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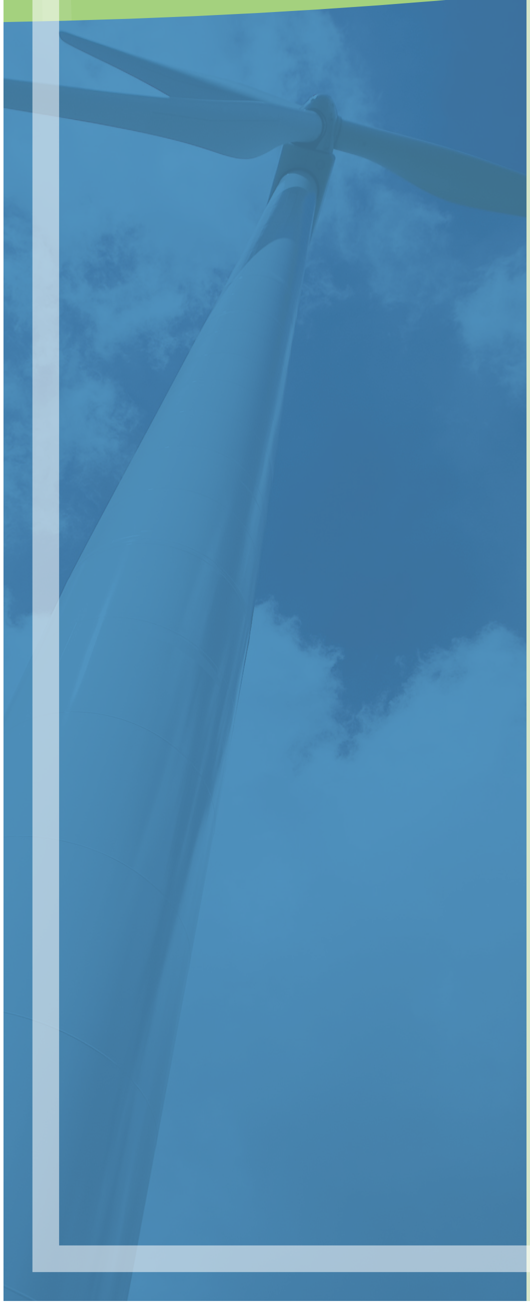

Landscape Factors Associated with Fatalities of Migratory Tree-Roosting Bats at Wind Energy Facilities: An Initial Assessment

Prepared by:

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AN AWWI TECHNICAL REPORT

Landscape Factors Associated with Fatalities of Migratory Tree-Roosting Bats at Wind Energy Facilities: An Initial Assessment

Wind Wildlife Research Fund
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Acronyms and Abbreviations

3DEP	3D Elevation Program
AWEA	American Wind Energy Association
AWWI	American Wind Wildlife Institute
AWWIC	American Wind Wildlife Information Center
BCI	Bat Conservation International
BCR	Bird Conservation Region
CanWEA	Canadian Wind Energy Association
DEM	Digital elevation model
DOF	Degrees of freedom
dwp	density-weighted proportion
GenEst	Generalized Estimator
GHG	Greenhouse Gas
GIS	Geographic Information System
GLM	Generalized Linear Models
ITP	Incidental Take Permit
km	Kilometer
LCI	Lower Confidence Interval
m	Meter
MW	Megawatt

NABCI	North American Bird Conservation Initiative
NALCMS	North American Land Change Monitoring System
NHD	National Hydrography Dataset
PCFM	Post-Construction Fatality Monitoring
QGIS	Quantum Geographic Information System
SAGA	System for Automated Geoscientific Analyses
TIGER	Topologically Integrated Geographic Encoding and Referencing
TPI	Topographic Position Index
UCI	Upper Confidence Interval
U.S.	United States
USFWS	United States Fish and Wildlife Service
USGS	United States Geological Survey

Abstract

Addressing risk to potentially vulnerable bat species from wind energy development has been identified as a high priority by the wind industry and other conservation stakeholders. Improving understanding of the large-scale ecological and geographical factors associated with potential collision risk is particularly important as many decisions regarding risk avoidance are made during the siting and design phases of a wind energy facility, and the identification of potentially higher or lower risk areas for bats can inform these early-stage decision processes as well as provide guidance for state or regional-level planning by agencies or conservation organizations. However, few studies have been conducted to explore the relationships among landscape-level factors and risk to bats from wind energy operations. This study examined fatality rates of three species of migratory tree-roosting bats commonly observed as fatalities at operational wind energy facilities - hoary bat (*Lasiurus cinereus*), silver-haired bat (*Lasionycteris noctivagans)* and eastern red bat (*Lasiurus borealis*) - in relation to landscape-scale features at varying scales in the midwestern and northeastern regions of the United States. A multistage process including ensemble learning (random forests) and predictive modeling (generalized linear models) was used to explore associations between bat fatality rates, based on data collected during post-construction fatality monitoring studies at individual wind energy facilities throughout the two regions, and various landscape metrics calculated at the local, 2.5-kilometer (km), 5-km and 25-km, scales. Findings indicated that landscape structure at the broadest scale examined was most strongly associated with fatality rates, and revealed both similarities and differences between the two regions. In the midwestern region, a positive association between fatality rates and the proportion of developed land occurring within 25-km facility buffers was observed for all three of the target species, a pattern that was also observed for hoary bat and silver-haired bat in the northeastern region. In the midwestern region a negative relationship with road density was also observed at the 25-km scale whereas at the turbine area (i.e., local, facility-level) scale fatality rates of the three target species tended to increase with road density. Hoary and eastern red bat fatality rates were also higher in the midwest region when small disaggregated patches of open, non-cultivated habitat as opposed to clumped, larger patches occurred within and adjacent to facilities. Finally, silver-haired bats were observed as fatalities at higher rates in the midwestern region when more turbines occurred on the broader landscape. Wetland structure was also associated with fatality rates in both regions. For example, in the northeastern region, fatality rates for hoary, and eastern red bats were highest when facilities were located in landscapes characterized by wetland complexes comprising large and small wetland patches. The landscape patterns revealed in this study and others can better inform future research and siting decisions and feed into an adaptive learning process that will, over time, reduce uncertainty and lead to an improved understanding of factors associated with bat collision risk at wind facilities. It is anticipated that this enhanced understanding will further assist in the development of more accurate tools for assessing this risk and lead to the identification of scientifically-informed options for avoiding, minimizing, and mitigating risk to bats.

1 Introduction

Over the last decade, wind energy has become one of the fastest growing sources of new electricity generation in the United States (U.S.), with over 97,000 megawatts (MW) of installed capacity in 41 states, Guam and Puerto Rico as of mid-2019 (American Wind Energy Association [AWEA] 2019a, 2019b). The rapid pace of wind development across North America as well as in Europe and globally has led to questions about the potential impacts of wind energy on bats and other wildlife (Rydell et al. 2010; Voigt et al. 2015; Frick et al. 2017; Allison et al. 2019). Concerns about wind-energy effects on bats have resulted in a growing body of research focused on identifying bat species that may be at risk from turbine blade collisions, informing siting decisions, and defining effective mitigation strategies to minimize potential impacts (Ellison 2012; Canadian Wind Energy Association [CanWEA] and DNV GL 2018). Although bat populations are difficult to monitor in terms of population status, trends and demographics (Kunz et al. 2007; Arnett et al. 2013; Goodrich-Mahoney 2014; Hammerson et al. 2017), bats are considered to be one of the most threatened groups of vertebrates in North America that are not associated with aquatic habitats, particularly in the northern and eastern regions of the continent (Hammerson et al. 2017). Conservation efforts aimed at bat populations are further challenged by a limited understanding of the influence of any single source of mortality on bat populations or on the effectiveness of mitigation strategies to minimize potential impacts (Ellison 2012; Thompson et al. 2017; Loss et al. 2019).

For wind energy facilities, uncertainties regarding risk to bats are particularly pronounced at the siting stage of development. Decisions pertaining to facility site selection, turbine micrositing, and defining turbine setback distances from potential bat-concentrating habitats are currently based on a general ecological understanding of species and habitat requirements. There is little published evidence, however, to indicate that siting facilities or turbines in or away from specific habitats or features is likely to avoid the risk of bat collisions. As a result, addressing risk to potentially vulnerable bat species by improving understanding of the large-scale ecological, geographical, and meteorological factors associated with this risk has been identified as a high priority by the wind industry and other conservation stakeholders (Thompson et al. 2017; CanWEA and DNV GL 2018). In April 2019, the American Wind Wildlife Institute (AWWI) and its members, having recognized a need for having a stronger understanding of landscape features that might explain variation in risk to potentially vulnerable bat species, commissioned DNV GL to conduct an analysis of the bat fatality data available in the American Wind Wildlife Information Center (AWWIC) database collected within U.S. Fish and Wildlife Service (USFWS) Regions 3 (Midwest Region) and 5 (Northeast Region). The primary goal of the analysis was to identify general associations between fatality rates observed at operational wind facilities and habitat factors at various landscape scales that can be used to inform risk-prediction assessments and siting decisions; specific objectives are detailed in Section 1.2.

1.1 Wind Energy and Migratory Tree-Roosting Bats

Although little is known about the potential for population-level impacts to bats from wind energy developments, migratory tree-roosting bats (i.e., species that typically roost in trees and perform long-distance migrations) appear to be the most vulnerable species in terms of collision risk (Barclay et al. 2017; Thompson et al. 2017). Characteristics of the migratory behavior (e.g., flight paths, height, navigation, stopover habitat) of the species most commonly observed at wind facilities (Barclay 1984; Cryan 2003; CanWEA and DNV GL 2018) are also not well understood; however, collision risk is expected to be greater during flights to and from breeding grounds due to the fact that migratory bats typically fly more frequently and at greater distances during these time periods (Cryan and Barclay 2009). In North America, over 70-% of bat fatalities recorded at wind energy facilities represent migratory species, with hoary bat (*Lasiurus cinereus*), silver-haired bat (*Lasionycteris noctivagans*), and eastern red bat (*Lasiurus borealis*) comprising the majority of fatalities observed at wind energy facilities in Canada and the U.S. . Ranges of these three species overlap the northeastern and central regions of the U.S. (Bat Conservation International [BCI] 2016), where overall bat fatality levels have been identified as a particular concern (Fargione et al. 2012; Gruver and Bishop-boros 2015). Although based on limited demographic data and contingent in large part on expert elicitation, recent modeling efforts also suggest that wind energy fatalities may contribute to population declines in hoary bat (Frick et al. 2017). Across regions, bat fatalities tend to peak during the fall migratory period, which spans from approximately mid-July through October (AWWI 2018a).

Risk to individual species is likely driven by differences in habitat associations as well as in foraging, breeding, migration and hibernation ecology, and phenology. Summaries of the factors associated with potential risk to the three target species in the analysis are provided below.

Hoary bat: Hoary bat is one of the most widespread bats in North America and is considered a common species throughout its range, which includes all states within USFWS Regions 3 and 5 (Weller et al. 2016; CanWEA and DNV GL 2018; AWWI 2018a). Population trends for the species are generally unknown, but some evidence indicates that population declines are occurring in some U.S. regions (Winhold et al. 2008; Frick et al. 2017; Rodhouse et al. 2019). Hoary bat is the most frequently observed species during post-construction fatality monitoring (PCFM) studies at wind energy facilities in North America, with examinations of published reports indicating that hoary bats comprise approximately 32% of total turbine-caused fatalities in the U.S. (AWWI 2018a) and approximately 31% of total turbine-caused fatalities in Canada (Bird Studies Canada et al. 2018). Hoary bat fatalities are widely distributed, having been observed at over 90% of facilities for which PCFM results are available (AWWI 2018a; Bird Studies Canada et al. 2018). Some studies indicate that male hoary bats may experience more fatalities than females and that adults are at greater risk than subadults (Baerwald and Barclay 2011; Burba 2013), potentially due to risky behaviors displayed during the breeding period (Cryan 2008). Little is known about migratory behavior (e.g., movement patterns) of the species, but risk of fatalities tends to be highest during peak fall migration periods (Baerwald and Barclay 2011). Hoary bat activity appears to be associated with forest edges or clearings (Jantzen and Fenton 2013), and the species tends to forage along streams and other waterbodies (Valdez and Cryan 2009). Hoary bat activity has also been potentially linked to low wind speeds, low moon illumination, low barometric pressure, and high cloud cover (Cryan and Brown 2007; Baerwald Barclay 2011).

Silver-haired bat: Silver-haired bat is found throughout most of North America including all states within USFWS Regions 3 and 5 (BCI 2016). Little is known about population size or trends for the species, but it is commonly found at wind energy facilities during fatality searches and makes up approximately 16% of reported fatalities in the United States (AWWI 2018a) and approximately 22% of reported fatalities in Canada (Bird Studies Canada et al. 2018). Silver-haired bats use a variety of habitats but appear to prefer mature hardwood stands in the vicinity of ponds or streams for roosting (Barclay et al. 1988) and disturbed areas such as small clearings or roadways for foraging (Owen et al. 2004). The species is also known to forage along watercourses (Kunz 1982) and in some cases have been shown to prefer small forested patches over contiguous forest stands (Ethier and Fahrig 2011).

Eastern red bat: Eastern red bat is likely one of the most abundant tree-roosting bats in the U.S. and known to occur in all states in USFWS Regions 3 and 5 (Arnett et al. 2009; Jones et al. 2009; BCI 2016). While population size and trends for the species are generally unknown, there has been some evidence to indicate that numbers are declining in some regions of the U.S. including the upper Midwest (Winhold et al. 2008; Alves et al. 2014). PCFM reports from wind energy facilities indicate that the species comprises approximately 24% of the total fatalities observed across the U.S. (AWWI 2018a) and approximately 21% in Canada (Bird Studies Canada et al. 2018). Eastern red bats often roost within the foliage of deciduous trees and appear to prefer mixed hardwood forests (Hutchinson and Lacki 2000; Mager and Nelson 2001). The species is generally associated with contiguous forests with limited openings but in some cases has been shown to use fragmented areas (Ethier and Fahrig 2011), for instance demonstrating a positive response to selective logging that opens up coniferous forest canopies (Jung et al. 1999).

In general, landscape factors at varying scales have the potential to influence both bat activity and bat fatality rates at wind energy facilities. Although studies that have taken a landscape-scale or multi-scale approach to bat-habitat associations are limited, research conducted in the U.S. and globally indicates that landscape structure and context at broad scales may play an important role in habitat selection or risk of fatality (Starbuck et al. 2015; Baerwald 2018). For example, North American migratory tree-roosting bats are generally associated with forest systems that they rely on for roosting and foraging, and multiple studies from the U.S. and Europe have demonstrated relationships between bat activity or abundance and forest patch attributes at scales ranging from less than 200 meters (m) to multiple kilometers (km) (Ethier and Fahrig 2011; Gillespie 2013; Starbuck et al. 2015; Maxell and Burkholder 2017). Other landscape factors demonstrated as having relationships to activity of North American and/or European bat species have included proximity to and extent of adjacent wetlands (Fulton et al. 2014; Maxell and Burkholder 2017), proximity to streams or rivers (Grindal et al. 1999; Gillespie 2013; Heist 2014; Maxell and Burkholder 2017; Silva et al. 2017), proximity to roads (Siemers and Schaub 2011; Maxell and Burkholder 2017), proportion of urbanized areas in the surrounding landscape (Starbuck et al.

2015), soil regimes (Maxell and Burkholder 2017), degree of surrounding landscape fragmentation (Ethier and Fahrig 2011; Johnson et al. 2008; Jantzen and Fenton 2013), and shape and configuration of various other landcover categories (Ferreira et al. 2015; Heim et al. 2015). Bat activity has also been shown to be associated with meteorological conditions such as wind speed, temperature, relative humidity and wind direction (Baerwald and Barclay 2011; Amorim et al. 2012; Gillespie 2013; Frick et al. 2012; Silva et al. 2017; Muthersbaugh et al. 2019;), some of which may be influenced by landscape factors related to topography or landcover.

