of Day of Study	-0.002	-0.003	-0.001
Pilot Hill	Hoary bats	0.875	Quadratic of Wind Speed	0.063	0.006	0.113

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Pilot Hill	Hoary bats	0.875	GR: Wind Direction N (6hr Lag)	-0.423	-1.085	0.246
Pilot Hill	Hoary bats	0.875	GR: Wind Direction S (6hr Lag)	1.040	0.333	1.764
Pilot Hill	Hoary bats	0.875	GR: Wind Direction W (6hr Lag)	0.733	0.040	1.444
Pilot Hill	Hoary bats	0.875	LO: Wind Direction N (6hr Lag)	-0.902	-1.621	-0.167
Pilot Hill	Hoary bats	0.875	LO: Wind Direction S (6hr Lag)	-0.357	-1.079	0.384
Pilot Hill	Hoary bats	0.875	LO: Wind Direction W (6hr Lag)	0.126	-0.633	0.902
Pilot Hill	Hoary bats	0.875	MO: Wind Direction N (18hr Lag)	1.102	0.369	1.884
Pilot Hill	Hoary bats	0.875	MO: Wind Direction S (18hr Lag)	0.948	0.003	1.927
Pilot Hill	Hoary bats	0.875	MO: Wind Direction W (18hr Lag)	0.761	-0.237	1.772
Pilot Hill	Hoary bats	0.875	PE: Wind Direction N (18hr Lag)	-0.409	-1.002	0.195
Pilot Hill	Hoary bats	0.875	PE: Wind Direction S (18hr Lag)	-0.984	-1.766	-0.223
Pilot Hill	Hoary bats	0.875	PE: Wind Direction W (18hr Lag)	-1.249	-2.062	-0.460
Pilot Hill	Big brown & silver-haired bats	0.631	Intercept	-2.768	-3.572	-2.010
Pilot Hill	Big brown & silver-haired bats	0.631	Wind Speed (m/s)	-0.168	-0.257	-0.081
Pilot Hill	Big brown & silver-haired bats	0.631	JA: 1hr-BP Change (12hr Lag, mbar)	-0.131	-0.207	-0.049
Pilot Hill	Big brown & silver-haired bats	0.631	MO: Wind Direction N	0.653	0.122	1.246
Pilot Hill	Big brown & silver-haired bats	0.631	MO: Wind Direction S	-0.073	-0.767	0.642

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Pilot Hill	Big brown & silver-haired bats	0.631	MO: Wind Direction W	0.557	-0.117	1.256
Pilot Hill	Big brown & silver-haired bats	0.631	PE: 3hr-BP Change (12hr Lag, mbar)	-0.052	-0.207	0.135
Pilot Hill	Big brown & silver-haired bats	0.631	PE: Wind Direction N (12hr Lag)	0.557	0.038	1.104
Pilot Hill	Big brown & silver-haired bats	0.631	PE: Wind Direction S (12hr Lag)	0.700	0.124	1.294
Pilot Hill	Big brown & silver-haired bats	0.631	PE: Wind Direction W (12hr Lag)	0.311	-0.256	0.895
Pilot Hill	Big brown & silver-haired bats	0.631	PE: 3hr-BP Change*WD N (12hr Lag)	0.154	-0.078	0.362
Pilot Hill	Big brown & silver-haired bats	0.631	PE: 3hr-BP Change*WD S (12hr Lag)	-0.344	-0.625	-0.074
Pilot Hill	Big brown & silver-haired bats	0.631	PE: 3hr-BP Change*WD W (12hr Lag)	-0.401	-0.679	-0.150
Kelly Creek	All bats	0.73	Intercept	0.211	-1.097	1.461
Kelly Creek	All bats	0.73	Wind Speed (m/s)	-0.530	-0.856	-0.168
Kelly Creek	All bats	0.73	1hr-BP Change (mbar)	-1.663	-2.343	-1.014
Kelly Creek	All bats	0.73	GR: 2hr-BP Change (6hr Lag, mbar)	0.198	0.112	0.281
Kelly Creek	All bats	0.73	Day of Study	-0.038	-0.047	-0.030
Kelly Creek	All bats	0.73	Quadratic of Wind Speed	0.030	-0.001	0.056
Kelly Creek	All bats	0.73	MI: Wind Direction N	0.375	-0.263	1.089
Kelly Creek	All bats	0.73	MI: Wind Direction S	0.135	-0.651	0.968
Kelly Creek	All bats	0.73	MI: Wind Direction W	1.586	0.613	2.558

