Reproducibility of a Geographical Study on the Effects of Wind Turbines on Bat Fatalities in the Northeast United States

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Abstract

With the expansion of wind energy as an alternative to fossil fuel use, it is important that we have the tools necessary to analyze ecological impacts. While geographic information studies (GIS) has many tools for this analysis, the lack of reproducibility in the field will lead to both decreased accuracy of results and slow down knowledge gain during a time in which research speed could prevent extinctions. In this integrative geography and biology thesis, I study the reproducibility of a geographical analysis to better understand barriers to its reproduction. The study, conducted by consulting group DNV GL for the Wind Wildlife Research Fund, analyzes the relationship between tree-roosting bat fatalities and landscape features at on-shore wind farms in the northeast United States (Peters et al. 2020). By making models and R scripts that reproduce the methods of this study, I improve its future reproducibility while analyzing the ways in which both the bat fatality studies used to provide data for the Peters et al. (2020) study and the study itself could have been reported better for clarity and transparency with regards to methods, data, and sources of uncertainty. The models and R scripts can be applied at various spatial scales to calculate landscape metrics (i.e., connectivity, percent area of land cover type, forest core area, etc.) and determine which are most correlated with hoary bat, eastern red bat, and silver-haired bat fatalities in a particular region. Methods, models, and R scripts are publicly available and could be applied to other spatial correlation studies as well.

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Equations

Acronyms

3DEP: 3D Elevation Program
AWWI: American Wind Wildlife Institute
AWWIC: American Wind Wildlife Information Center
DEM: Digital Elevation Model
DEP: Digital Elevation Position
DNV GL: Det Norske Veritas/Germanischer Lloyd
dwp: density-weighted proportion
GIS: Geographic Information System/Science
MW: Megawatt
NALCMS: North American Land Change Monitoring System
NDA: Non-disclosure agreement
NHD: National Hydrography Dataset
QGIS: Quantum Geographic Information System
ArcGIS: Aeronautical Reconnaissance Coverage Geographic Information System
SAGA: System for Automated Geoscientific Analyses
TIGER: Topologically Integrated Geographic Encoding and Referencing
TPI: Topographical Position Index
USFWS: US Fish & Wildlife Service
USGS: United States Geological Survey

Introduction

Brief on wind energy and bats

Wind energy has emerged as a promising alternative to fossil fuels as the effects of climate change have already been playing out both in the United States and around the world. However, in the eastern US, it has been estimated that along forested ridgetops, between 15.3 and 41.1 bats are killed per MW of installed capacity per year (Kunz et al. 2007). In terms of individual counts, one study estimated 880,000 deaths in 2012 given a 51,630 MW capacity in the US, which comes out to 17 bats per MW (Smallwood 2013). Wind turbine collisions are one of the two leading causes of bat fatalities, primarily affecting tree-roosting bats because they migrate (Bennett 2020, personal communication; O'Shea et al. 2016). The other leading cause of bat fatalities is white-nose syndrome, which primarily affects cave-dwelling bats because they are more clustered (Bennett 2020, personal communication; Choi et al. 2020, O'Shea et al. 2016). Prior to 2000, leading causes of bat mortality globally included chemical contaminants and humans intentionally killing bats for population control (vampire bat), human food, and food depredation control (O'Shea et al. 2016).

While migratory tree bats in the northeast US are not currently listed as threatened or endangered, Frick et al. (2017) has predicted detrimental population effects in hoary bats with wind energy expansion. Hoary bats experience collisions at the highest rates, but there is also concern for other bat species. While perhaps wind turbine collisions are not causing significant population effects currently (though it is very difficult to quantify bat populations to know for sure), if wind energy is scaled up with climate change, bat species may experience extreme population effects to the point of extinction (Dowling 2020).

There are a few hypotheses that relate bat fatalities to land cover. The linear corridor hypothesis states that "wind energy facilities constructed along forested ridgetops create clearings with linear landscapes that are attractive to bats" (Kunz et al. 2007). Another hypothesis states that wind turbines create edge habitat suitable for bats (or perhaps the insects they feed on), increasing their population and thus collisions (Allison 2018, Allison et al. 2019, Kunz et al. 2007). Identifying the relationship between landscape factors and bat fatalities at wind turbines may help point to behavioral hypotheses for collisions, which can then inform siting (e.g., in unforested areas, if these hypotheses are supported) or which deterrence methods researchers should focus on to maximize effectiveness.