It is also likely that local and landscape factors associated with bat activity are context-dependent, wherein habitat selection and other ecological processes vary according to the broader landscape (Gehrt and Chelsvig 2003; Jackson 2013; McGarigal et al. 2016). Context-dependency in habitat selection is particularly prevalent in highly mobile species like migratory bats (Fuentes-Montemayor et al. 2017). Indeed, studies have indicated that bat-habitat associations differ between predominately wooded or urbanized landscapes and those comprised primarily of open, agricultural lands (Gehrt and Chelsvig 2003; Elmore et al. 2005; Jackson 2013; White et al. 2017), with landscape-scale characteristics potentially playing a greater role in driving habitat use in more homogeneous, agricultural landscapes (Fuentes-Monemayor et al. 2017; Monck-Whipp et al. 2018, but see Starbuck et al. 2015).

Although several landscape-level factors related to bat presence and habitat use have been identified, few studies have been conducted to assess potential landscape factors associated with bat fatality risk from wind energy facilities. Recent analysis of publicly available hoary bat fatality data from Ontario indicates that a greater extent of cultivated crops, trees, and water within the broader landscape may impact fatality rates (Baerwald 2018). Conversely, Thompson et al. (2017) found that across the U.S. there was a negative relationship between grassland cover and reported bat fatality rates; however, these results were likely due to national-scale patterns driven by higher fatality rates typically observed in the Northeast relative to less forested areas such as the Southwest. The Thompson et al. (2017) study also only included two facilities in the Midwest region of the U.S. Risk to bats from wind energy collisions is also likely to be context-dependent and to differ between facilities juxtaposed within predominantly forested regions such as the Northeast and those in regions dominated by open, agricultural lands such as the Midwest. Factors associated with potential risk to bats are also likely to occur at multiple scales within these differing landscape contexts, and few multi-scale studies have been conducted to identify the scales at which landscape characteristics may influence bat activity or collision risk.

1.2 Objective and Scope of Analysis

The overall goal of the study was to provide scientific support for predicting fatality rates at wind energy facilities for hoary bat, eastern red bat, and silver-haired bat based on location and surrounding landscape characteristics. Additional landscape features that have the potential to be relevant to the three target species were also identified and examined, based on available habitats within USFWS Regions 3 and 5, species natural history and ecology, and known species-habitat associations. Specific objectives of the research were to:

- Compile findings from PCFM studies for the three target species, identify data gaps, and acquire additional data as needed in coordination with AWWI;
- Standardize available fatality data to the extent practicable for incorporation into predictive models;
- Calculate landscape metrics at multiple scales likely to be associated with the three target species, for wind energy sites in the fatality dataset and based on available publications and reports;
- Identify landscape features associated with observed fatality rates for each of the three target species through a multistage process including ensemble learning (random forests) and predictive modeling; and

- Assess generalities and differences among species and regions and discuss the value of the study's findings for predicting risk to bats at wind energy facilities not included in the analysis.

2 Methods

2.1 Fatality Data

The AWWIC database, a cooperative initiative of wind energy companies and AWWI, is maintained by AWWI and contains data collected during PCFM studies at individual wind energy facilities. As of July 2018, the AWWIC database contained information from 227 PCFM studies conducted at 146 wind energy facilities in the U.S., including records of 15,786 bat fatality incidents from 210 studies (AWWI 2018a). DNV GL and AWWI consulted the AWWIC database to evaluate the quantity and properties of bat fatality data currently in the database, identify potential data gaps, and define target areas for acquiring additional data.

Data from wind energy facilities were retained for analysis based on the following criteria defined by DNV GL and AWWI:

- Were from facilities located within the range of the three target species (i.e., hoary bat, eastern red bat, and silver-haired bat);
- Were from facilities located in USFWS Region 3 or Region 5;
- Were collected by scheduled searches throughout the temporal window that encompassed peak fall migration periods for all three species, defined as 15 July - 15 October;
- Were based on formal PCFM studies that accounted for, at minimum, searcher detection bias and carcass removal bias (Huso et al. 2016; Johnson et al. 2016);
- Were from facilities that were not known to be implementing curtailment (i.e., raised cut-in speeds) at one or more turbines during the PCFM period; and
- Included the following additional fields – facility location (latitude/longitude), facility size (number of turbines, total operating capacity in MW), mean hub height, year, start and end dates of PCFM, search plot size, number of turbines searched, mean search interval (days between searches), searcher efficiency rate (percent observed), carcass persistence rate (average time of carcass removal), and raw counts of hoary bat, eastern red bat, and silver-haired bat fatalities observed during PCFM studies (excluding incidental observations).

The temporal window criterion was implemented to ensure that the peak migration periods for each of the target species was fully captured within each study; peak migration in the northeastern U.S. and southern Canada typically occurs from mid-July through late-September for hoary and eastern red bats, whereas silver-haired bat migration tends to occur from mid-August to mid-October (AWWI unpublished data; AWWI 2018a; CanWEA and DNV GL 2018; Bird Studies Canada et al. 2018). Additional fields associated with facility conditions and study design were identified as necessary for fatality data standardization or for potential integration into predictive fatality models.

A total of 52 PCFM studies from 34 wind energy facilities in the AWWIC database initially met the filtering criteria. A subsequent data call was issued to AWWI members from 3 May - 30 June 2019, resulting in a revised total of 69 studies from 47 wind facilities to be included in the analyses, with the final dataset comprising 6,904 fatality records of the three target species. Of these represented facilities, 20 were located in USFWS Region 3 and 27 were located in Region 5. Within Region 3, sites with applicable data primarily occurred in Iowa and Illinois (Figure 1), whereas site distribution was skewed towards New York and Maine in Region 5 (Figure 2). Studies retained for analysis were conducted between 2006 and 2015.

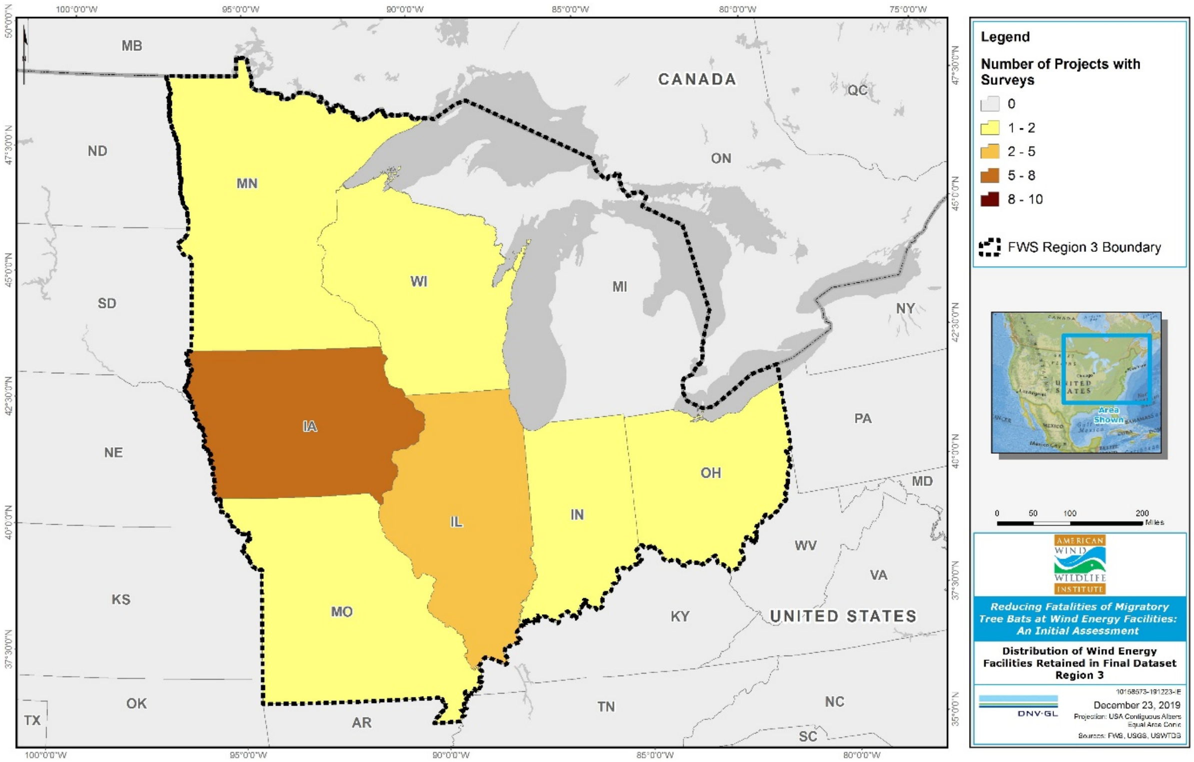

Figure 1. Distribution of wind energy facilities retained in final dataset: U.S. Fish and Wildlife Service (USFWS) Region 3.

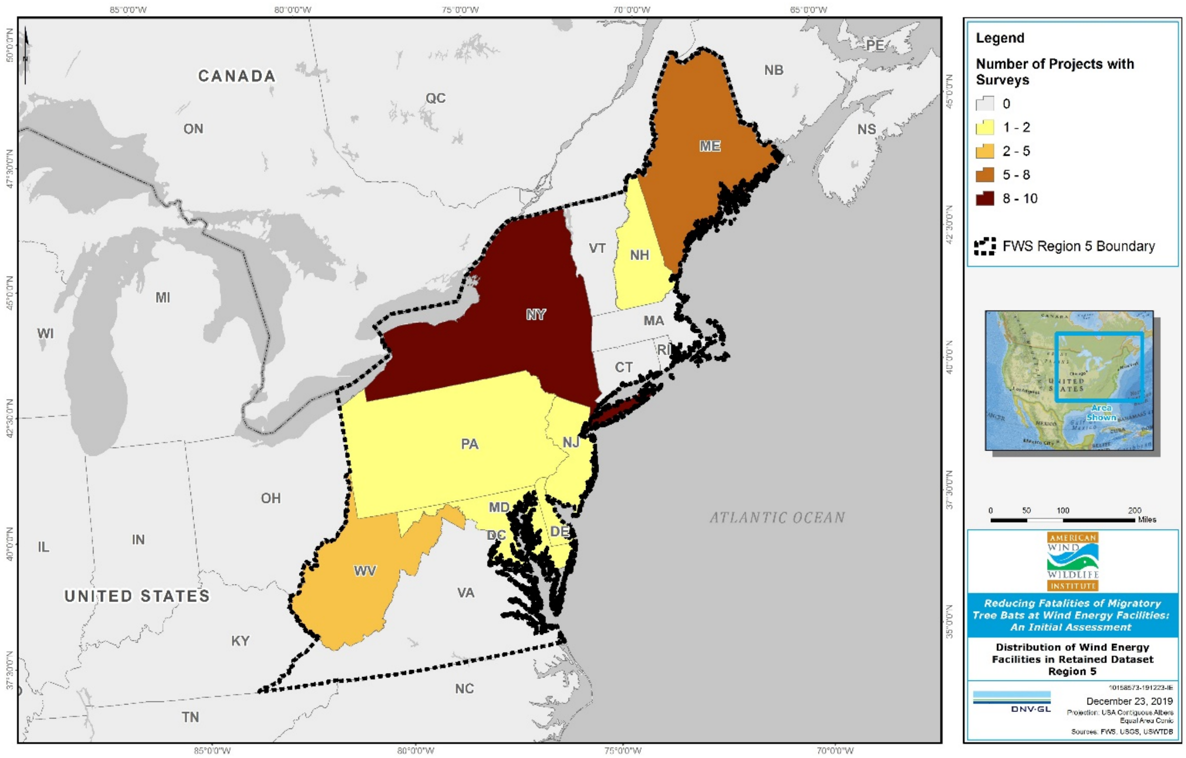

Figure 2. Distribution of wind energy facilities retained in final dataset: U.S. Fish and Wildlife Service (USFWS) Region 5.

In addition to raw counts of the three focal species, reporting from each of the studies used in the analysis also included cumulative fatality estimates for all bats (i.e., all species combined), with results recorded as total estimated number of fatalities per turbine per study year and/or total estimated number of fatalities per MW per study year. Fatality estimates were not reported for individual species including the three focal species of the current study. Reported total fatality estimates were derived from various estimation methodologies (i.e., equations) including those developed by Shoenfeld (Shoenfeld Estimator, n=29 studies; Shoenfeld 2004), Huso (Huso Estimator, n=21; Huso 2011), Smallwood (Smallwood Estimator, n=2; Smallwood 2007), Jain (Jain Estimator, n=13; Jain et al. 2007) and modified versions thereof. A small number of studies (n=3) employed the Empirical Pi (i.e., binomial trials) estimation method, which treats overall detection probability ($\hat{g}$, or probability that a carcass is available for detection and detected) as a simple product of carcass persistence probability and searcher efficiency (described in Korner-Nievergelt et al. 2012; Huso et al. 2016). One older study reported only the Naïve Estimate (Johnson et al. 2003), which is prone to severe bias (e.g., underestimating fatality rates by as much as 98.5%; Huso 2011) and is typically not used in more current studies (Erickson et al. 2014).

Choice of estimator has been demonstrated to have significant influence on avian and bat fatality estimates, each of which is prone to various levels of bias contingent on study conditions (Bernardino et al. 2013; Johnson et al. 2016; Huso et al. 2016; CanWEA and DNV GL 2018; Péron 2018); whether or not a method produces biased estimates depends on how well the data meet the implicit assumptions of the method chosen. It has therefore proved challenging to compare estimates among facilities and regions, with various approaches being applied such as: weighting estimates based on average bias observed in comparative or simulation studies (Erickson et al. 2014); analyzing reported estimates under the assumption that the best estimator was adopted for each study (Arnett et al. 2013; AWWI 2018b); calculating estimates for individual species using assumed proportional take (Thompson et al. 2017); proactively designing studies to use a particular estimator (Baerwald and Barclay 2009); or, data permitting, re-calculating estimates to conform to a single estimator (Zimmerling et al. 2013; Bird Studies Canada et al. 2018; Zimmerling and Francis 2016; Baerwald 2018). It is generally understood that there are now more robust methods available for comparing estimates among wind energy facilities, such as the Generalized Estimator (GenEst), which was recently developed by the U.S. Geological Survey (USGS) and collaborators (Dalthorp et al. 2018) and is specifically designed to minimize potential bias within individual studies and allow for comparative analysis among studies, and process-based, capture-recapture model structures (Péron et al. 2013; Péron and Hines 2013; Péron 2018). However, these methods are data intensive and require multiple facility-level attributes that are often not captured or reported on within individual studies, including the majority of studies included in the AWWIC database.

Based on the available data for the current study, it was determined that the best approach to standardization was to calculate a modified Shoenfeld fatality estimate (Shoenfeld 2004; Strickland et al. 2011) from raw counts of each species recorded between 15 July and 15 October as:

(1) $$n = \frac{c}{\left(\frac{t*p}{I} * \frac{e^{\left(\frac{I}{t}\right)}-1}{e^{\left(\frac{I}{t}\right)}-1+p}\right) \times dwp}$$

Where:

n = estimated number of fatalities

c = number of fatalities observed

t = average time of carcass persistence in days

p = proportion of carcasses found by searchers

I = average interval between searches in days

dwp = density-weighted proportion of carcasses that were available for detection during searches

The Shoenfeld Estimator was selected because sufficient data required to generate the estimate were provided for all available studies, whereas detailed data (e.g., carcass persistence distribution) needed for more recently-developed estimators (Huso 2011) were not. Furthermore, fatality rates were estimated for the three target species based on raw data rather than on reported total bat fatality estimates (e.g., by isolating detection probability [$\hat{g}$] estimates for all species combined and applying to raw counts for each species), because the individual conditions and detailed methodologies of each study, and therefore level of bias, were unknown (Huso et al. 2016).

The Shoenfeld Estimator was initially developed as an attempt to correct for underestimation of fatalities by the Naïve Estimator (Huso 2011) and uses Monte Carlo/bootstrapping methods for estimating confidence intervals (Bernardino et al. 2013). As there are numerous assumptions associated with the Shoenfeld Estimator, it should be acknowledged that it is likely that one or more assumptions were violated in the current study. Assumptions of the model include (Sonnenberg and Erickson 2011; Warren-Hicks et al. 2013; Strickland et al. 2011; list excerpted and modified from CanWEA and DNV GL 2018):

- An exponential carcass removal rate;
- All bats killed are eventually either found (and removed) by researchers or removed by scavengers;
- Regular search intervals (an earlier version of equation assumed that search intervals were a Poisson process [Shoenfeld 2004]);
- All searchers achieve the average searcher efficiency rate;

- All carcasses (old and new) have the same probabilities of discovery (discovery failures are entirely random with respect to carcass age);
- Fatality rates and searcher efficiency are approximately constant over time; and
- Bleed-through (i.e., carcasses not detected by searchers persist until a subsequent search, making it available for future detection) occurs throughout the study.