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Kelly Creek	All bats	0.73	LA: Wind Direction N (6hr Lag)	0.618	0.165	1.101
Kelly Creek	All bats	0.73	LA: Wind Direction S (6hr Lag)	-0.143	-0.745	0.465
Kelly Creek	All bats	0.73	LA: Wind Direction W (6hr Lag)	-0.110	-0.880	0.619
Kelly Creek	All bats	0.73	PE: Wind Direction N (6hr Lag)	0.262	-0.153	0.683
Kelly Creek	All bats	0.73	PE: Wind Direction S (6hr Lag)	0.151	-0.364	0.665
Kelly Creek	All bats	0.73	PE: Wind Direction W (6hr Lag)	-0.496	-1.071	0.066
Kelly Creek	All bats	0.73	Wind Direction N	-0.588	-1.096	-0.106
Kelly Creek	All bats	0.73	Wind Direction S	-0.143	-0.597	0.301
Kelly Creek	All bats	0.73	Wind Direction W	-0.350	-0.836	0.125
Kelly Creek	All bats	0.73	1hr-BP Change*WD N	2.171	1.104	3.251
Kelly Creek	All bats	0.73	1hr-BP Change*WD S	0.996	0.027	1.992
Kelly Creek	All bats	0.73	1hr-BP Change*WD W	-0.549	-2.062	0.886
Kelly Creek	Eastern red bats	0.778	Intercept	-2.346	-4.596	-0.383
Kelly Creek	Eastern red bats	0.778	Wind Speed (m/s)	-0.222	-0.444	-0.010
Kelly Creek	Eastern red bats	0.778	2hr-BP Change (mbar)	-1.283	-2.004	-0.576
Kelly Creek	Eastern red bats	0.778	Day of Study	-0.054	-0.081	-0.031
Kelly Creek	Eastern red bats	0.778	ST: Wind Direction N	0.140	-0.862	1.285

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Kelly Creek	Eastern red bats	0.778	ST: Wind Direction S	-1.347	-2.924	0.153
Kelly Creek	Eastern red bats	0.778	ST: Wind Direction W	-16.577	-300.470	26.412
Kelly Creek	Eastern red bats	0.778	PE: Wind Direction N (18hr Lag)	0.753	-0.193	1.772
Kelly Creek	Eastern red bats	0.778	PE: Wind Direction S (18hr Lag)	-1.387	-3.782	0.287
Kelly Creek	Eastern red bats	0.778	PE: Wind Direction W (18hr Lag)	1.482	0.321	2.695
Kelly Creek	Eastern red bats	0.778	FU: 2hr-BP Change (12hr Lag, mbar)	0.095	-0.268	0.394
Kelly Creek	Eastern red bats	0.778	FU: Wind Direction N (12hr Lag)	-0.185	-1.666	1.551
Kelly Creek	Eastern red bats	0.778	FU: Wind Direction S (12hr Lag)	1.319	-0.009	2.990
Kelly Creek	Eastern red bats	0.778	FU: Wind Direction W (12hr Lag)	0.316	-1.198	2.090
Kelly Creek	Eastern red bats	0.778	JO: 3hr-BP Change (12hr Lag, mbar)	-0.116	-0.503	0.311
Kelly Creek	Eastern red bats	0.778	JO: Wind Direction N (12hr Lag)	-0.681	-1.798	0.488
Kelly Creek	Eastern red bats	0.778	JO: Wind Direction S (12hr Lag)	0.405	-0.745	1.612
Kelly Creek	Eastern red bats	0.778	JO: Wind Direction W (12hr Lag)	-0.656	-2.020	0.710
Kelly Creek	Eastern red bats	0.778	FU: 2hr-BP Change*WD N (12hr Lag)	-0.453	-0.819	-0.043
Kelly Creek	Eastern red bats	0.778	FU: 2hr-BP Change*WD S (12hr Lag)	-0.168	-0.672	0.521
Kelly Creek	Eastern red bats	0.778	FU: 2hr-BP Change*WD W (12hr Lag)	-0.027	-0.529	0.607
Kelly Creek	Eastern red bats	0.778	JO: 3hr-BP Change*WD N (12hr Lag)	-0.304	-0.790	0.135