Study overview

To better understand how bat fatalities at wind turbines relate to land cover, and the methodology behind how one would analyze this, I reproduced a study by Peters et al. (2020). This study was conducted by consulting group DNV GL (Det Norske Veritas/Germanischer Lloyd) for the American Wind Wildlife Institute analyzing the relationship between tree-roosting bat fatalities (hoary bat, eastern red bat, and silver-haired bat) and landscape features (bodies of water, types of land cover, wetlands, roads, elevation, connectivity and fragmentation of forest blocks, and edge habitat) at on-shore wind farms in the northeast United States (Peters et al. 2020). The study compiles bat fatality studies at wind turbine sites and uses a fatality estimator (modified Shoenfeld estimator) to standardize raw fatality counts across sites (Shoenfeld 2004). Then, Peters et al. (2020) calculate landscape metrics to characterize the composition of land cover around turbines at various spatial scales, and measure the correlation between estimated bat fatalities and landscape metrics.

The Peters et al. (2020) study found that the hoary bat and eastern red bat experienced more fatalities in areas with more urbanization on the broader landscape and near smaller wetlands or a mixture of small and large wetlands. Silver-haired bat fatalities increased with distance from streams and rivers (Peters et al. 2020). Most significant relationships were at the 25-km scale (Peters 2020). In reproducing the study, I identify gaps in both its reporting and the reporting of the bat fatality studies it draws on for data.

By attempting to reproduce the study, I aim to better understand the barriers to producing statistically sound meta-analyses and identify gaps in reporting that would allow for reproducibility of methods and results, as well as better understand how applicable the study is to wind turbine siting. I also create QGIS models and R scripts that together reproduce (with a few differences due to the lack of full reporting) the methods of Peters et al. (2020), providing a detailed, accessible record of my work—something that, ideally, future geographical studies will include. This allows others to check my work, makes it much easier to reproduce or replicate the study, and allow others to learn from my methods. While I was also not able to run the full model due to a bat fatality data availability, ideally, these models and R scripts will allow others to reproduce Peters et al. (2020) in the future, when there is enough fatality data available. The results of these methods include predictive modelling statistics for each bat species. From these numbers, a bat fatality risk map can be created as an effective way to communicate the findings of the meta-analysis and as tangible tool for future wind turbine siting. Interactive maps can also improve siting by communicating effectively risk factors based on a multitude of variables, and a bat fatality risk layer could be useful to be later incorporated into already existing models used by energy planners (Rodman & Meentemeyer 2006). However, siting can be a complicated process, taking into account favorable wind patterns, low environmental impacts, public acceptance, radar considerations, transmission line access, cost, military airspace, wildlife habitat, and of course, bird and bat fatality risk. As turbines are built, there are fewer and fewer spaces that are considered ideal for future projects, so siting by bat fatality risk may not even be possible at this point (Lantz 2020, Renz 2020). Bat fatality risk is still a very important measure to know, though, as it can inform the degree to which deterrence mechanisms should be implemented, and can help to increase awareness and protection of declining bat species (Rodman & Meentemeyer 2006). Surprisingly, Peters et al. (2020) did not provide a map or online tool that communicated fatality risk values by location.

This project will both delve into the relationship between humans and spatial geographic modelling in environmental planning, as well as the relationship between humans and the environmental effects of wind turbines due to siting and use. In addition to improving siting processes and conservation methods with the tools to create a bat fatality risk map, I hope to increase understanding of reproducibility in geographic research, a field with broad environmental applications, to create methodological improvements necessary for academic confidence and studies' incorporation into policy.

Literature Review

Wind energy

As of October 2020, there were 65,548 wind turbines in the USGS Turbine Database including both onshore and offshore turbines, with a total rated capacity of 108,942 MW. A one-MW wind turbine can displace 1,800 tons of carbon dioxide emitted from fossil fuels per year, or save 60 million gallons of water used for nuclear energy per year (EESI, n.d.). Therefore, many foresee an increased reliance on wind energy necessary to replace other carbon-emitting energy sources in consideration of climate change.

Currently, wind turbines in the northeast US are mostly sited along mountain ridges (Allegheny Mountains and Appalachian Mountains), adjacent to Lake Erie, and along the coast of Massachusetts (Figure 1, Figure 2). While this study only focuses on onshore turbines, offshore wind energy development is rapidly growing as costs have decreased (Lantz 2020). However, because not much is known about offshore bat migration patterns, and fatality estimators have not been developed for offshore contexts, more research is necessary. Onshore fatality studies may help provide a framework for reproducible and replicable studies based offshore.

Wind speed is one of the most important factors for wind turbine siting; for large wind turbines, average annual wind speed should be greater than 7 m/s; for small, grid-connected wind turbines, greater than 4.5 m/s; and for small, off-grid wind turbines, greater than 3 m/s (Rodman & Meentemeyer 2006). In addition to wind speed, there are a variety of factors that limit wind turbine siting prospects, including public acceptance, radar considerations, transmission line access, cost, military airspace, wildlife habitat, and of course, bird and bat fatality risk (Lantz 2020, Renz 2020). As wind energy expands, fewer ideal locations will remain, and more tradeoffs and compromises between stakeholders will need to be made as more land uses compete (Lantz 2020, Renz 2020). Moreover, as the demand for wind energy sources increases, particularly with the aid of government support and legislation pushing for renewable energy, there will be less time to research its effects, so it is important to do as much research as possible now (Johnson & Erhardt 2016, Lantz 2020).