The Shoenfeld Estimator assumes exponential carcass removal by scavengers and is thus sensitive to changes in removal rates (Erickson et al. 2014; Johnson et al. 2016). The estimator also assumes constant searcher efficiency over time and space, which is difficult to achieve in reality as searcher efficiency is likely to vary according to season, habitat types, time of day, time since survey was initiated, search conditions and searcher (Sonnenberg and Erickson 2011; Korner-Nievergelt et al. 2012; Warren-Hicks et al. 2013; Bernardino et al. 2013; Peters et al. 2014). Carcasses missed in prior searches may be more likely to be overlooked on subsequent visits, especially as they decompose (Warren-Hicks et al. 2013; Huso et al. 2016). Violation of the constant searcher efficiency assumption is less likely to bias results when shorter search intervals are implemented (Huso 2011; review in CanWEA and DNV GL 2018). The Shoenfeld Estimator is generally understood to bias fatality rates low, especially when carcass persistence and searcher efficiency variables vary over time (Huso 2011). The Shoenfeld estimator may generate results similar to more robust models (e.g., Huso Estimator) when search intervals are long and carcass persistence times are short, but often differ substantially when search intervals are short and carcass persistent times are long (Erickson et al. 2014).

The Shoenfeld Estimator as initially designed did not explicitly take into account the density-weighted proportion (dwp) of carcasses that are available for observation during each PCFM search (Huso and Dalthorp 2014; Huso et al. 2016; Simonis et al. 2018); the estimator (Equation [1]) was therefore modified in the current study to account for dwp. The dwp was estimated for each of the wind energy facilities in the current study based on two components: (1) the distribution of carcasses around each turbine, and (2) the area searched around each turbine. The distribution of carcasses around a turbine is typically skewed, with greater numbers of carcasses near the turbines and density of carcasses decreasing as a function of distance from the turbine (Kerns et al. 2005; Hull and Muir 2010; Good et al. 2012; Huso and Dalthorp 2014). Additionally, not all areas within a search plot are searchable, and any unsearchable areas reduce the proportion of the carcass distribution effectively searched. Unsearchable areas can be estimated by mapping the types and extent of vegetation or other ground conditions present within the search area and used to adjust the proportion of the carcass distribution searched; however, this information was not available within the AWWIC database. Ground cover conditions can also substantially affect searcher efficiency (Peters et al. 2014), which may be explicitly accounted for by using newer estimation methods such as GenEst (Simonis et al. 2018) but not addressed in this study due to data limitations.

Robust methods have been proposed for determining carcass fall distributions by using data driven models to improve the accuracy and precision of fatality estimates (Huso and Dalthorp 2014; Simonis et al. 2018). The facility-level data requirements for implementing these models (e.g., carcass locations, visibility class), however, were not available in the AWWIC database, requiring a general assumption regarding carcass distributions across all wind energy facilities in the current study. Because a subset of facilities within the AWWIC database included information on the distance of each reported bat carcass from the turbine being searched (n = 6,917 total carcasses; 6,193 target species carcasses[1]), the subset distribution was used to infer the distribution of carcasses within concentric circles (10-m bins; weighted according to whether a search included that bin) around turbines across all facilities within the study (Table 1), with the acknowledgement that application of this broad assumption does not account for variation among facilities, impact of searchable areas on observed distributions, and influence of temporal factors known to impact fall distributions, such as wind direction and wind speed (Huso et al.

[1] 3,012 eastern red bats; 2,007 hoary bats; and 1,174 silver-haired bats.

2018). For instance, emerging research indicates that as many as 5-10% of bat carcasses may fall beyond 90 m from a turbine at some wind energy facilities (D. Dalthorp, personal comm.), and it is acknowledged that the approach applied here may bias counts low by inferring that all carcasses across facilities were distributed within 100 m of turbines.

Table 1. Assumption: bat carcass distribution around turbines (applied to all wind energy facilities included in the analysis).

Search bin (m)	Assumed proportion of carcasses within band*	Cumulative proportion of carcasses in plot
0-10	0.216	0.216
11-20	0.180	0.396
21-30	0.126	0.522
31-40	0.200	0.722
41-50	0.094	0.816
51-60	0.069	0.884
61-70	0.069	0.953
71-80	0.024	0.977
81-90	0.020	0.997
91-100	0.003	1.00

*Based on proportion of carcasses observed at a subset of wind energy facilities, weighted by number of searches that included the concentric bin within the search plot.

Because the data within the AWWIC database did not include facility-specific information with respect to ground cover and searchable areas, broad assumptions were applied based on published results from North America (Quebec MFFP 2018; AWWI 2018a) and consultation with experienced industry practitioners to estimate area searched within plots, with the acknowledgement that these assumptions are highly generalized and in reality impacted by individual facility conditions such as landcover and plot-clearing activities (Table 2).

Table 2. Assumption: Searchable area around turbines (applied to all wind energy facilities included in the analysis).

Search bin (m)	Assumed proportion of band that is searchable	Cumulative proportion of plot that is searchable
0-10	1.00	1.000
11-20	0.90	0.925
21-30	0.90	0.911
31-40	0.70	0.819
41-50	0.60	0.740
51-60	0.60	0.697
61-70	0.30	0.592
71-80	0.20	0.500
81-90	0.10	0.416
91-100	0.10	0.356

Overall dwp for each facility within the study, contingent on plot size searched, was estimated as the total proportion of carcasses that were available for detection within each plot (cumulative product of the proportion of carcasses in each band and proportion of searchable area in each band; Table 3).

Table 3. Assumption: density-weighted proportion (dwp) of carcasses that were available for observation (applied to wind energy facilities included in the analysis according to reported search plot size).

Search plot radius (m)*	Cumulative proportion of carcasses that were available for observation
40	0.631
50	0.688
60	0.729
70	0.750
80	0.754
90	0.756
100	0.757

*Search plot radius rounded up to nearest 10-m bin size. Radii for plot sizes that were reported as square were estimated as ½ plot length.

Finally, searching a subset of turbines at a wind energy facility also leaves a portion of the cumulative carcass distribution at the wind energy facility unsampled, and was accounted for by relativizing estimates as estimated fatalities per turbine. Table 4 provides a summary of attributes for the final fatality dataset included in the landscape analyses (see Section 2.3); note that across-facility values (mean, minimum, maximum) are based on reported averages from individual facilities and do not account for variation within studies. Distribution of mean fatality estimates from facilities included in the analyses are provided in Appendix A.

Table 4. Summary of fatality data included in landscape models.

Attribute		Mean (SD)
Facility size (n turbines)		56.5(48.4)
Facility size[1] (MW)		108.7(105.4)
Turbine capacity[2] (MW)		1.9(0.4)
Turbine size[3](m)		82.2(6.8)
Rotor diameter[4](m)		85 (11.6)
Search interval[5] (days)		7.57(5.82)
Carcass persistence (days)		8.43(8.14)
Searcher efficiency (percent detected)		58.17(18.9)
Search plot radius (m)		73. 83(22.17)
Turbines searched (percent searched)		73.31(30.57)
Raw counts (total carcasses observed during PCFM):		
	Hoary bat (n = 1,802)	26.57(41.44)
	Eastern red bat (n = 2,324)	33.96(56.65)
	Silver-haired bat (n = 810)	12.23(19.87)
Fatality estimates (per turbine per year)[6]		
	Hoary bat	3.39(5.52)
	Eastern red bat	3.97(6.71)
	Silver-haired bat	3.58(18.27)

[1]Total nameplate capacity of facility
[2]Average nameplate capacity of turbines within facility
[3]Average turbine hub height within facility
[4]Average turbine rotor diameter within facility
[5]Average search interval within PCFM study
[6]Shoenfeld fatality estimate derived from raw counts; see text for details

DNV GL acknowledges that the data processing applied to the available fatality data prior to analysis represent broad simplifications based on assumptions that were almost certainly violated. However, in consultation with AWWI and other industry and fatality-estimation experts, it was determined that, based on the structure and content of the AWWIC data available, applying generalized assumptions to the raw carcass-observation data was preferable to applying reported $\hat{g}$ (i.e., overall detection probability reported for all bat species, regardless of estimator used) to the raw data for each of the target species. The goal of the study is to identify general associations in bat fatalities as they relate to landscape factors, and it is believed that this approach to the data may reveal broad-scale patterns in fatality rates which can be further explored and potentially corroborated with targeted studies specifically designed to address related questions, such as the effects of landscape on species movements or behaviors.

2.2 Landscape Metrics

Various characteristics of the landscapes surrounding wind facilities in the AWWIC database were quantified at multiple scales. Few multi-scale landscape studies have been conducted to examine bat-habitat relationships, and studies that have examined bat response to the landscape at varying spatial scales indicate that large-scale patterns may be associated with bat habitat use or risk of fatality at wind facilities (e.g., Starbuck et al. 2015; Chambers et al. 2016; Baerwald 2018). Therefore, a multi-scale landscape approach was taken with the intent of identifying not only landscape characteristics associated with risk, but the scale at which these may associations occur. Landscape characteristics and scales examined were based on factors identified as those likely to influence bat use and/or risk of bat fatalities. Landscape processing followed a multistep process including: the identification of relevant landscape metrics through a literature review, consultation with AWWI, and discussions with subject matter experts; the definition of landscapes to be quantified; data processing of input geospatial datasets; and the calculation of metrics.

2.2.1 Literature Review: Landscape Metrics

DNV GL conducted a literature review to identify landscape metrics potentially relevant to bat fatalities at wind facilities (i.e., shown to be associated with bat activity or with fatality rates observed at wind facilities; Table 5). It is acknowledged that landscape factors found to be associated with other bat species (i.e., non-focal species), particularly those from European studies, may not be applicable to hoary, eastern red, and silver-haired bat; however, this exercise was conducted as an exploratory effort to identify potential scales, in general, at which bats may respond to the landscape, with a particular emphasis on identifying patterns that emerged across species and regions. It is also acknowledged that bat activity rates have generally not been demonstrated to be related to increased turbine collision risk (Hein et al. 2013; Heist 2014), but these studies were included in the preliminary assessment due to a scarcity of landscape-level research on bat fatality rates.

The most commonly identified metrics were related to the percent area or total area of land cover classes in a landscape, or the distance between a wind facility to the nearest patch of a given land cover class. After consultation with AWWI and subject matter experts, DNV GL expanded the pool of metric types to quantify other landscape characteristics such as patch size, land cover dominance, patch aggregation, and land cover diversity. The spatial scales chosen for analyses included local (facility-level, see Section 2.2.2), 2.5 km, 5 km, and 25 km. Although finer-scale habitat factors (e.g., tree composition, hedgerows, individual human structures) are also likely to influence bat habitat use and potential risk (Gehrt and Chelsvig 2003; Naughton 2012; Lacoeuilhe et al. 2018), the data allowed only one fatality-estimate per species per facility (see Section 2.1) and therefore facility-level was the finest scale examined.

2.2.2 Landscape Definition

Landscapes were defined as buffers around the 47 wind energy facilities with available post-construction bat fatality data. The turbine locations for each facility (Hoen et al. 2019) were buffered by 2.5 km, 5 km, and 25 km, then dissolved by facility name. A fourth extent, referred to as “turbine area”, was created by applying a negative buffer of 2,420 m to the dissolved 2.5 km polygons (Figure 3), to capture potential local-area effects. The negative buffer application resulted in polygons that encompassed all turbines within each facility, leaving a minimum gap of 80 m from the outermost turbines locations. The rationale for leaving an 80 m gap was to approximate an average search distance in bat fatality surveys (Table 4). In summary, DNV GL considered four spatial extents around 20 wind facilities in Region 3 and 27 facilities in Region 5, for a total of 80 and 108 landscapes respectively.

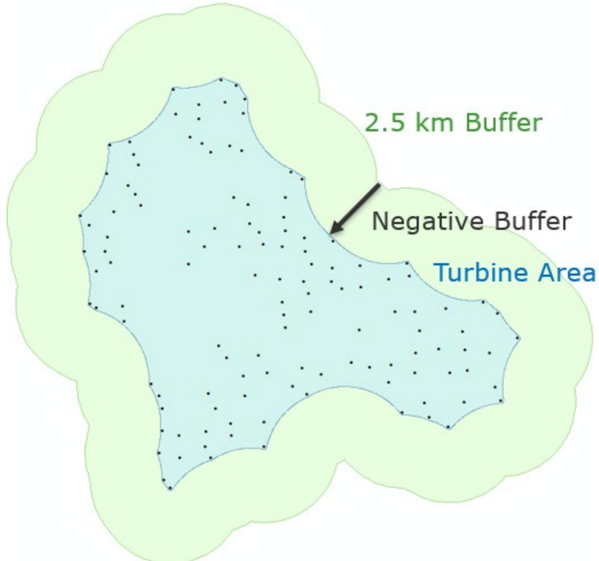

Figure 3. Illustration of turbine area-scale (represented by blue boundary) definition. Points represent individual turbine locations.

Table 5. Summary of landscape metrics literature review. Studies include those from North America and Europe that identified landscape-scale factors associated with bat activity or risk of fatality from wind energy facilities; exploratory review includes non-target species.

Metric	Defined Landscape Scale	Source
Distance to agricultural areas	0.5 km buffer	Silva et al. 2017
Distance to forests	Uncertain	Maxell and Burkholder 2017
Distance to forests	0.5 km buffer	Gillespie 2013
Distance to forests	1 km buffer	Gillespie 2013
Distance to forests	0.2 km buffer	Heist 2014; Heim et al. 2015
Distance to roads	Uncertain	Loeb and O'Keefe 2006; Siemers and Schaub 2011
Distance to streams	Uncertain	Maxell and Burkholder 2017
Distance to streams	0.5 km buffer	Gillespie 2013; Silva et al. 2017
Distance to streams	1 km buffer	Gillespie 2013
Distance to water	Uncertain	Baerwald 2018; Silva et al. 2017
Distance to water	0.2 km buffer	Heist 2014
Number of patches – Forest	2.5 km buffer	Ethier and Fahrig 2011
Number of wetlands adjacent to a forest patch	Uncertain	Fulton et al. 2014
Percentage of Landscape – Grassland	500 m buffer and 1 km buffer	Thompson et al. 2017
Percentage of Landscape – Cropland	25 km buffer	Baerwald 2018
Percentage of landscape – Forest	2.5 km buffer	Ethier and Fahrig 2011; Johnson et al 2008
Percentage of landscape – Forest	0.5 km buffer	Ferreira et al. 2015; Silva et al. 2017
Percentage of landscape – Forest	0.2 km buffer	Heim et al. 2015; Silva et al. 2017
Percentage of landscape – Forest	16 km buffer	Starbuck et al. 2015
Percentage of landscape – Urban	16 km buffer	Starbuck et al. 2015
Percentage of landscape – Non-forest	0.5 km buffer	Ferreira et al. 2015
Percentage of Landscape – Shrub	0.5 km buffer	Silva et al. 2017

Metric	Defined Landscape Scale	Source
Presence of forested ridges (binary)	Uncertain	Ellison 2012
Terrain roughness	Uncertain	Baerwald 2018
Topographic position index	Uncertain	Baerwald 2018
Total area – Forest	Uncertain	Jantzen and Fenton 2013
Total core area – Forest	Uncertain	Jantzen and Fenton 2013
Total edge – Forest	0.5 km buffer	Ferreira et al. 2015
Total edge depth area – Forest	Uncertain	Jantzen and Fenton 2013
Total length of roads	0.5 km buffer	Ferreira et al. 2015

2.2.3 Data Processing

Multiple Geographic Information System (GIS) data sources were used as inputs for the landscape metric calculations (Table 6). Land cover was the input dataset used for calculating most of the landscape metrics (Table 7). The primary source of land cover data was the 2010 North American Land Change Monitoring System (NALCMS) (Natural Resources Canada/Canada Centre for Mapping and Earth Observation [NRCan/CCMEO] et al. 2015) The year 2010 was considered suitable since it approximately falls within the middle of the collected fatality data temporal range (2006–2015), with the acknowledgement that landcover structure and patterns likely fluctuated somewhat during this time period. The NALCMS land cover map classifies land within Regions 3 and 5 into 11 land cover classes with a 30 x 30 m pixel size. Of the 11 land cover classes, four were for different forest types, and three were for open cover types. To better reflect bat usage of landscapes, the forest and open land cover classes were each aggregated into single classes, resulting in a new land cover dataset with a total of six classes (Figure 4; Table 7). A final step taken to best reflect bat use of landscapes was to distinguish smaller waterbodies from large waterbodies. This distinction between the two types of waterbodies was made by supplementing the aggregated NALCMS dataset with ocean and lake (> 500 m^2) delineations from Natural Earth (Natural Earth 2017). The merged Natural Earth ocean and lake datasets were then converted from vector polygon format to a raster grid with a 30 x 30 m pixel size (i.e., the same spatial resolution as the NALCMS). The rasterized Natural Earth dataset was subsequently mosaicked on top of the aggregated NALCMS dataset, with the Natural Earth pixels replacing the underlying values from NALCMS. The result of the mosaicking was the final merged land cover dataset with seven land cover classes (Table 7).