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Kelly Creek	Eastern red bats	0.778	JO: 3hr-BP Change*WD S (12hr Lag)	0.356	-0.363	0.997
Kelly Creek	Eastern red bats	0.778	JO: 3hr-BP Change*WD W (12hr Lag)	1.048	0.111	1.854
Kelly Creek	Hoary bats	0.871	Intercept	-0.386	-4.382	2.878
Kelly Creek	Hoary bats	0.871	2hr-BP Change (mbar)	-1.233	-1.990	-0.518
Kelly Creek	Hoary bats	0.871	Day of Study	-0.069	-0.103	-0.042
Kelly Creek	Hoary bats	0.871	Wind Speed (m/s)	-0.148	-1.552	1.737
Kelly Creek	Hoary bats	0.871	Quadratic of Wind Speed	-0.058	-0.286	0.092
Kelly Creek	Hoary bats	0.871	ST: Wind Direction N (6hr Lag)	0.194	-0.743	1.281
Kelly Creek	Hoary bats	0.871	ST: Wind Direction S (6hr Lag)	-1.070	-2.519	0.295
Kelly Creek	Hoary bats	0.871	ST: Wind Direction W (6hr Lag)	-1.877	-4.305	-0.128
Kelly Creek	Big brown & silver-haired bats	0.584	Intercept	-1.634	-2.826	-0.498
Kelly Creek	Big brown & silver-haired bats	0.584	Wind Speed (m/s)	-0.421	-0.590	-0.262
Kelly Creek	Big brown & silver-haired bats	0.584	1hr-BP Change (mbar)	-1.023	-1.650	-0.376
Kelly Creek	Big brown & silver-haired bats	0.584	LA: 1hr-BP Change (18hr Lag, mbar)	0.174	0.066	0.267
Kelly Creek	Big brown & silver-haired bats	0.584	PE: Wind Direction N (6hr Lag)	1.331	0.573	2.162
Kelly Creek	Big brown & silver-haired bats	0.584	PE: Wind Direction S (6hr Lag)	0.665	-0.268	1.608
Kelly Creek	Big brown & silver-haired bats	0.584	PE: Wind Direction W (6hr Lag)	-0.066	-1.138	0.956

Site	Species	Area under the receiver operating curve (AUC)	Parameter	Value	Lower bound	Upper bound
Kelly Creek	Big brown & silver-haired bats	0.584	ST: 1hr-BP Change (12hr Lag, mbar)	-0.074	-0.218	0.092
Kelly Creek	Big brown & silver-haired bats	0.584	ST: Wind Direction N (12hr Lag)	-0.791	-1.493	-0.061
Kelly Creek	Big brown & silver-haired bats	0.584	ST: Wind Direction S (12hr Lag)	-0.791	-1.770	0.119
Kelly Creek	Big brown & silver-haired bats	0.584	ST: Wind Direction W (12hr Lag)	-0.763	-1.645	0.101
Kelly Creek	Big brown & silver-haired bats	0.584	ST: 1hr-BP Change*WD N (12hr Lag)	0.120	-0.168	0.394
Kelly Creek	Big brown & silver-haired bats	0.584	ST: 1hr-BP Change*WD S (12hr Lag)	0.161	-0.878	1.063
Kelly Creek	Big brown & silver-haired bats	0.584	ST: 1hr-BP Change*WD W (12hr Lag)	-0.655	-1.010	-0.325

m/s = meters per second; BP = barometric pressure; WD = wind direction; hr= hour.