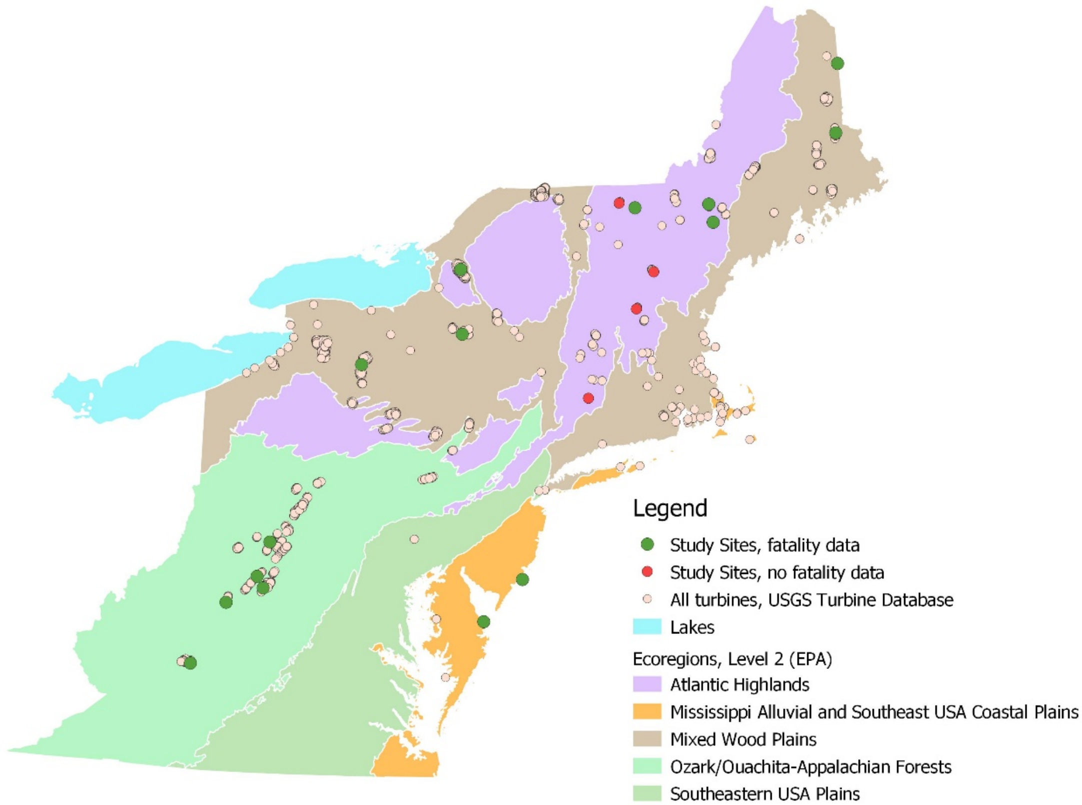

Figure 1. Map of Region 5 (USFWS) with level 2 ecoregions (EPA), Lake Erie, Lake Ontario, turbines from the USGS Turbine Database (as of 9/25/20), and the sites with studies found in the AWWIC database (sites calculated using Mean Coordinates tool in QGIS 3.6.2 to create one point for each project site when multiple turbines).