Table 6. GIS datasets used in the landscape analysis.

Layer	Dataset Full Name	Dataset Acronym	Type
Land Cover	North American Land Change Monitoring System (2010)[a]	NALCMS 2010	Raster
	Natural Earth[b]	Natural Earth	Vector – Polygon
Digital Elevation Model	3D Elevation Program[c]	3DEP	Raster
Roads	Topologically Integrated Geographic Encoding and Referencing system[d]	TIGER	Vector – Polyline
Rivers and Streams	National Hydrography Dataset[e]	NHD	Vector – Polyline
Wind Turbines	US Wind Turbine Database (version 2.0 – April 2019)[f]	USWTDB	Vector – Point

[a]NRCan/CCMEO et al. 2015.
[b]Natural Earth 2017
[c]USGS 2017
[d]U.S. Census Bureau 2018
[e]USGS, n.d.
[f]Hoen et al. 2019

Table 7. Mapping of source dataset classes to the final land cover layer used in the landscape analysis.

Source Dataset	Original Classes	Classes for Analysis
NALCMS	Water*	Small to Moderate Waterbodies
	Urban	Developed
	Temperate or sub-polar shrubland	Open – Non-Cultivated
	Temperate or sub-polar grassland	
	Barren lands	
	Temperate or sub-polar needleleaf forest	Forest
	Sub-polar taiga needleleaf forest	
	Temperate or sub-polar broadleaf deciduous forest	
	Mixed forest	
	Cropland	Cultivated Crops
	Wetland**	Wetlands
Natural Earth	Lakes > 500 km^2	Large Waterbodies
	Oceans	

* Areas of open water, generally with less than 25 percent cover of non-water cover types. This class refers to areas that are consistently covered by water (NRCan/CCMEO et al. 2015).

** Areas dominated by perennial herbaceous and woody wetland vegetation which is influenced by the water table at or near surface over extensive periods of time. This includes marshes, swamps, bogs, mangroves, etc., either coastal or inland where water is present for a substantial period annually (NRCan/CCMEO et al. 2015).

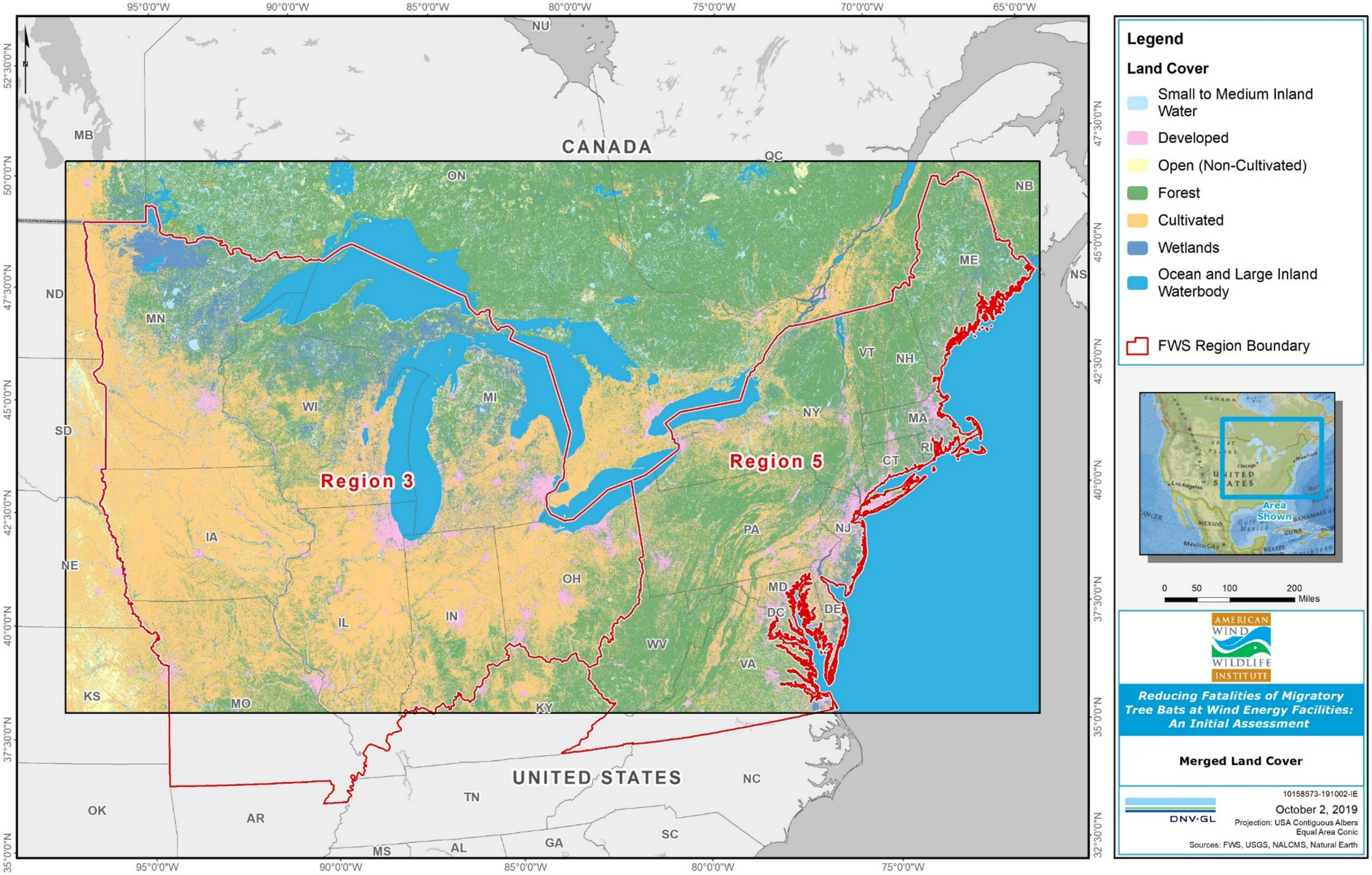

Figure 4. Merged Region 3 and Region 5 land cover map. Land cover extent covers the subset of wind projects included in the analyses plus 100 km.

A digital elevation model (DEM) with a 100 x 100 m cell size was extracted from the USGS 3D Elevation Program (3DEP) web coverage service in QGIS 3.4 for all states within Regions 3 and 5 (USGS 2017). The topographic position index (TPI) was derived from the DEM using the System for Automated Geoscientific Analyses (SAGA) tool, accessed through QGIS 3.4 (Conrad et al. 2015). The TPI calculation involves comparing a focal cell in an elevation grid to the average elevation of all the cells in a specified neighborhood around the focal cell (Weiss 2001). A cell with a positive value means that it has an elevation higher than the neighborhood average, and a negative value means the cell elevation is lower than the neighborhood average. The size of the neighborhood impacts the scale of topographic features that can be identified. Smaller neighborhoods are suitable for identifying small topographic features (e.g. variation in soil topography for a farm field) while larger neighborhoods are useful for larger features (e.g. large canyons and ridges). For the analysis, TPI was calculated using a 2,000 m neighborhood without distance weighting, which allowed for the identification of larger ridges and valleys (Weiss 2001).

Road center line data was downloaded from Topologically Integrated Geographic Encoding and Referencing (TIGER) system for all states within Regions 3 and 5 and merged into a single dataset (U.S. Census Bureau 2018). All road classes in the data (i.e., from major highways to small resource roads) were considered in the analysis.

Streams and rivers from the National Hydrography Dataset (NHD) were downloaded for all states within Regions 3 and 5 (USGS, n.d.). The NHD is a complex geodatabase that includes linear hydrography (“NHDFlowline”) and polygon hydrography (“NHDArea”). A single polyline dataset for streams and rivers was created by merging all “StreamRiver” NHDFlowlines with all “ArtificialPath” NHDFlowlines that spatially intersected “StreamRiver” NHDAreas.

2.2.4 Landscape Metric Calculation

A total of 55 metrics were calculated for each of the defined landscapes (Table 8). The linear densities of roads and streams/rivers were calculated in ArcGIS 10.3.1 (ESRI 2014) for each landscape as the total length of roads or streams/rivers divided by the total landscape area. Similarly, the point density of operational turbines was calculated as the number of turbines divided by the total area of the landscape.

Minimum distance metrics for land cover were calculated in ArcGIS 10.3.1 by iteratively performing spatial joins between the turbine area and the nearest land cover patch of the focal class. Spatial joins were also iteratively performed between the turbine areas and the nearest stream/river and nearest operational turbine of a neighboring wind facility. Minimum-distance metrics were calculated once for each facility (i.e., not calculated individually at each spatial scale [turbine area, 2.5 km, 5 km, 25 km])[2].

All other metrics were calculated in Fragstats 4.2.1 (McGarigal et al. 2012). Percent-area metrics quantify the proportional abundance of land cover classes. Percent area was also calculated for valleys and ridges in Fragstats by inputting landscapes that consisted of three classes: “ridge”, “valley”, or “other.” Ridges and valleys were identified from the TPI layer based on the standard deviation. Values greater than one standard deviation above the mean were classified as ridges while values greater than one standard deviation below the mean were classified as valleys. To define forest core area in each landscape, an edge depth of 40 m was calculated for each forest patch (i.e. the outermost 40 m of each forest patch) and excluded from area calculations. Edge density (McGarigal et al. 2012) was calculated as the sum of all edge segments for a given patch type divided by the total landscape area. Mean patch size measures indicate average total area of a discrete group of pixels classified as being in the same land cover class. Largest patch index was calculated as the percentage of the landscape occupied by the largest patch of a

[2] The rationale for this approach was to minimize redundancy. For example, if a feature was found 400 m from the turbine area, it would be the closest feature within 2.5 km, 5 km, and 25 km. Furthermore, a feature occurring in the turbine area would have a distance of 0 m at all scales.

given class. Aggregation and clumpiness indices represent measures of aggregation/dispersion of patches (detailed in McGarigal et al. 2012). The aggregation index (AI) describes the adjacency of habitat ‘‘cells’’ and ranges between 0 (when habitat distribution is maximally disaggregated; no adjacencies between cells of the same class) to 1 (when the landscape is totally homogenous), and has been used as a measure to quantify habitat connectivity in other bat landscape studies (Roscioni et al. 2014). The clumpiness index (CI) is somewhat similar to the AI but is calculated at the patch level. The CI equals -1 when the focal patch type is maximally disaggregated, 0 when the focal patch type is distributed randomly, and approaches 1 when the patch type is maximally aggregated. Lastly, Simpson’s evenness index is an aggregate measure that quantifies the evenness of the proportions of all land covers present in the landscape (McGarigal et al. 2012); thus, the Simpson’s index functionally serves as a measure of homogeneity across each landscape.

Table 8. Calculated landscape metrics.

Metric Type	Feature Type	Source Layer	Analysis Source
Linear Density (length of feature per unit area)	Roads	TIGER	ArcGIS 10.3.1
	Streams and Rivers	NHD	
Point Density	Number of operational wind turbines	USWTDB	
Minimum Distance to Feature	Small to Moderate Waterbodies	Merged Land Cover	
	Large Waterbodies	Merged Land Cover	
	Wetlands	Merged Land Cover	
	Open (Non-Cultivated)	Merged Land Cover	
	Cultivated Crops	Merged Land Cover	
	Forest	Merged Land Cover	
	Developed	Merged Land Cover	
	Streams and Rivers	NHD	
	Operational turbine of a neighboring facility	USWTDB	
Percent Area	Small to Moderate Waterbodies	Merged Land Cover	Fragstats 4.2
	Large Waterbodies	Merged Land Cover	
	Wetlands	Merged Land Cover	
	Open (Non-Cultivated)	Merged Land Cover	
	Cultivated Crops	Merged Land Cover	
	Forest	Merged Land Cover	
	Developed	Merged Land Cover	
	Valleys	3DEP	
	Ridges	3DEP	
	Forest Core Area	Merged Land Cover	

Metric Type	Feature Type	Source Layer	Analysis Source
Edge Density	Total landscape (all classes)	Merged Land Cover	
	Forest	Merged Land Cover	
	Open (Non-Cultivated)	Merged Land Cover	
	Cultivated Crops	Merged Land Cover	
Mean Patch Size	Small to Moderate Waterbodies	Merged Land Cover	
	Large Waterbodies	Merged Land Cover	
	Wetlands	Merged Land Cover	
Mean Patch Size	Open (Non-Cultivated)	Merged Land Cover	Fragstats 4.2
	Cultivated Crops	Merged Land Cover	
	Forest	Merged Land Cover	
	Developed	Merged Land Cover	
Largest Patch Index	Small to Moderate Waterbodies	Merged Land Cover	
	Large Waterbodies	Merged Land Cover	
	Wetlands	Merged Land Cover	
	Open (Non-Cultivated)	Merged Land Cover	
	Cultivated Crops	Merged Land Cover	
	Forest	Merged Land Cover	
	Developed	Merged Land Cover	
Aggregation Index	Small to Moderate Waterbodies	Merged Land Cover	
	Large Waterbodies	Merged Land Cover	
	Wetlands	Merged Land Cover	
	Open (Non-Cultivated)	Merged Land Cover	
	Cultivated Crops	Merged Land Cover	
	Forest	Merged Land Cover	

Metric Type	Feature Type	Source Layer	Analysis Source
	Developed	Merged Land Cover	
Clumpiness Index	Small to Moderate Waterbodies	Merged Land Cover	
	Large Waterbodies	Merged Land Cover	
	Wetlands	Merged Land Cover	
	Open (Non-Cultivated)	Merged Land Cover	
	Cultivated Crops	Merged Land Cover	
	Forest	Merged Land Cover	
	Developed	Merged Land Cover	
Simpson's Evenness Index	Total landscape (all classes)	Merged Land Cover	

2.3 Statistical Analyses

2.3.1 Case Weighting

Prior to incorporation into ensemble learning (random forests) and predictive modeling efforts, cases (e.g., individual studies) were weighted to account for non-independence among samples, which can lead to inflated Type I error (i.e., rejection of null hypothesis when null is true) if not addressed (Zar 1999). For cases that represented different PCFM studies conducted at the same wind energy facility, cases were weighted according to the number of studies conducted at that facility:

(2) $$w_t = \frac{1}{n}$$

Where:

w_t = temporal weighting factor

n = number of PCFM studies from that facility that were retained for analysis

For models that included spatial parameters measured at the 25-km scale, cases where 25-km buffers overlapped with neighboring facilities were also weighted for spatial non-independence:

(3) $$w_s = \frac{a}{a+b}$$

Where:

w_s = spatial weighting factor

a = total area within 25-km buffer

b = total area of 25-km buffer overlap with 25-km buffer(s) of neighboring facilities

Each case was weighted as w_t x w_s for final incorporation into the models. Use of a case-weighting methodology was chosen over other potential methods for accounting for non-independence of samples (e.g. blocking, repeated measures) and spatial autocorrelation (e.g., Moran's I, distance weighting based on functional response; Santos et al. 2013; Roscioni et al. 2014; Yalcin and Leroux 2018), to simplify the modeling process and because of sample-size limitations, which could cause overparamerization of models (e.g., through blocking or incorporation of interactions) and prevent model convergence.