Figure 5 lists two-letter airport codes.

Appendix C. Fatalities and Weather Model Parameters

Site	Species	AUC	Parameter	Value	Lower Bound	Upper Bound
Both	All bats	0.943	Intercept	0.518	NA	NA
Both	Eastern red bats	0.415	Intercept	-2.127	-3.959	-0.517
Both	Eastern red bats	0.415	Temperature (Fahrenheit)	0.140	0.056	0.236
Both	Hoary bats	0.833	Intercept	4.250	2.619	6.300
Both	Hoary bats	0.833	Day of Study	-0.092	-0.134	-0.059
Both	Hoary bats	0.833	MO: Wind Direction North (N; 12hr Lag)	-0.081	-2.199	2.498
Both	Hoary bats	0.833	MO: Wind Direction South (S; 12hr Lag)	-0.665	-1.901	0.505
Both	Hoary bats	0.833	MO: Wind Direction West (W; 12hr Lag)	-3.809	-6.066	-1.941
Both	Silver-haired bats	0.678	Intercept	-2.457	-3.651	-1.441
Both	Silver-haired bats	0.678	Day of Study	0.038	0.017	0.062
Pilot Hill	All bats	0.691	Intercept	0.950	-0.545	2.571
Pilot Hill	All bats	0.691	Day of Study	0.077	-0.016	0.173
Pilot Hill	All bats	0.691	Quadratic of Day of Study	-0.001	-0.003	0
Pilot Hill	All bats	0.691	PE: Wind Direction N (18hr Lag)	16.321	-123.690	NA
Pilot Hill	All bats	0.691	PE: Wind Direction S (18hr Lag)	0.982	-0.118	2.208
Pilot Hill	All bats	0.691	PE: Wind Direction W (18hr Lag)	-1.065	-2.555	0.336

Site	Species	AUC	Parameter	Value	Lower Bound	Upper Bound
Pilot Hill	Eastern red bats	0.672	Intercept	-0.405	-1.825	0.890
Pilot Hill	Eastern red bats	0.672	Day of Study	0.083	-0.009	0.186
Pilot Hill	Eastern red bats	0.672	Quadratic of Day of Study	-0.002	-0.004	0
Pilot Hill	Hoary bats	0.833	Intercept	2.378	0.465	4.578
Pilot Hill	Hoary bats	0.833	Day of Study	0.077	-0.046	0.206
Pilot Hill	Hoary bats	0.833	Quadratic of Day of Study	-0.003	-0.005	-0.001
Pilot Hill	Hoary bats	0.833	MO: Wind Direction N (12hr Lag)	-1.055	-3.005	0.905
Pilot Hill	Hoary bats	0.833	MO: Wind Direction S (12hr Lag)	-0.935	-2.410	0.370
Pilot Hill	Hoary bats	0.833	MO: Wind Direction W (12hr Lag)	-3.014	-5.065	-1.280
Pilot Hill	Silver-haired bats	0.622	Intercept	-0.612	-1.326	0.024
Pilot Hill	Silver-haired bats	0.622	JO: Wind Direction N	-0.029	-1.141	1.035
Pilot Hill	Silver-haired bats	0.622	JO: Wind Direction S	-0.808	-2.417	0.501
Pilot Hill	Silver-haired bats	0.622	JO: Wind Direction W	2.519	0.761	4.945
Kelly Creek	All bats	0.661	Intercept	2.649	1.040	5.667
Kelly Creek	All bats	0.661	PE: 2hr-BP Change (6hr Lag, mbar)	-2.634	-4.590	-1.210
Kelly Creek	All bats	0.661	LO: Wind Direction N	3.115	-0.958	11.517
Kelly Creek	All bats	0.661	LO: Wind Direction S	1.557	-1.367	4.353
Kelly Creek	All bats	0.661	LO: Wind Direction W	0.594	-8.411	12.577