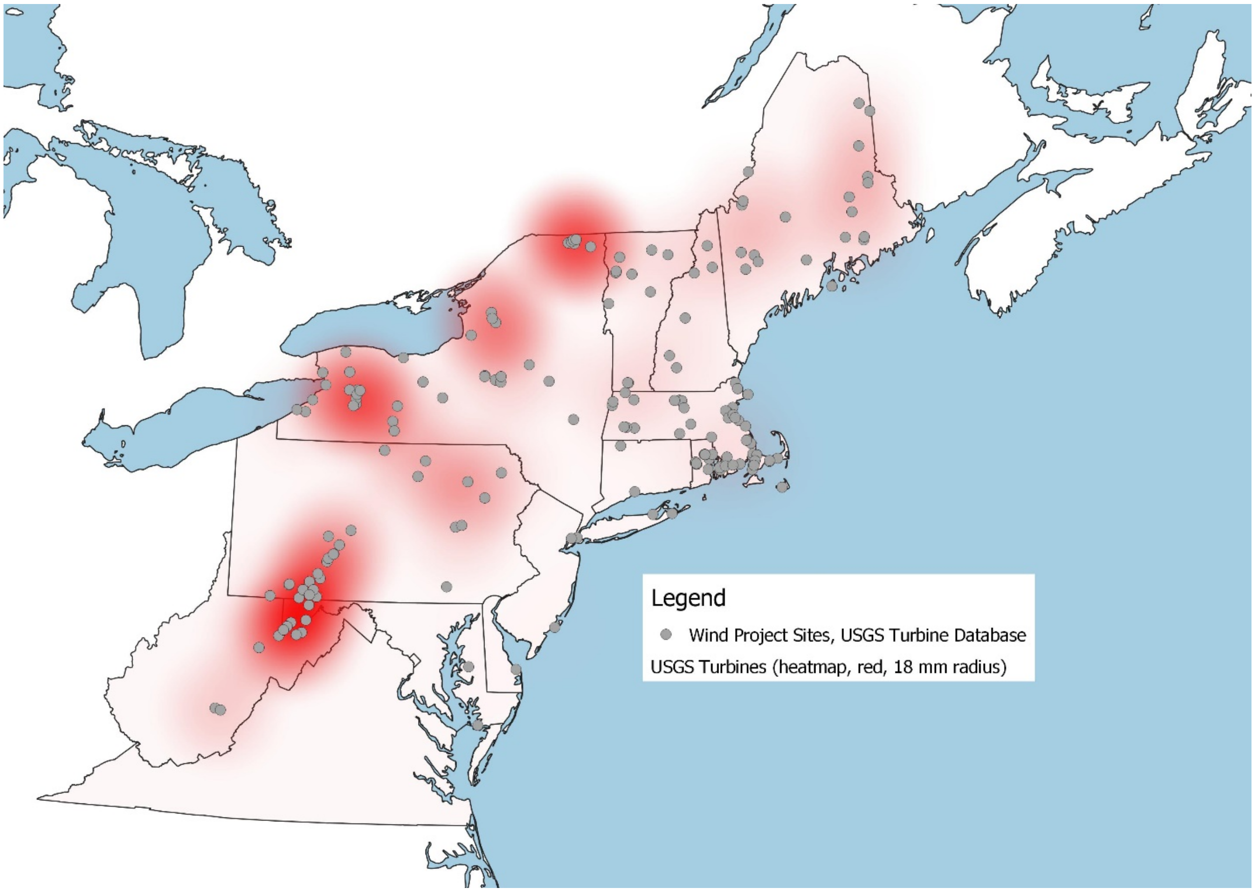

Figure 2. Map of Region 5 (USFWS) with heatmap based on individual turbines in USGS Turbine database (as of 9/25/20). Blue dots representing wind projects calculated using Mean Coordinates tool in QGIS 3.6.2.
[Used 18 mm for heatmap radius. Heatmap applied to individual turbines (shown in Figure 1)].

Wind turbine collisions

Between 2008 and 2017, 44 wind facilities in the northeast United States (USFWS Region 5) submitted bat and bird fatality reports to the US Fish & Wildlife Service (USFWS). According to this body of data, at least one individual from 128 bird and bat species has been killed by wind turbines (Choi et al. 2020). 17% of the fatalities reported were bats, with 90% of those being migratory tree bats (hoary bats, eastern red bats, and silver-haired bats) and the other 10% being cave-dwelling bats (big brown bats and little brown bats) (Choi et al. 2020). Monthly mortality peaked in September and May for birds, and August for bats (Choi et al. 2020)

Although bat fatalities only comprised 17% of reported bird and bat fatalities, total bat fatality estimates in the US are between 600,000 and 949,000, whereas for birds, estimates have ranged between 140,000 and 679,000—though these are likely underestimates given wind expansion since the studies were conducted (Choi et al. 2020). Wind development is thought to affect bats more than birds, as bat mortality has been estimated to be higher than bird mortality at the majority of US wind facilities, and bats tend to have longer life cycles and lower reproductive rates than birds (Choi et al. 2020).

Excluding unidentified individuals, passerines were the most commonly killed order, making up 78% of fatalities. Raptors made up just 5% of fatalities and included hawks, vultures, owls, one eagle, and one falcon. Other affected bird species included wood warblers, red-eyed vireos, black-throated blue warblers, black-billed cuckoos, ruffed grouse, wild turkeys, and turkey vultures. Of the bird fatalities, migrants made up 59%, partial migrants made up 34%, and residents made up 8%. 123 of the 128 bird species were protected under the Migratory Bird Treaty Act, and 108 were protected under the Neotropical Migratory Bird Conservation Act (Choi et al. 2020). Although more research on bird collision risk is necessary as well, my study focuses solely on bats.

Bat ecology & endangerment

There are two primary types of bats: migratory tree bats and cave-dwelling bats. In the northeast US, there are three common types of tree bats (eastern red bat, hoary bat, silver-haired bat) and six types of cave bats (northern long-eared bat, little brown bat, Indiana bat, tricolored bat, big brown bat, and small-footed bat) (DEC NY, n.d., Williams 2006). Tree bats live year-round in trees, but migrate south during the winter, foraging for insects and roosting in trees as they go (Fleming 2019). Cave bats, on the other hand, hibernate in caves or mines in the winter, though during the summer they often live in buildings, bridges, rock crevices, beneath loose bark, or in trees (DEC NY, n.d.). Wind turbines are much more likely to kill tree bats than cave bats because tree bats migrate (Bennett 2020). While tree bats are not listed as endangered, many cave bats are listed as endangered due to white-nose syndrome. Bats in New England tend to breed in the fall, and the young are born in June or July (DEC NY, n.d.). Nearly all are nocturnal and use echolocation to navigate space (DEC NY, n.d.).