2.3.2 Random Forests Analysis

Due to the large number of landscape parameters under consideration and the limited size of the recorded fatality dataset available in this study, the size of the parameter space was reduced such that parameters which did not have a significant relationship to the fatality estimates were not considered in model-fitting and to avoid over-fitting of the eventual models. A random forest model, a commonly used method in data science for reducing the number of input parameters for a model (i.e., feature selection) was fit to the data separately for each of the three target species. The random forest model is composed of multiple decision trees and included all landscape parameters as well as turbine height and total number of turbines in each facility. The variable "Year" (i.e., year the PCFM study was concluded) was also included in the model to account for potential interannual variation in fatality rates. Regional categories, such as USFWS Ecoregions or North American Bird Conservation Initiative (NABCI) Bird Conservation Regions (BCR) were not included as covariates due to limitations on degrees of freedom (DOF; i.e., there are 6-9 BCRs or Ecogregion classes within the midwestern and northeastern regions, each of which expends one DOF, as opposed to continuous or dichotomous variables in the models which each expend one DOF only). Within the strategies used to fit the model, input variables were ranked based on how important they were to produce the final ensemble model result. This ranking is based on how much each feature contributes to decreasing the overall weighted variance. A feature importance value was assigned to each input parameter. By examining these feature importance ranking, a reduced subset of parameters was produced which was expected to have the most value in fitting other types of models to the dataset. Further exploratory data analysis including correlation analysis was performed to confirm feature independence assumptions; if two variables were determined to be highly correlated (r > 0.6), one variable was removed from subsequent models to avoid multicollinearity (i.e., imprecise partial regression coefficients [Zar 1999], increased roundoff error, impacts associated with model averaging [see Section 4.2]). This subset of suggested features was then reviewed by expert biologists within DNV GL to produce a candidate set for inclusion in predictive modeling. Cases that included null data for aggregation indices such as aggregation and clumpiness metrics (Section 2.2.4) were also removed from analysis (i.e., landscape included ≤ 1 patch of a class), resulting in a dataset representing 63 years of PCFM studies from 42 wind energy facilities.

2.3.3 Predictive Modeling

One set of candidate models was constructed to predict bat fatalities for each species and region. It was *a priori*, in coordination with AWWI, that separate analyses would be conducted for each of the two target regions due to differences in the overall landscape compositions of each region. This decision was made under the presumption that habitat selection patterns as well as patterns of bat fatality risk were likely to differ between the predominantly agricultural USFWS Region 3 and predominantly forested USFWS Region 5.

Each set of candidate models consisted of generalized linear models (GLM) to model bat fatality rate (bats/turbine/fall season; spatio-temporally weighted) as a function of up to three of the independent predictor variables that were identified through the random forests analyses; the number of predictor variables included per model was capped *a priori* at three, in coordination with AWWI, to avoid overfitting and to facilitate interpretation. Given that the DNV GL adjusted Shoenfeld bat fatality rate response variable is not an integer type, but a continuous decimal and the sample sizes for each region were reasonably large, the Gaussian family was used. Several continuous independent variables were transformed prior to analysis, as a subset of the landscape parameters calculated for the sites under study had bimodal distributions and/or high-valued outliers that would disproportionately affect mean values and subsequent GLM model fitting. For example, there are many sites for which the mean patch size of wetlands within 25 km is zero or close to zero but for some sites this value is significantly greater than zero. In order to fit the GLM using such variables, the following transformation was applied:

(4) $$X' = \log\left(X - (\min(X) - 1)\right)$$

Where:

X = variable to be transformed

Table 9. Transformed variables.

Landscape Parameter	Scale
Mean Patch Area – Forest	5 km
Mean Patch Area – Wetlands	25 km
Edge Density – Wetlands	25 km
Mean Patch Area – Open	Turbine Area
Mean Patch Area – Forest	Turbine Area
Minimum distance to turbine of nearby facility	Turbine Area
Linear density – Roads	Turbine Area
Mean Patch Area – Developed	25 km
Mean Patch Area – Forest	2.5 km

Akaike's information criterion adjusted for small sample size (AICc) was used to determine the best approximating model of habitat selection at each scale (Burnham and Anderson 2002). Models that fell within two AICc points of the lowest-ranked model were considered strong candidates, with the acknowledgement that some of these models may have included uninformative parameters (Arnold 2010). Adjusted pseudo coefficient of determination (R^2) values (Nagelkerke (1991), were examined for all strong candidate models as a goodness-of-fit measure. Parameter estimates and 95% confidence intervals presented represent weighted averages from all strong candidate models, and incorporate model-selection uncertainty in our estimates of variance and resulting confidence intervals (Burnham and Anderson 2002). All P-values presented were derived from the strongest candidate model, with significance accepted at $P \leq 0.05$. All analyses were performed in `R` (R 3.6.1; R Core Team 2013). Analysis of variable importance was done through model averaging of the variables in the AICc model ranking using the `glmuti and MuMIn` packages in `R` (Calcagno 2019; Barton 2019), with the acknowledgement that model averaging may impact bias and model performance (see Section 4.2).

3 Results

3.1 Random Forests

Following the random forest analysis of the parameters in combination with knowledge about bat habitats as detailed in Section 1.1, the reduced parameter sets contained within Table 10 below were identified as potential parameters for the fitting of subsequent models:

Table 10. Random Forest Results: Informative Variables included in GLM candidate models.

Landscape Parameter	Scale	Hoary Bat	Eastern Red Bat	Silver-haired Bat	Parameter Name
% of Landscape – Forest	Turbine Area	x		x	TA. PLAND.Forest
Aggregation Index – Forest	Turbine Area	x	x	x	TA.AI.Forest
Mean Patch Area – Forest	Turbine Area	x			TA.AREA_MN.Forest
Mean Patch Area – Forest	2.5 km		x		2.5k.AREA_MN.Forest
Mean Patch Area – Forest	5 km	x			5k.AREA_MN.Forest
Mean Patch Area – Wetlands	25 km	x			25k.AREA_MN.Wetlands
Edge Density – Wetlands	25 km	x	x	x	25k.ED.Wetlands
Largest Patch Index – Wetlands	25 km	x	x	x	25k.LPI.Wetlands
Mean Patch Area – Developed	25 km			x	25k.AREA_MN.Developed
Clumpiness Index – Developed	25 km		x		25k.CLUMPY.Developed
Edge Density - Cultivated Crops	25 km	x		x	25k.ED.Crop
Linear Density – Roads	25 km	x	x	x	25k.LinDens_Road
Linear Density – Roads	Turbine Area	x	x	x	TA.LinDens_Road
Mean Patch Area – Open	Turbine Area		x		TA.AREA_MN.Open
Simpson's Evenness Index	Turbine Area	x			TA.SIEI
Minimum Distance to Turbine of Nearby Facility	Turbine Area	x	x		TA.MinDistTo_Turb
Point Density of Turbines	2.5 km			x	TA.PointDens_Turbines

Landscape Parameter	Scale	Hoary Bat	Eastern Red Bat	Silver-haired Bat	Parameter Name
Point Density of Turbines	25 km			x	25k.PointDens_Turbines
Minimum Distance to Stream or River	Turbine Area	x	x	x	TA.MinDistTo_StreamRiver
Clumpiness Index - Open	2.5 km	x	x		2.5k.CLUMPY.Open
% of Landscape – Developed	25 km	x	x	x	X25k.PLAND.Developed
% of Landscape – Wetlands	25 km	x	x	x	X25k.PLAND.Wetlands
% of Landscape – Forest	25 km	x	x	x	X25k.PLAND.Forest
Year		x	x	x	Year PCFM concluded

For illustrative purposes, Figures 5 and 6 depict the model average variable importance considering all models containing up to three independent variables from the random forest model subset (See Section 3.2). An exhaustive search of all permutations of up to three variables was performed. The importance value for a particular predictor is equal to the sum of the weights/probabilities for the models in which the variable appears. A vertical red line is drawn at an importance value of 0.8. This threshold is commonly used as a guide to assist in differentiation between important and less important variables. While any variable at or above 0.8 is of strong importance, those variables below 0.8 may still be included in the best fitting predictive models (Section 3.2).

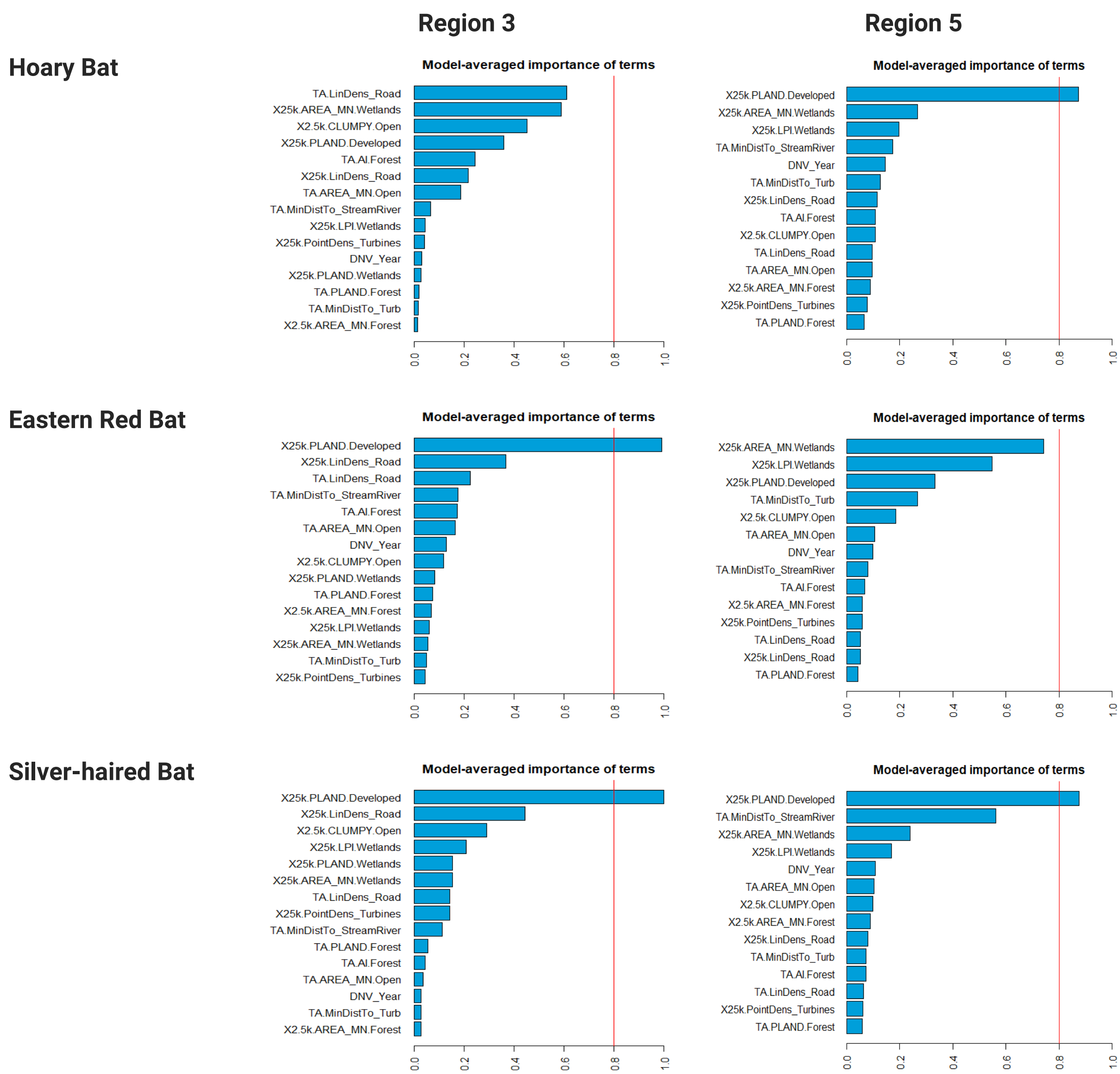

Figure 5. GLM Model-averaged importance of terms from all candidate models. Vertical red line at .80 indicates differentiation between important and less important variables. Independent variable codes are defined in Table 10.

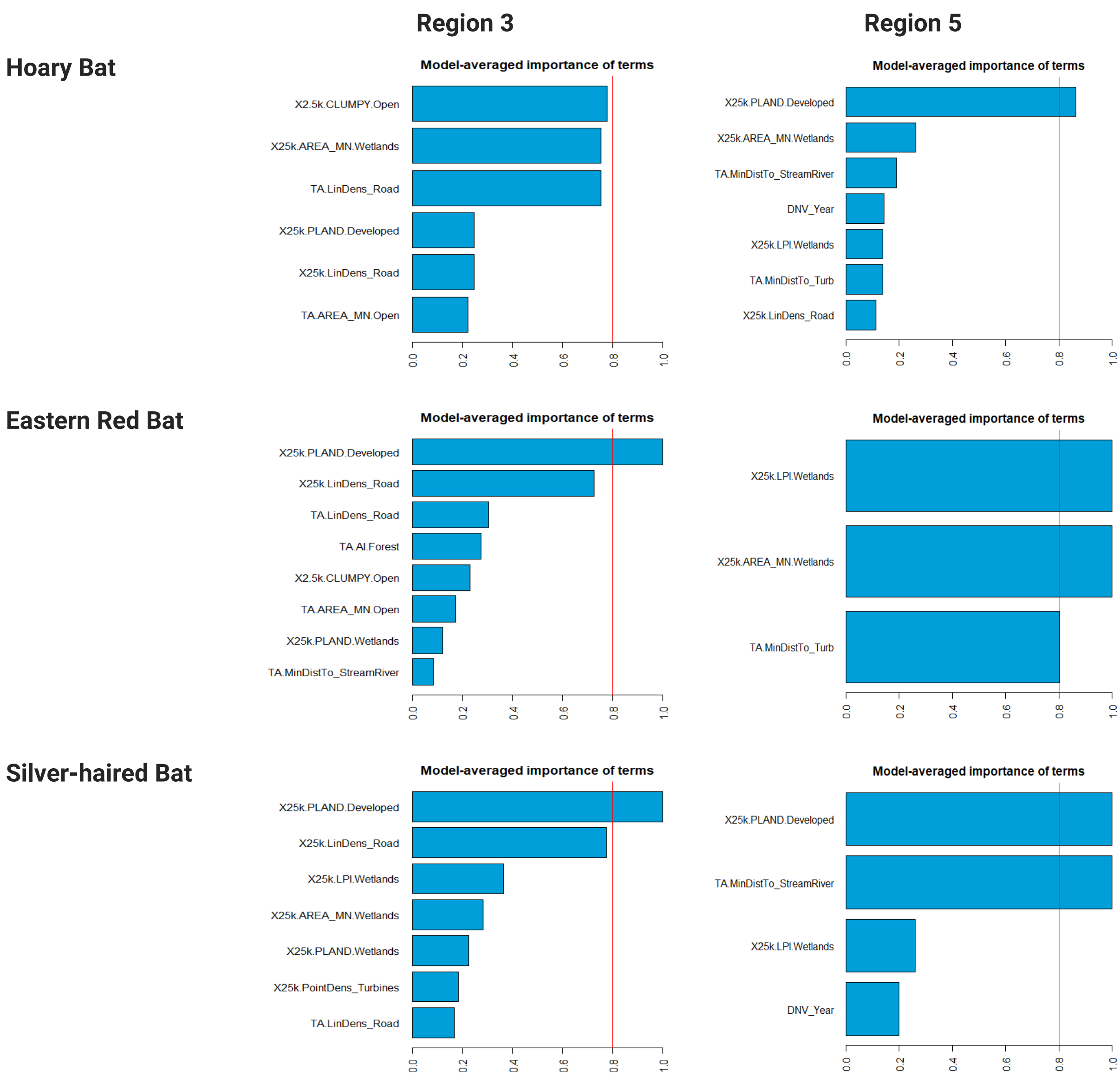

Figure 6. GLM Model-averaged importance of terms from models within 2 AICc of best fit model. Vertical red line at .80 indicates differentiation between important and less important variables. Independent variable codes are defined in Table 10.

3.2 Predictive Modeling

Predictive models were fit on all available data. There were instances of large outliers present in all cases as shown in Figure 7. As the dataset used for analysis was small and there was no indication that the outliers were erroneous entries, the GLM fits were made using all available data including outliers.