Site	Species	AUC	Parameter	Value	Lower Bound	Upper Bound
Kelly Creek	All bats	0.661	LO: 1hr-BP Change (mbar)	1.331	-0.078	2.626
Kelly Creek	All bats	0.661	LO: 1hr-BP Change*WD N	1.309	1.164	1.445
Kelly Creek	All bats	0.661	LO: 1hr-BP Change*WD S	-2.679	-5.300	-0.223
Kelly Creek	All bats	0.661	LO: 1hr-BP Change*WD W	1.979	-8.163	12.503
Kelly Creek	Eastern red bats	1	Intercept	-0.949	NA	NA
Kelly Creek	Silver-haired bats	0.509	Intercept	-0.182	-1.215	0.819
Kelly Creek	Silver-haired bats	0.509	RA: Wind Direction N (6hr Lag)	0.182	-2.569	2.936
Kelly Creek	Silver-haired bats	0.509	RA: Wind Direction S (6hr Lag)	-2.862	-5.292	-1.124
Kelly Creek	Silver-haired bats	0.509	RA: Wind Direction W (6hr Lag)	-0.329	-1.945	1.225

hr = hour; BP = barometric pressure; WD = Wind Direction.

Figure 5 lists two-letter airport codes.

Appendix D. Bat Activity and Fatality Model Parameters

Appendix D1. Parameters from the regression of 2018 bat carcass counts from previous night and partial night acoustic call count from both the Kelly Creek and Pilot Hill Wind Farms. Parameter values are on a log scale

Species	Parameter	Estimate	Lower Bound	Upper Bound
Eastern Red Bat	Intercept	-82.891	-140.184	-30.990
	Early night calls	0.201	0.072	0.314
	Julian date	0.673	0.251	1.141
	Julian date (quadratic)	-0.001	-0.002	-0.001
Hoary Bat	Intercept	-99.405	-200.759	-20.662
	Early night calls	-0.234	-0.468	-0.028
	Mid night calls	0.069	0.014	0.116
	Julian date	0.852	0.195	1.708
	Julian date (quadratic)	-0.002	-0.004	0
All Bats	Intercept	-48.052	-79.651	-17.808
	Late night calls	0.043	0.002	0.081
	Julian day	0.395	0.150	0.650
	Julian day (quadratic)	-0.001	-0.001	0

Appendix D2. Parameters from the regression of 2018 bat carcass counts from previous night and entire night acoustic call count from both the Kelly Creek and Pilot Hill Wind Farms. Parameter values are on a log scale.

Species	Parameter	Estimate	Lower Bound	Upper Bound
Eastern Red Bat	Intercept	-95.681600	-152.899000	-44.191700
	Calls per night	0.083375	0.0279080	0.132014
	Julian date	0.765563	0.347592	1.230704
	Julian date (quadratic)	-0.001560	-0.002500	-0.000720
Hoary Bat	Intercept	-110.593000	-214.592000	-29.120900
	Calls per night	0.023146	-0.012600	0.055338
	Julian date	0.936899	0.258990	1.814657
	Julian date (quadratic)	-0.002020	-0.003870	-0.000610
All Bats	Intercept	-53.926300	-87.506100	-22.079300
	Calls per night	0.007986	-0.000660	0.015959
	Julian date	0.4385770	0.182354	0.708403
	Julian date (quadratic)	-0.000910	-0.001450	-0.000390