70% of bats worldwide consume flying insects, helping to control insect pests (DEC NY, n.d.). This can be particularly helpful for agriculture as fewer pesticides need to be used (DEC NY, n.d., Williams 2006). The results of Peters et al. (2020) confirmed that in general, bats tend to be near aquatic habitats due to higher insect abundance and as a drinking source.

While Thompson et al. (2017) found that insectivorous long-distance migrants prefer open landscapes which allow for fast, non-dodging flight, Fleming (2019) found low turbine-related bat mortality in grasslands due to low bat activity or abundance in open landscapes. Conflicting findings necessitate more research on the relationship between bat fatalities and land cover type.

Migration patterns are still not well understood, although acoustic monitoring, DNA barcoding, stable isotope analyses, and GPS tagging of live bats are currently being used to collect information (Hale 2020, personal communication; Weller et al. 2016). Hoary bats are the most frequently killed species at wind turbines, and that it has the widest migration range of all North American small mammals (Cryan & Brown 2007). Hoary bats are particularly difficult to study because they roost individually, travelling in groups only during migration (Friedenberg et al. 2020, Weller et al. 2016). However, in the United States, it has been found that hoary bats tend to migrate south or to the coasts (Weller et al. 2016). Frick et al. (2017) estimate that in the next 50 years, the hoary bat population may decline up to 90% given an initial population of 2.5 million. While it is very difficult to estimate bat populations, Friedenberg et al. (2020) state that this estimation by Frick et al. (2017) is the most comprehensive estimate currently available. As the body of literature grows, we will be able to better understand overall trends extracted from localized studies.

Offshore bat activity is also difficult to assess; Sjollema et al. (2014) measured bat activity off the mid-Atlantic coast by using ultrasonic detectors mounted on ships. Given acoustic monitoring provides information on only the presence of bats in an area, it is difficult to extrapolate information about population dynamics. However, Sjollema et al. (2014) found that 78% of passes were eastern red bats. They also found that bat activity decreased as wind speed increased, and bat activity did not differ with distance from the shore (Sjollema et al. 2014). While the study was limited to a maximum of 21.9 km from the shore (Sjollema et al. 2014), bats are known to cross large bodies of water and may use remote islands as temporary roosts or stopover sites during migration (Peterson et al. 2014).

Fatalities at wind turbines have been found to be correlated with low wind speeds, and before or after storm fronts when large numbers of bats tend to migrate (Fleming 2019). In a study based on a remote island off the coast of California that focused on hoary bats, migration was correlated with low wind speeds, low moon illumination, and high cloud cover (Cryan & Brown 2007). Another study, based at a wind project in New York, found that bat migration was correlated with warmer days and lower wind speeds (Reynolds 2010). Habitat destruction and polluted waterways are also threats to migratory insectivorous bats (Fleming 2019). While migration patterns, weather correlations, and water pollution are not analyzed as part of the Peters et al. (2020) study, these variables should be considered in future studies in addition to landscape patterns. The lack of inclusion of these variables in the Peters et al. (2020) study increases uncertainty in its results.

Bat fatality mitigation strategies

There is some evidence that migratory tree bats are attracted to wind turbines, with one hypothesis being that they may mistake them for trees (Hale 2020). Therefore, deterrence mechanisms are being developed and studied, including acoustic and visual deterrents (e.g., UV light, painting blades; May et al. 2020, WEST 2020). However, there are many challenges to implementing deterrence technology as it is difficult to access if broken, and rain, snow, and ice can deteriorate equipment (Cryan 2020). While there is a technology called IdentiFlight that uses machine learning to identify eagles from wind turbines in real time to better identify high risk times and potentially stop blades upon eagle identification, it has not yet been applied to bats (Duerr 2020).

Curtailment is the reduction of energy production below a turbine's capability, and it can be used in various ways to decrease bat fatalities. One way is by locking wind turbine blades in place during times of high bat traffic, and tradeoffs between bat fatalities and wind energy potential are being analyzed (WEST 2020). Another way to decrease bat fatalities is increasing cut-in speeds to decrease the time the blades are moving slower; this has been shown to decrease bat fatalities by an average of 50% (Arnett et al. 2010; Hale 2020, personal communication). This strategy is supported by another study that found that bats are at higher risk on nights with low wind speeds and thus slower blade rotational speed (Horn et al. 2010). However, increasing cut-in speeds can be costly and does not necessarily address the root cause of bat endangerment (Hale 2020). It is important to note that the word "curtailment" is used to refer to a wide variety of practices, including restricting energy flow to the energy grid to avoid overflow or shutting off turbines to abide by noise or shadow flicker agreements, but these practices are generally not what are meant when discussing curtailment in relation to bats (EWEA, n.d.).