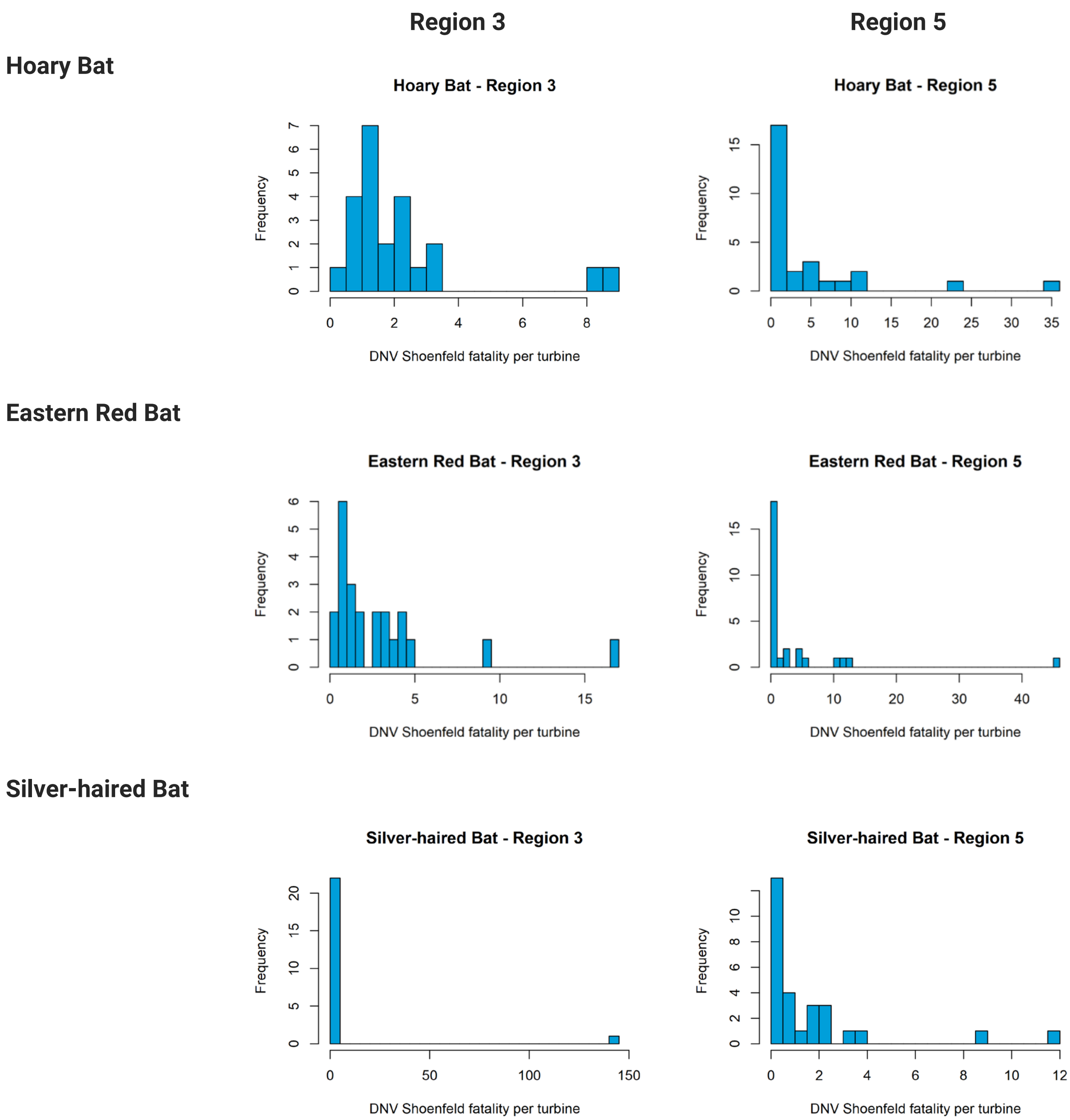

Figure 7. DNV GL-adjusted Shoenfeld fatality per turbine distributions.

The best-performing predictive models differed among regions and species (Tables 11 and 12). Most landscape parameters that emerged as being related to bat fatality rates were those that represented characteristics calculated at the broadest scale examined in this study (25 km), with three additional factors calculated at smaller spatial scales emerging as potential predictors for USFWS Region 3. Overall relationship patterns differed between the two regions, and to a lesser extent among species, although multiple relationships seemed to be generalizable across two or more of the target species within regions.

In Region 3, a positive association between fatality rates and the proportion of developed land occurring within 25-km facility buffers was observed across all three of the target species, whereas a negative relationship with road density was observed. Conversely, at the turbine area scale, fatality rates of the three target species tended to increase with road density. At smaller spatial scales, hoary and eastern red bat fatality rates were also higher when turbine areas contained small (i.e., within turbine areas), disaggregated (i.e., within 2.5 km) patches of open, non-cultivated habitat as opposed to clumped, larger patches. Wetlands also appeared to be associated with hoary and silver-haired bat fatality rates, with rates for both species tending to be higher at facilities with large wetlands within 2.5 km, and silver-haired bat rates tending to be higher when available wetland habitat within 25 km was low. Silver-haired bat fatalities also increased when wind turbine density within 25 km was high.

Similar to Region 3, in Region 5 hoary bat and silver-haired bat fatalities were higher at facilities with greater urbanization within 25 km. Eastern red bat fatality rates were highest when facilities were located in landscapes (25 km buffer areas) characterized by wetland complexes comprising at least one large wetland (indicated by a positive relationship with largest patch index) and multiple small wetlands (indicated by a negative relationship with mean patch size).

Table 11. Top performing generalized linear models (GLM), Region 3. Models defined as having strong support include those with AICc scores within two points of the top-performing model.

Model Description*	$k^{\dagger}$	LL**	ΔAICc	$w^{\dagger\dagger}$	R^{2***}
Hoary Bat					
Linear Density – Roads (Turbine Area) + Clumpiness Index – Open (2.5 km) + Mean Patch Area – Wetlands (25 km)	5	-42.94	0.00	0.53	0.68
Clumpiness Index – Open (2.5 km) + Linear Density – Roads % of Landscape – Developed (25 km)	5	-43.70	1.53	0.25	0.66
Mean Patch Area – Open (Turbine Area) + Linear Density – Roads (Turbine Area) + Mean Patch Area – Wetlands (25 km)	5	-43.80	1.74	0.22	0.66
Eastern Red Bat					
Clumpiness Index – Open (2.5 km) + Linear Density – Roads (25 km) + % of Landscape – Developed (25 km)	5	-51.64	0	0.23	0.77
Linear Density – Roads (Turbine Area) + Linear Density – Roads (25 km) + % of Landscape – Developed (25 km)	5	-51.76	0.24	0.20	0.77
Mean Patch Area – Open (Turbine Area) + Linear Density – Roads (25 km) + % of Landscape – Developed (25 km)	5	-51.93	0.57	0.17	0.77
Linear Density – Roads (25 km) + % of Landscape – Developed (25 km) + % of Landscape – Wetlands (25 km)	5	-52.28	1.27	0.12	0.76
Aggregation Index – Forest (Turbine Area) + Linear Density – Roads (Turbine Area) + % of Landscape – Developed (25 km)	5	-52.45	1.61	0.10	0.75
Aggregation Index – Forest (Turbine Area) + % of Landscape – Developed (25 km)	4	-54.28	1.96	0.09	0.71
Aggregation Index – Forest (Turbine Area) + Minimum Distance to Streams/Rivers (Turbine Area)	4	-54.28	1.96	0.09	0.32
Silver-haired Bat					
Mean Patch Area – Wetlands (25 km) + Linear Density – Roads (25 km) + % of Landscape – Developed (25 km)	5	-92.55	0	0.28	0.88

Model Description*	***k*†**	**LL****	**ΔAICc**	***w*††**	***R*²***
Largest Patch Index – Wetlands (25 km) + % of Landscape – Developed (25 km) + % of Landscape – Wetlands (25 km)	5	-92.78	0.46	0.23	0.88
Linear density – Roads (25 km) + % of Landscape – Developed (25 km) + Point Density of Turbines (25 km)	5	-92.98	0.86	0.18	0.88
Linear Density – Roads (Turbine Area) + Linear Density – Roads (25 km) + % of Landscape – Developed (25 km)	5	-93.08	1.06	0.17	0.88
Linear Density – Roads (25 km) + Largest Patch Index – Wetlands (25 km) + % of Landscape – Developed (25 km)	5	-93.26	1.42	0.14	0.88

* Model variables further described in Section 2.2; scale at which calculated indicated in parentheses.
† The number of estimable parameters in the model including intercept and error term.
** LL, - x log-likelihood of the model, given the data (Burnham and Anderson 2002).
†† Akaike model weights (Burnham and Anderson 2002).
*** Nagelkerke Pseudo R2 for GLM (Nagelkerke 1991).

Table 12. Top performing generalized linear models (GLM), Region 5. Models defined as having strong support include those with AICc scores within two points of the top-performing model.

Model Description*	***k*†**	**LL****	**ΔAICc**	***w*††**	***R*^{2}*****
Hoary Bat					
% of Landscape – Developed (25 km)	3	-84.78	0	0.29	0.58
Minimum Distance to Streams/Rivers (Turbine Area) + % of Landscape – Developed (25 km)	4	-83.85	0.88	0.19	0.61
Year + % of Landscape – Developed (25 km)	4	-84.12	1.43	0.14	0.60
Minimum Distance to Turbine of Nearby Facility (Turbine Area) + Mean Patch Area – Wetlands (25 km) + Largest Patch Index – Wetlands (25 km)	5	-82.67	1.52	0.14	0.64
Mean Patch Area – Wetlands (25 km) + % of Landscape – Developed (25 km)	4	-84.27	1.73	0.12	0.60
Linear Density – Roads (25 km) + % of Landscape – Developed (25 km)	4	-84.37	1.92	0.11	0.59
Eastern Red Bat					
Minimum Distance to Turbine of Nearby Facility (Turbine Area) + Mean Patch Area – Wetlands (25 km) + Largest Patch Index – Wetlands (25 km)	5	-87.02	0	0.8	0.66
Silver-haired Bat					
Minimum Distance to Streams/Rivers (Turbine Area) + % of Landscape – Developed (25 km)	4	-51.8	0	0.54	0.67
Minimum Distance to Streams/Rivers (Turbine Area) + Largest Patch Index – Wetlands (25 km) + % of Landscape – Developed (25 km)	5	-51.04	1.46	0.26	0.69
Year + Minimum Distance to Streams/Rivers (Turbine Area) + % of Landscape – Developed (25 km)	5	-51.3	1.99	0.2	0.68

* Model variables further described in Section 2.2; scale at which calculated indicated in parentheses.
† The number of estimable parameters in the model including intercept and error term.
** LL, - x log-likelihood of the model, given the data (Burnham and Anderson 2002).
†† Akaike model weights (Burnham and Anderson 2002).
*** Nagelkerke Pseudo R2 for GLM (Nagelkerke 1991)

Table 13. Parameter estimates (LCI, 95% lower confidence intervals; UCI, 95% upper confidence intervals) for factors related to Region 3. Weighted estimates are derived from the top performing generalized linear models (GLM) displayed in Table 11. Bolded values indicate significant landscape effect at P < 0.05.

Parameter*	**Estimate**	**LCI**	**UCI**	***p***
Hoary Bat				
Intercept	11.48	-3.63	26.59	0.137
Linear Density – Roads (Turbine Area)	1.82	0.95	2.68	< 0.0001
Clumpiness Index – Open (2.5 km)	-22.09	-36.47	-7.70	0.003
Mean Patch Area – Wetlands (25 km)	1.92	0.99	2.84	< 0.0001
Linear Density – Roads (25 km)	-4.73	-7.49	-1.97	< 0.001
% of Landscape – Developed (25 km)	1.31	0.84	1.77	< 0.0001
Mean Patch Area – Open (Turbine Area)	-2.08	-3.47	-0.69	0.003
Eastern Red Bat				
Intercept	-0.60	-24.21	23.01	0.96025
Clumpiness Index – Open (2.5 km)	-21.60	-41.40	-1.81	0.032
Linear Density – Roads (25 km)	-4.44	-8.32	-0.57	0.025
% of Landscape – Developed (25 km)	1.73	0.69	2.76	0.001
Linear Density – Roads (Turbine Area)	1.45	-0.03	2.94	0.054
Mean Patch Area – Open (Turbine Area)	-1.97	-3.89	-0.05	0.044
% of Landscape – Wetlands (25 km)	-0.30	-0.62	0.02	0.064
Aggregation Index – Forest (Turbine Area)	0.12	-0.02	0.26	0.082
Silver-haired Bat				
Intercept	-45.97	-118.40	26.46	0.214
Mean Patch Area – Wetlands (25 km)	-11.36	-20.67	-2.04	0.017
Linear Density – Roads (25 km)	-35.28	-64.19	-6.37	0.017
% of Landscape – Developed (25 km)	16.49	8.09	24.90	< 0.001
Largest Patch Index – Wetlands (25 km)	-70.35	-171.87	31.16	0.174
% of Landscape – Wetlands (25 km)	13.43	4.27	22.59	0.004
Point Density of Turbines (25 km)	137.50	15.71	259.29	0.027
Linear Density – Roads (Turbine Area)	9.70	0.96	18.46	0.030

* Model variables further described in Section 2.2; scale at which calculated indicated in parentheses.

Table 14. Parameter estimates (LCI, 95% lower confidence intervals; UCI, 95% upper confidence intervals) for factors related to Region 5. Weighted estimates are derived from the top performing generalized linear models (GLM) displayed in Table 12. Bolded values indicate significant landscape effect at P < 0.05.

Parameter	**Estimate**	**LCI**	**UCI**	***p***
Hoary Bat				
Intercept	-185.60	-0.001	1080.96	0.774
% of Landscape – Developed (25 km)	2.44	1.04	3.83	< 0.001
Minimum Distance to Streams/Rivers (Turbine Area)	0.02	-0.01	0.06	0.213
Year	0.63	-0.56	1.83	0.298
Minimum Distance to Turbine of Nearby Facility (Turbine Area)	0.79	-0.07	1.66	0.072
Mean Patch Area – Wetlands (25 km)	-7.36	-0.18	2.79	0.155
Largest Patch Index – Wetlands (25 km)	5.67	1.03	10.32	0.017
Linear Density – Roads (25 km)	-2.70	-9.14	3.75	0.412
Eastern Red Bat				
Intercept	19.62	10.86	28.39	< 0.0001
Minimum Distance to Turbine of Nearby Facility (Turbine Area)	1.15	0.14	2.16	0.026
Mean Patch Area – Wetlands (25 km)	-14.32	-19.68	-8.97	< 0.0001
Largest Patch Index – Wetlands (25 km)	7.91	2.12	13.71	0.007
Silver-haired Bat				
Intercept	-72.44	-509.00	364.11	0.745
Minimum Distance to Streams/Rivers (Turbine Area)	0.01	0.002	0.03	0.023
% of Landscape – Developed (25) km	0.97	0.66	1.28	< 0.0001
Largest Patch Index – Wetlands (25 km)	0.66	-0.51	1.83	0.270
Year	0.17	-0.21	0.55	0.375

* Model variables further described in Section 2.2; scale at which calculated indicated in parentheses.

4 Discussion

Although data limitations required applying broad assumptions and standardization methods prior to analysis, this study identified several landscape factors that appear to be associated with risk to hoary bat, eastern red bat, and silver-haired bat from wind energy facilities in the Northeast and Midwest regions of the U.S. Some regional differences in fatality-landscape patterns were observed but some factors emerged that were common to both USFWS Region 3 and Region 5.