If mortality rates are consistent with rate of exposure, even a 25% decrease in hoary bat collisions likely will not be enough to prevent extinction with the level of "build-out" (expansion of wind turbine construction) necessary to substantially decrease the country's carbon emissions (Dowling 2020). Therefore, curtailment and current deterrence methods will likely not be enough to prevent extinction, highlighting the importance of deterrence development before it is too late (Dowling 2020).

Roles of private sector and government policy in bat research

Bats face a multitude of other stressors apart from wind turbines, including habitat destruction, polluted waterways, the global decline of insects, and diseases (Fleming 2019, Hale 2020). The wind industry is taking the lead on this issue by investing a lot of resources into solutions, and taking responsibility for an issue that involves aspects outside of its control (Hale 2020). Some argue that other industries and sectors should therefore become more involved and invested in research and solutions as well (Hale 2020, personal communication). This includes those directly contributing to bat habitat loss and other stressors. However, given all humans benefit in some way from bats, there is an imperative as a broader stakeholder to contribute to research and solutions (Hale 2020, personal communication; Hale 2020).

Although listing bats as endangered would allow bat researchers to more easily acquire regulatory support for their research, costs and red tape associated with regulation can make research and wind project development very difficult (Hale 2020, personal communication; Hale

2020; McIvor 2020). It is therefore important to do research and implement bat protection measures, not only to protect the species itself but also to avoid the burdens that come with endangerment regulations (McIvor 2020).

Landscape ecology

Landscape ecology allows one to understand a landscape through patterns over space and time, often using a hierarchal approach (e.g., gap, stand, watershed, landscape) to understanding how mosaics of patches form a landscape (Urban et al. 1987). It is often used to study disturbances and regenerative processes (Urban et al. 1987).

While GIS tools appear to be commonly used in landscape ecology, studies tend to use ESRI (proprietary) software such as ArcGIS, ArcView, and ArcInfo (Steiniger & Hay 2009). QGIS and SAGA, both free, do not seem to be used often (Steiniger & Hay 2009).

Peters et al. (2020) use a SAGA tool through QGIS for one part of their analysis and FRAGSTATS for many of the landscape metrics calculations, with the rest of the spatial analysis done in ArcGIS. The use of proprietary software, such as ArcGIS, is common in the field of landscape ecology (Steiniger & Hay 2009). Peters et al. (2020) also use methods common to landscape ecology, including distance measurements, calculating diversity and evenness, and using digital terrain models such as a DEM (Steiniger & Hay 2009). The use of common and accessible software and methods helps increase reproducibility.

Reproducibility & replicability in geography

The reproducibility of a study is determined by whether using the same data and methods can lead to similar results (Kedron et al. 2019) The replicability of a study is determined by whether similar results can be obtained using new data but the same methods (Kedron et al. 2019). Reproducibility and replicability allow for more confidence in study methods and results but rely on well-documented methods, data sources, and results in the original study. Sources of uncertainty can occur throughout the scientific process, from conceptual uncertainties (e.g., applying a theory incorrectly, using the wrong scale, changing contexts) to measurement uncertainties (e.g., finding original data, resolution, completeness, and consistency of the data), to analytical uncertainties (e.g., not having access to full methods, lack of standards for reporting, uncertainty or change within software or tools, not being able to extrapolate methods from textual reporting), to communication uncertainties (e.g., if publications are free and open to the public, if studies are published in the first place, especially those with non-significant results) (Kedron et al. 2019). This wide variety of sources of uncertainty have led some to believe that “replicability in geographical analysis may not be an obtainable objective” (Kedron et al. 2019). However, expansion and use of open source GIS has the potential to create an ethic of transparency and full reporting in the field of geography, decreasing sources of uncertainty (Longley 2008).

Replicability in geography can also be difficult because spatial heterogeneity and spatial dependence inherent to geographical analyses make causal inference difficult to both demonstrate and apply to other locations or situations. Spatial heterogeneity, the uneven distribution of a variable across space, makes averages relatively uncharacteristic of the landscape and makes studies dependent on geographic boundaries (Kedron et al. 2019). Spatial dependence, the relatedness of things that are closer together, means that the response at an individual location to an independent variable may change depending on its interacting with surrounding location (Kedron et al. 2019). However, analyzing and improving reproducibility and replicability may allow for a better understanding of the degree to which demonstrated causal effects can be applied (Kedron 2019).

While in other fields, including ecology (Kelly 2019), psychology (Open Science Collaboration 2015), computational neuroscience (Topalidou & Rougier 2015), and social science (Camerer et al. 2018), there have been attempts to reproduce and replicate results, there do not seem to be many geographical reproducibility and replicability studies (Kedron et al. 2019).

However, there are a few. Ostermann and Granell (2017) focused on volunteered geographic information (VGI) within geographic information science (GIScience), finding that not one of the 58 papers they find provided access to raw data or analysis code and tools (Ostermann & Granell 2017). Nüst et al. (2018) also studied GIScience studies and found that reproducibility levels were low due to lack of incentive (Nüst et al. 2018). Konkol et al. (2019) studied the reproducibility of computational geoscience code, finding that even with source code, there were many issues with running the code and/or differences in results (Konkol et al. 2019).

While few studies publish models of their methods, even if a model is created and published, one often needs the original—usually proprietary— software to run the models

(Steiniger & Hay 2009). This can often be a huge barrier as proprietary software can be expensive. Moreover, algorithms behind proprietary tools tend not to be public (open source), making it difficult to identify potential disparities between what a study is attempting to do and what a tool actually does.

With regard to the Peters et al. (2020) study specifically, it is important to attempt to reproduce the study to better understand how data inclusion or exclusion, methods, and lack of detail in reporting can affect the ability to reproduce the study or lead to different results. Better understanding sources of uncertainty can help with future study designs that produce more consistent results. The use of QGIS and R, both free and open source, will allow others to see, learn from, and execute the methods. This decrease barriers to doing similar analyses because my work can be used as an example case.

Ecological meta-analyses

Given many individual studies, ecological meta-analyses allow for a standardization and comparison across studies to better understand processes or states across space and/or time. They give context for isolated studies and can answer larger questions that isolated studies cannot, providing a systematic review of a topic (Harrison 2011).

Meta-analysis is "the statistical synthesis of the results of separate studies" (Gurevitch et al. 2001). It is said to be "the grist for the mill of ecological forecasting, perhaps the most important endeavor of 21st century ecology" (Ellison 2010). Generally, ecological meta-analyses compare relationships, or effect sizes, across studies. "Bootstrapping" allows for a statistical aggregation of results from many small studies (Adams et al. 1977). Although not always included when defining and explaining meta-analyses, meta-analyses can also aggregate values, as opposed to effect sizes, across various studies (Gerstner et al. 2017, Harrison 2011). For example, studying population abundance of freshwater and terrestrial insects across studies would not be considered an effect size, which implies a calculation of a relationship between population and another variable, but still qualifies as a meta-analysis (van Klink et al. 2020). Another example of a meta-analysis on values rather than effect sizes is the infection fatality rate of COVID-19 (Meyerowitz-Katz & Merone 2020).

Given the uncertainty and methodological variation inherent in many ecological studies, it has been expressed that ecological meta-analyses are impossible, or at the very least extremely difficult to achieve (Whittaker 2010). However, other scientists fight this idea, stating that with transparent and detailed enough methods, it is possible to identify trends with confidence (Ellison 2010). Important details necessary for inclusion into ecological meta-analyses include reporting raw data with units, an extensive explanation of methods that has also ideally been used in previous papers, negative or non-significant results, exact geographical locations, environmental features, species names, spatial scale, temporal scale, and meta-data (Gerstner et al. 2017).

With more research on how to improve meta-analyses' statistical uncertainty and reproducibility, and with a more intentional approach to constructing meta-analyses by designing multipart studies as opposed to bringing together studies "ad hoc", ecological meta-analyses have the potential to provide statistically-sound results (Ellison 2010, Nichols et al. 2019, Nichols et al. 2021).

Peters et al. (2020) may not be considered a meta-analysis as strictly defined (Harrison 2011). However, because other studies that compare values, as opposed to an effect size, do define themselves as meta-analyses, and Peters et al. (2020) follow the basic principles of comparing values (estimated number of bat fatalities per turbine per year) across fatality studies' various methods and results, I consider the study to be a meta-analysis (van Klink et al. 2020, Meyerowitz-Katz & Merone 2020). This comparison via a meta-analysis is achieved using modified Shoenfeld estimator to standardize fatality studies across sites and methodology.

Bat fatality estimation models

Raw bat fatality counts are conducted by different field researchers, at different wind turbine sites, using different methodology, and raw counts do not account for total fatalities. Therefore, a fatality estimator is used to standardize across sites by adjusting raw counts to provide total fatality estimates per site. Estimates are typically reported as number of fatalities per turbine per year and help to quantify the effects of wind turbines on bat populations.

Fatality estimators take into account differences in study methodology and spatial context, including the radius of the study area, the timing of searches, the amount of time a carcass stays on the ground, and searcher efficiency. These measurements allow the estimator to adjust raw fatality counts to include carcasses outside of the searched area, removed by scavengers or deteriorated, or missed by searchers (Huso et al. 2016).