The level of urbanization on the broader landscape (i.e., 25-km scale) was positively associated with bat fatality rates observed in both Region 3 (all three target species) and Region 5 (hoary bat, silver-haired bat). This finding was somewhat surprising as previous studies have indicated that bat response to urban habitats may be context-dependent. For instance, whereas the most studies have demonstrated decreases in overall bat activity and species richness with increasing levels of urbanization (Dixon 2012; Hale et al. 2012; Jung and Threlfall 2015; Krauel and LeBuhn 2016; Starbuck et al. 2016), positive responses by some species to urbanization have been observed in open, agriculturally-dominated landscapes (Gehrt and Chelsvig 2003, 2004; Coleman and Barclay 2012). It has been suggested that heterogeneous urban landscapes may represent islands of habitat for some bats within landscapes dominated by intensive agriculture, such as in the midwestern U.S. (Gehrt and Chelsvig 2003). The processes behind the increased fatality rates observed in the current study in both regions with respect to urbanization are unclear, but fatality rates may reflect altered habitat use patterns based on landscape composition and potential attraction or avoidance of urbanized areas. For instance, anthropogenic structures provide roosts for some bat species (O'Shea and Bogan 2003; Jameson and Willis 2014), and many bat species, including hoary, eastern red, and silver-haired bats, may forage in urban landscapes. Urban watercourses (Fulton et al. 2014; Bazelman 2016) may also attract bats. Other urban features likely to influence bat activity include anthropogenic noise, lighting, plant roost availability and diversity, and prey availability (reviews in Stone et al. 2015; Rowse et al. 2016; Moretto and Francis 2017).

Hoary and eastern red bats were also observed as fatalities more often when facilities and adjacent areas (i.e., within 2.5 km) in Region 3 were characterized by small, disaggregated patches of open, non-cultivated habitats, as opposed to large, homogeneous open areas (e.g., cultivated crops and grasslands). Although the juxtaposition of these open patches relative to other habitat types was not explicitly modeled and none of the fragmentation indices explored in the analyses (i.e., edge densities by habitat class) emerged as significantly related to fatality rates, it is likely that the disaggregated patch structure of grasslands and shrublands were associated with a more heterogenous habitat structure. Studies from northwestern Europe have indicated that wind energy facilities located in more heterogeneous habitats within agricultural landscapes may pose greater risk to bats (Rydell et al. 2010). Bat foraging and activity in general tend to increase along edges, particularly along "hard" edges such as along small woodlots and in fragmented forests (Ethier and Fahrig 2011; Jantzen and Fenton 2013; Schuster et al. 2015), and it is plausible that the smaller grassland and shrubland patches at the local scale in the current study were interspersed with small, forest patches. In general, forest patches in an otherwise open landscape have the potential to attract bats, particularly during migration (Loeb and O'Keefe 2006).

In Region 3, fatalities of the three target species demonstrated a positive relationship to road density at the turbine area scale, but a negative relationship at the 25-km scale. Several studies have demonstrated a positive relationship between bat activity rates and roads (Grindal and Brigham 1999; Cryan and Barclay 2009; Ferreira et al. 2015; Maxell and Burkholder 2017; Pourshoushtari et al. 2018), potentially because they provide travel corridors and are characterized by habitat edges (Kunz et al. 2007; Cryan and Barclay 2009). Increased bat activity within the turbine area could therefore increase collision risk, although the relationship between activity rates and risk remains unclear. It is also unclear as to why a negative association with roads was observed at the broader scale, but because road density was found to be only weakly correlated with proportion of urban areas (R2 = 0.42), the increased road densities in this study may have been driven by the presence of rural roads, which typically occur in open areas (grasslands, cultivated crops) and would therefore not be likely to create hard edges or well-defined travel corridors. Small roads with minimal traffic do not tend to influence bat activity in general (Moretto and Francis 2017); however, it may be the case that bats responded to lights or other factors potentially associated with rural roads. Silver-haired bat fatalities also increased when wind turbine density within 25 km was high, indicating risk may be higher when multiple wind energy facilities occur in the same area.

Bat fatalities in both regions also appeared to be associated with wetland configuration. For instance, in Region 5, there was a negative association between mean wetland size, and a positive association with largest wetland patch index (i.e., proportion of area covered by the largest patch), with fatality rates of eastern red bat at the 25-km scale. Hoary bat fatalities were also negatively associated with mean wetland patch size. Taken together, these findings indicate that eastern red and hoary bats may have been at increased risk in areas with wetland complexes comprising multiple small or mixed large and small wetland patches. Silver-haired bat fatalities increased with distance from the nearest stream or river. Other studies have identified proximity to water sources such as streams and large waterbodies as associated with bat activity rates (Grindal et al. 1999; Perry et al. 2008) or risk of turbine collision (Thompson et al. 2017; Baerwald 2018; review in CanWEA and DNV GL 2018), but DNV GL is not aware of any studies that have identified the presence of multiple, small wetlands as a potential correlate to bat collision risk. In general, aquatic habitats tend to provide preferred foraging areas for bats due to increased insect abundance and as drinking sources; thus, the presence of multiple wetlands on the landscape may influence increased bat use in some areas.

Findings indicated, overall, that landscape structure at broad spatial scales (i.e., 25 km) may be as or more informative for assessing potential fatality risk at wind energy facilities than are local-scale characteristics. Although to our knowledge few bat studies in North America have been conducted at large spatial scales, those of which we are aware also found that landscape-scale factors were more strongly associated with bat activity (Starbuck et al. 2015; 16 km scale) or turbine collision risk (Baerwald 2018; 25 km scale) than local-scale factors.

4.1 Study Limitations

There are several limitations to this study that preclude the formulation of any conclusive inferences regarding fatality rates of migratory tree-roosting bats in the northeastern and midwestern U.S. For instance, the data provided in AWWIC do not represent a random sample of wind facilities currently operating in Regions 3 and 5 but were instead contingent on data sharing by operators and on public documents, the latter of which are typically only available for higher-risk facilities operating under Incidental Take Permits (ITP) or other regulatory permits. Therefore, the fatality rates included in our analyses may have been biased high in some areas (e.g., where ITP for Indiana bat [*Myotis sodalis*] and northern long-eared bat [*Myotis septentrionalis*] are frequently required) and low in others. Lack of randomization could have thus resulted in spurious results; for instance, if facilities operating under ITP were clustered and shared landscape characteristics that were not actually influencing collision risk. It is not clear how this issue can be resolved for future U.S. multi-facility studies, as there is no mandatory reporting requirement for wind facilities. However, it is recommended that future studies allocate significant effort towards data acquisition so that adequate representation of current operating facilities is achieved; acquisition of comprehensive data sets will also avoid limitations we experienced with respect to sample size (e.g., inability to address interactions among independent variables or meso-scale patterns such as USFWS Ecoregions or BCR).

The study also treated data from all facilities in the AWWIC database as equal and did not account for differences in PCFM study value (e.g., PCFM studies that violated Shoenfeld estimator assumptions would presumably result in lower-quality estimates). Interpretation of the data was also somewhat restricted due to the broad assumptions that were applied across PCFM study results prior to analysis. Assumptions regarding searcher efficiency, carcass persistence and dwp were almost certainly violated, although it is unclear as to the extent of the violations, whether violations were stronger for specific categories of wind energy facilities (for instance, in particular geographic areas), or if violations resulted in overall directional bias (e.g., all facilities overestimated or underestimated). Furthermore, by taking the mean values for searcher efficiency and carcass persistence the analyses did not account for variation (e.g., among searchers or landcover types) within facilities, and the level of uncertainty associated with these mean values is unknown. Newer, more data-intensive methods are available to account for overall uncertainty in detection probability (overall $\hat{g}$) estimates such as parametric bootstrapping (Madsen et al. 2019) but were not an option for this study due to data limitations. Finally, there are several limitations to standardizing data via the Shoenfeld Estimator, including that the estimator tends to underestimate fatality rates (Huso 2011) and doesn't account for changes in carcass observability over time, which can cause substantial bias when searcher efficiency is low and carcass persistence is high (Madsen et al. 2019). Overall, reliance on the broad assumptions applied in the current study means that results should be interpreted with caution. To better inform future multi-facility fatality studies, it is recommended that wind energy facilities and others conducting formal PCFM keep detailed, shareable data records that include information required for robust and more transparent fatality estimation methods (e.g., carcass distribution data, detailed records of search times) using GenEst or other available tools.

Finally, our analysis employed a model-averaging approach to parameter estimation. There are known issues with model averaging (Cade 2015; Banner and Higgs 2017; Dormann et al 2018); for instance in cases of outliers, structural breaks and small models, the use of model averaging often leads to bias and poor forecasting in averaged models. It is also known that high correlation between predictor variables, or multicollinearity, can distort model averaged results and impact actual single regression fits. In the current study, multicollinearity was reduced as practicable by eliminating highly-correlated independent variables prior to inclusion in GLM. While acknowledging the issues associated with model averaging, it should be noted that the goal of this work was to identify the key variables impacting fatalities and the relative relationships between these variables, rather than identifying a single best model for each species and region to be used for predicting fatality rates. Therefore, within this scope of exploratory data analysis, model averaging was a useful tool for understanding the relationship between and across the variables in each species and region case.

Despite the limitations of the current study, the methods, analyses and findings presented here provide a useful basis for gaining a broader understanding of large-scale landscape factors that may influence risk to bats at wind energy facilities in the two regions studied, as well as across regions that were not included in the study. This effort was meant to serve as an exploratory exercise to identify patterns of landscape-fatality relationships that may be in effect, and the models presented herein are not expected to have high predictive value. The factors identified in this effort, along with the results of similar studies, however, can inform future efforts to better understand these patterns, including comparative studies and the development of more intensive predictive methods such as landscape mapping to identify potentially high-risk (or low-risk) areas being considered for wind energy development.

4.2 Study Implications

Gaining a better understanding of the landscape and habitat correlates associated with bat fatalities at wind energy facilities is important because many decisions regarding risk avoidance are made during the siting and design phases of a facility. Identifying effective facility- and micro (i.e., turbine)- siting strategies to reduce bat fatalities is a priority for the conservation community, as well as for the wind energy industry because it may preclude more costly monitoring and mitigation measures at later facility stages (CanWEA and DNV GL 2018). However, although there are several guidelines and regulations in the U.S. and Canada for initial site selection and layout design (e.g., implementing setback distances), few scientific studies have been conducted to evaluate the effectiveness of employing such pre-construction measures for reducing bat fatalities during operation (USFWS 2012; Alberta Environment and Sustainable Resource Development [ESRD] 2013). For instance, research findings to date do not indicate that increased bat activity, as measured by current, pre-construction acoustic monitoring methods, is associated with fatality rates at operating wind facilities (Hein et al. 2013; Heist 2014). Other factors that are specific to individual species and can help inform wind energy siting, such as breeding or migratory movement patterns and behavior, also continue to receive intensive study but are not fully understood. The wind industry has nonetheless continued to employ avoidance and minimization strategies during siting based on a limited understanding of bat risk and low-predictive confidence in effectiveness. Thus, studies such as the current landscape analyses conducted for USFWS Regions 3 and 5 can be used to better inform future siting decisions undertaken by the wind industry as a whole and may potentially lead to improved predictive tools for early-stage site evaluations that will contribute to reduced bat fatalities. For instance, according to the results of this study it may be beneficial to assess potential risk at wind energy facilities in USFWS Regions 3 and 5 based on location within the broader landscape, particularly with respect to urbanization (both regions), grassland habitat configuration (Region 3), and wetland coverage or configuration (both regions). It is recommended that further studies be completed throughout these and other regions to better inform the development of such tools.

The growth of the wind energy sector can help meet the growing electricity demand in the U.S. while reducing the impact of greenhouse gas (GHG) emissions from fossil fuel reliance; for example, in 2018 wind energy avoided over 200 million metric tons of CO_2 emissions (AWEA 2019a). The impacts of climate change caused by GHG emissions represent some of the greatest threats to bat populations worldwide (Loeb and Winters 2012; Sherwin et al. 2013; Zimmerling and Francis 2016). For example, climate impacts will likely affect some bat species' ability to use habitats for critical life functions, may cause resource decoupling (i.e., timing of prey availability is no longer compatible with bat ecological requirements) (Rodenhouse et al. 2009; Jones et al. 2009), and are expected to result in range contractions for temperate-climate species (Loeb and Winters 2012). At the same time, it is recognized that bats may be killed by wind turbines, with modeling efforts suggesting wind energy-caused fatalities may result in population-level effects for some species (Zimmerling and Francis 2016) and no effects for others (USFWS 2016). Because wind energy production can contribute positively (i.e., by reducing GHG emissions) as well as negatively (i.e., by killing bats) to the health of bat populations, gaining a better understanding of the habitat types and landscape features that may attract and potentially concentrate bats, and the extent to which the presence of these features increases collision risk at wind facilities, is a priority for promoting growth of the industry while minimizing bat fatalities caused by the increasing number of wind turbines on the landscape. The landscape patterns revealed in this study and others can better inform siting decisions and feed into an adaptive learning process that will, over time, reduce uncertainty and lead to an improved understanding of factors associated with bat collision risk at wind facilities. It is anticipated that this enhanced understanding will further assist in the development of more accurate tools for assessing this risk and lead to the identification of scientifically-informed options for avoiding, minimizing and mitigating risk to bats (CanWEA and DNV GL 2018; Allison et al. 2019).

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6 Appendix A: Distribution of Fatality Rates

Figures A-1 through A-6 depict mean fatality rate estimates, by state, included in the landscape analyses for individual species. Detailed methodology for estimating fatality rates, including number of studies from which fatality rates were estimated, is provided in Section 2.1 of this report.

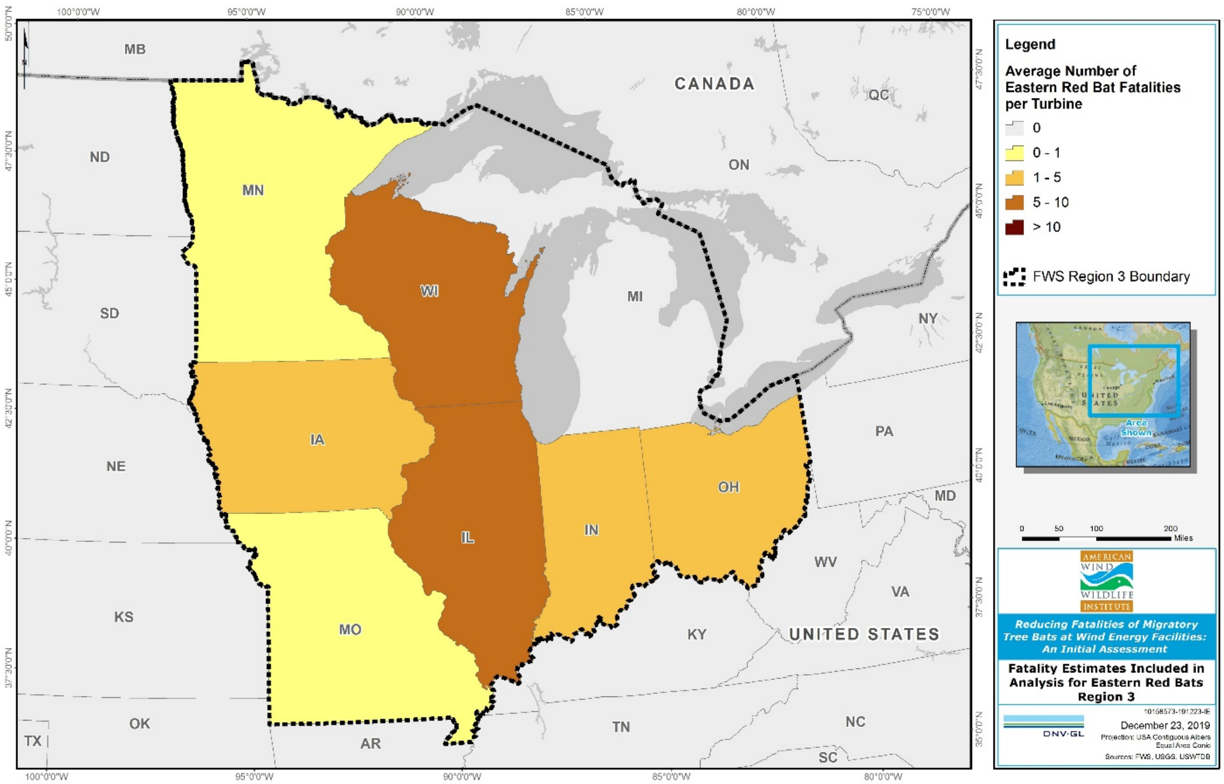

Figure A-1. Distribution of estimated mean fatality rates (mean fatalities, per turbine, averaged across facilities included in the landscape analysis) for eastern red bat (*Lasiurus borealis*) in U.S. Fish and Wildlife Service (USFWS) Region 3.

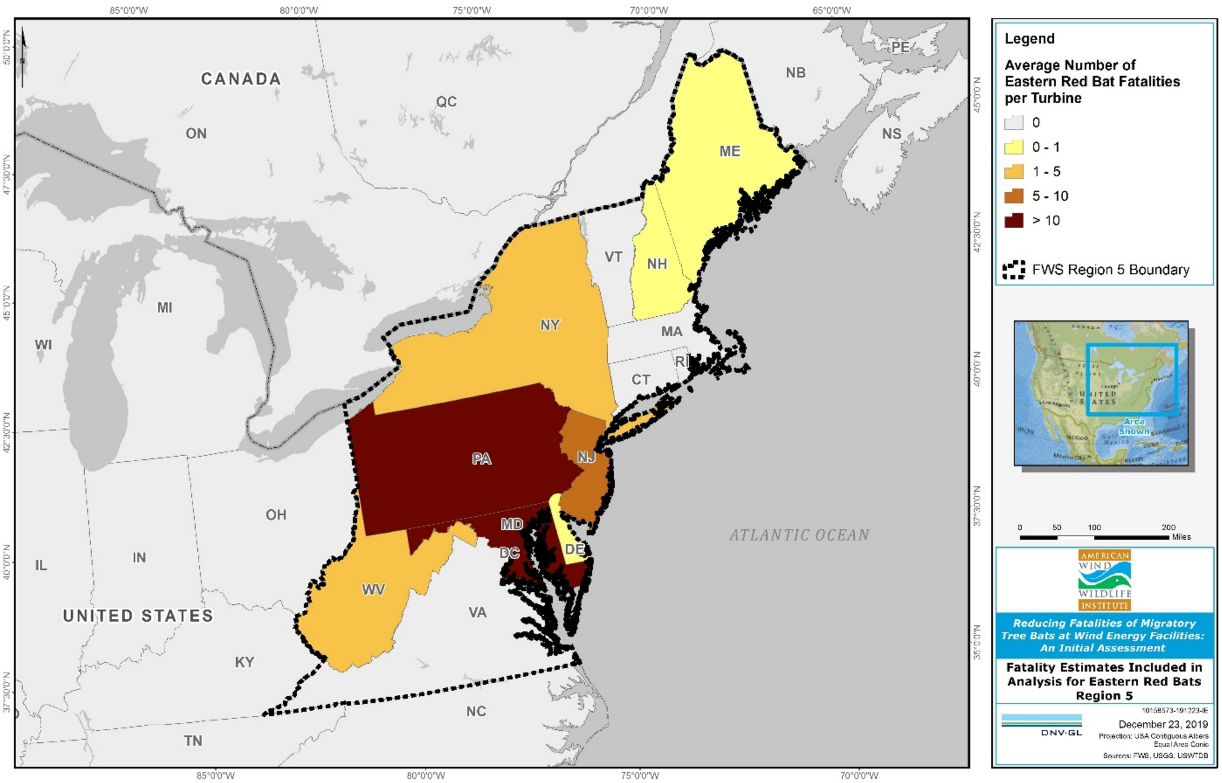

Figure A-2. Distribution of estimated mean fatality rates (mean fatalities, per turbine, averaged across facilities included in the landscape analysis) for eastern red bat (*Lasiurus borealis*) in U.S. Fish and Wildlife Service (USFWS) Region 5.

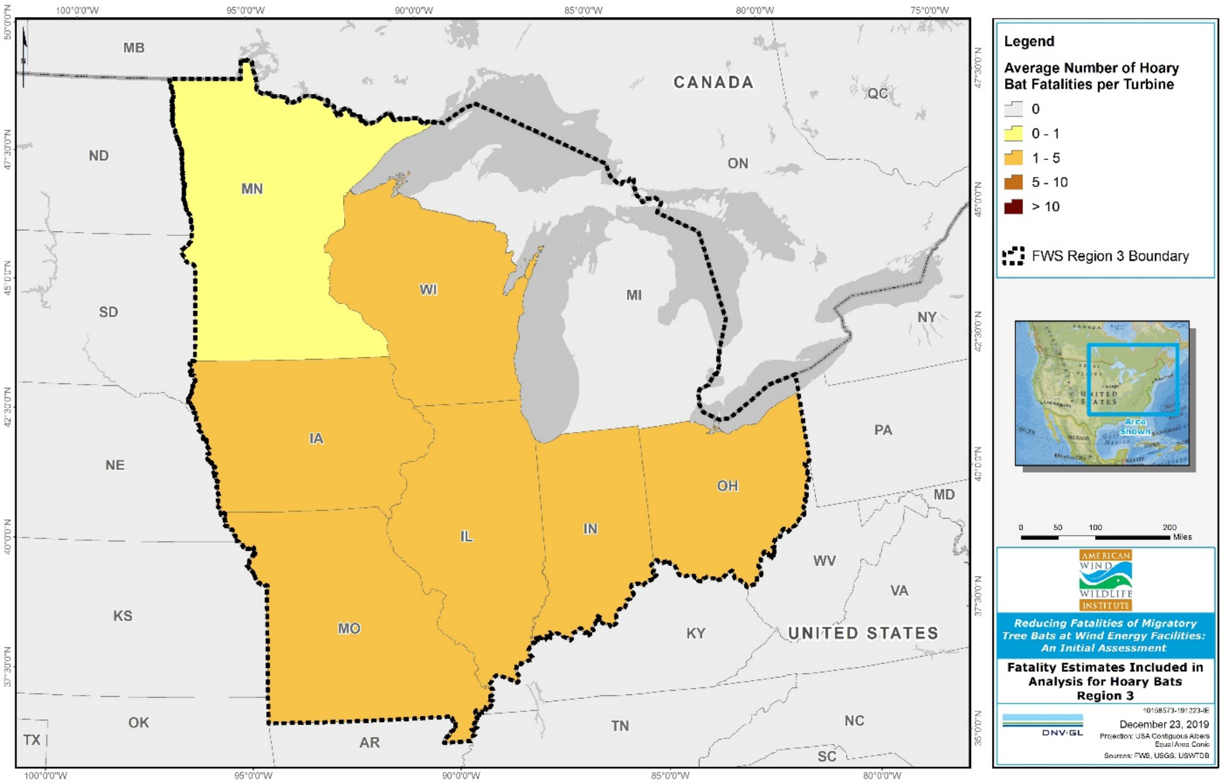

Figure A-3. Distribution of estimated mean fatality rates (mean fatalities, per turbine, averaged across facilities included in the landscape analysis) for hoary bat (*Lasiurus cinereus*) in U.S. Fish and Wildlife Service (USFWS) Region 3.

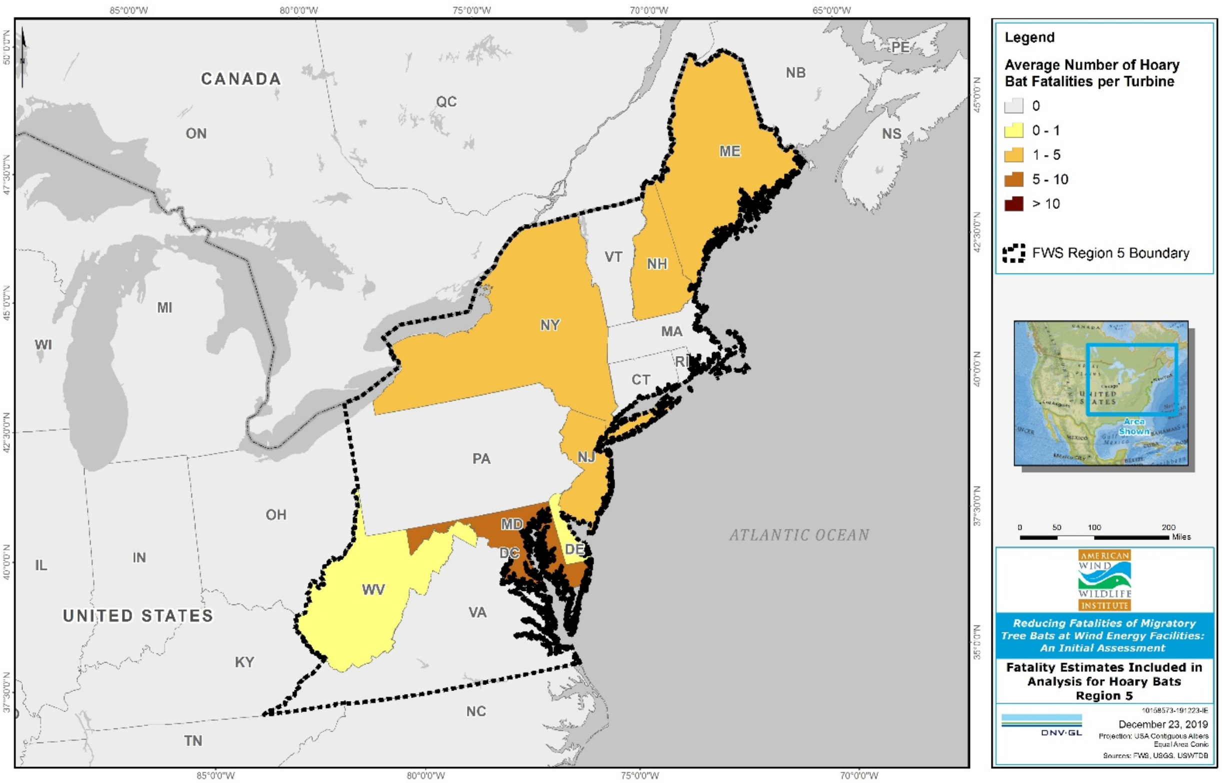

Figure A-4. Distribution of estimated mean fatality rates (mean fatalities, per turbine, averaged across facilities included in the landscape analysis) for hoary bat (*Lasiurus cinereus*) in U.S. Fish and Wildlife Service (USFWS) Region 5.

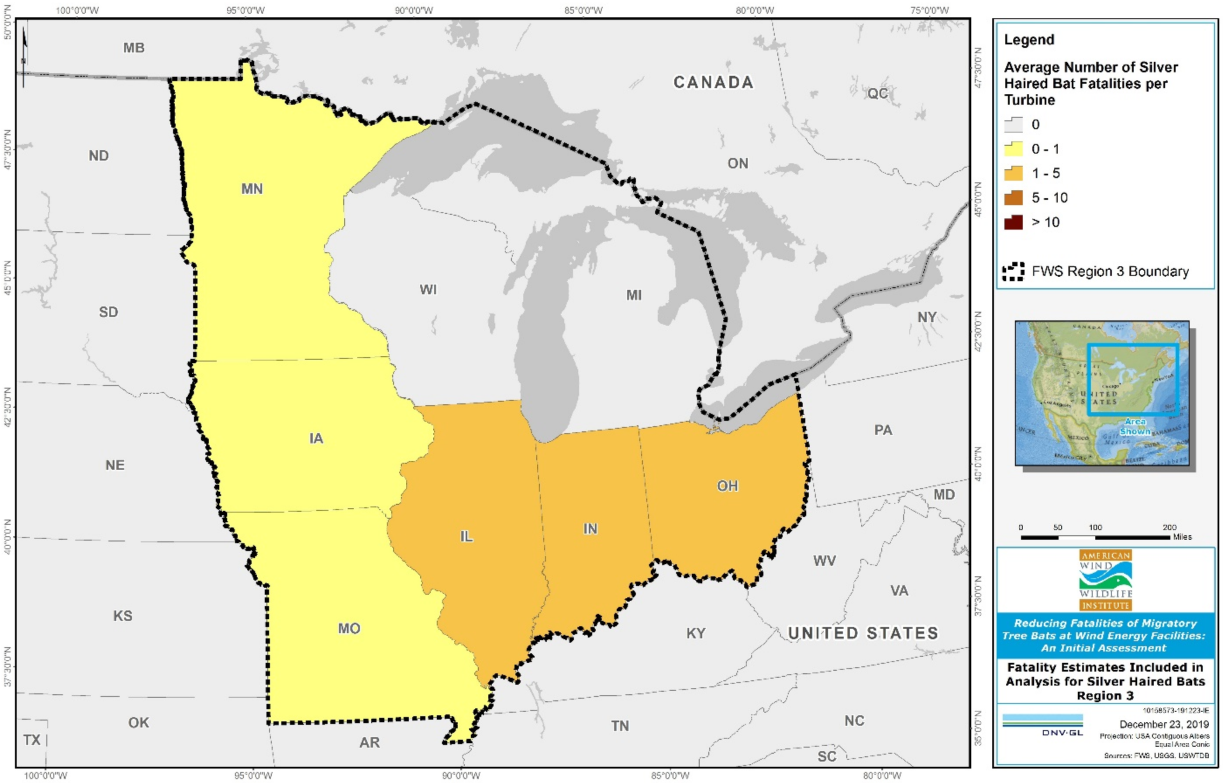

Figure A-5. Distribution of estimated mean fatality rates (mean fatalities, per turbine, averaged across facilities included in the landscape analysis) for silver-haired bat (*Lasionycteris noctivagans*) in U.S. Fish and Wildlife Service (USFWS) Region 3.

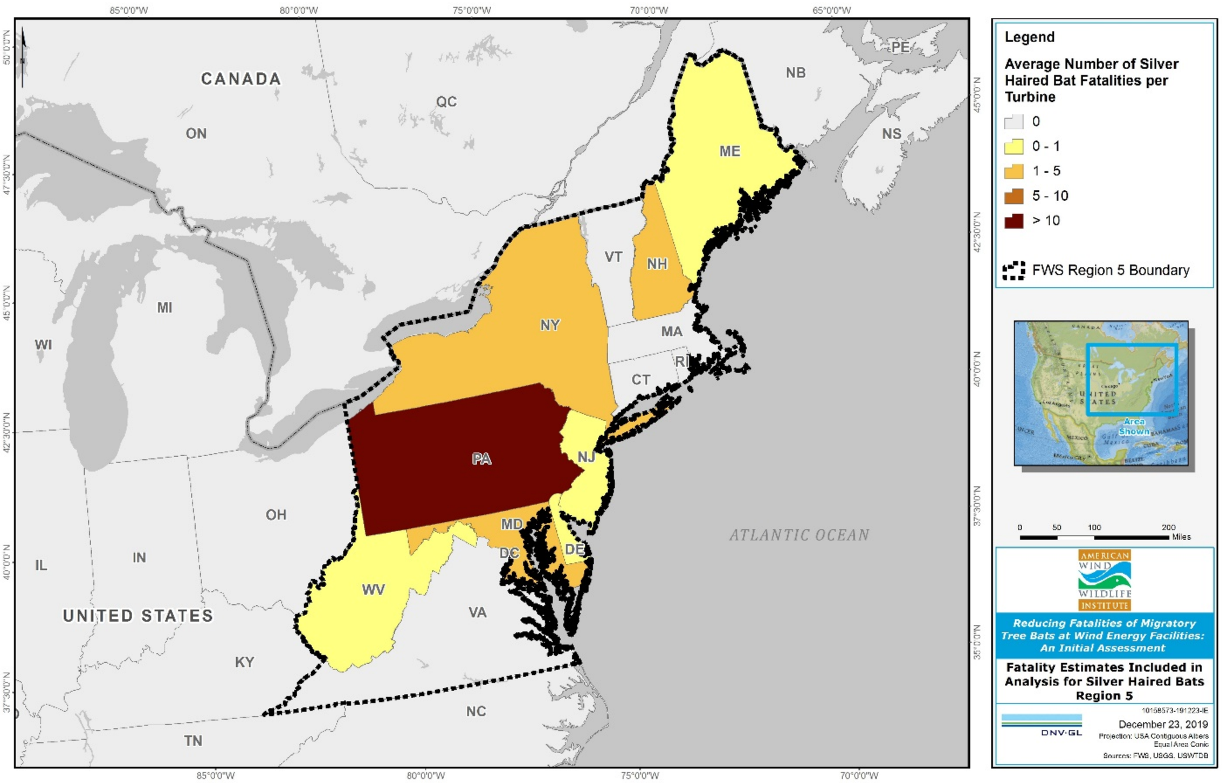

Figure A-6. Distribution of estimated mean fatality rates (mean fatalities, per turbine, averaged across facilities included in the landscape analysis) for silver-haired bat (*Lasionycteris noctivagans*) in U.S. Fish and Wildlife Service (USFWS) Region 5.