In a typical post-construction fatality monitoring study, which is the fourth step (Tier IV) of the USFWS voluntary land-based wind energy guidelines (WEGs), searchers walk transects of study plots around wind turbines to find and identify bat carcasses (USFWS 2012). Carcasses are randomly distributed in the study plot to test what proportion are found by searchers and to measure how long they stay before they are taken by a predator. Fatality estimators use this information to adjust raw fatality counts for carcasses searchers may not have found.

Many estimators have been developed over the years, including the Naïve (2003), Shoenfeld (2004), Huso (2010), Korner-Nievergelt et al. (2011), Korner-Nievergelt et al. (2015), Wolpert (2013), and Dalthrop et al. (2014) estimators. The Naïve estimator was developed *ad hoc*, primarily by Wally Erickson of Western EcoSystems Technology, Inc. (WEST, Inc.) (Erickson et al. 2000). The Erickson et al. (2000) estimator, however, assumed that carcass arrivals and removals were in balance leading to an underestimation, but with the help of Peter Shoenfeld a "periodic" estimator was created that accounted for removal of carcasses after observation (Shoenfeld 2004). However, the Shoenfeld estimator is still often an underestimate because it assumes a constant carcass removal rate when generally, in reality, carcasses disappear quickly at first and slow over time (Huso 2021, personal communication). In response, Huso (2010) developed an estimator that allows any form of persistence distribution (e.g., Weibull, log-normal, log-logistic, etc.; Huso et al. 2016). Korner-Nievergelt et al. (2011) allowed for *k*, searcher efficiency, to vary between 0 and 1 instead of being a binary variable, so that a carcass not detectable in the first search may become detectable in following searches ("bleed-through"; Huso et al. 2016). In an updated version of the model, Korner-Nievergelt et al. (2015) allow for non-exponential persistence distributions and for carcasses to arrive during search intervals (Huso et al. 2016). Wolpert (2013) created a generalized, partially periodic estimator that incorporates aspects of the Erickson (2000), Shoenfeld (2004), Huso (2011) and Korner-Nievergelt et al. (2015) estimators, allowing for non-constant scavenging rates, and non-binary and variable searcher efficiency (Huso et al. 2016). Dalthorp et al. (2014) is similar to the Wolpert (2013) but allows for a non-constant carcass arrival rate and combines into one factor (*k*) the effects of bleed-through and carcass aging on searcher efficiency (Huso et al. 2016). Dalthorp et al. (2014) is the best estimator for low counts or rare species (Huso 2021, personal communication).

The Generalized Fatality Estimator (GenEst), published by the USGS in cooperation with the Bureau of Land Management and the National Renewable Energy Laboratory in 2018 in the form of a free software, hopes to be the single estimator that combines previous knowledge and can apply to any fatality study, as previous estimators often applied differently depending on a situation (Dalthorp & Huso, n.d.). Strickland et al. (2011) states that it is best to use multiple estimators and compare them, as all have biases. However, this was before the GenEst estimator, which has been shown to have no bias (Huso 2020). The GenEst estimator, however, requires full data, rather than summaries, which makes it difficult to use on past studies which have only published summarized data (Huso 2021, personal communication). While Shoenfeld (2004) does provide a methodological approach to uncertainty using the Monte Carlo algorithm (Shoenfeld 2004), another benefit to the GenEst estimator is that it provides a more accurate calculation of uncertainty than previous estimators (Huso 2020).

The Shoenfeld estimator was selected for the Peters et al. (2020) meta-analysis because of the limited availability of data reported in the studies in the American Wind Wildlife Information Center (AWWIC) database, from which Peters et al. (2020) primarily gathered fatality data. Newer estimators require more information than many studies provide, such as ground cover conditions for GenEst (Simonis et al. 2018) and carcass persistence distribution for the Naïve Estimator (Huso 2010).

While the Shoenfeld estimator is used primarily in the context of bird and bat collisions with wind turbines, it has also been applied to other situations of animal mortality by anthropogenic hazards, including roadkill (Gerow 2010, Teixeira 2010, Teixeira 2016), avian collisions with distribution lines (Gustin et al. n.d., Stake 2009), avian collisions with solar panels (Walston et al. 2016), and avian mortality from pesticide exposure (Etterson 2013).

The Shoenfeld estimator was modified in the Peters et al. (2020) study to account for density-weighted proportion (*dwp*) of carcasses available for observation during the search. The following assumptions were:

- *An exponential carcass removal rate;*
- *All bats killed are eventually 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.*

(Peters et al. 2020, 14-15).

In addition to taking into account observed fatalities, average time of carcass persistence, proportion of carcasses found by searchers (searcher efficiency), and average interval between searches in days, as the Shoenfeld estimator (2004) does, the modified Shoenfeld estimator used in the Peters et al. (2020) meta-analysis also takes into account *dwp*. Peters et al. (2020) created a conversion from search area radius to *dwp*, but it does not seem to be a commonly accepted conversion and makes many assumptions about carcass distribution:

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

Table 1. Conversion from search area radius to density weighted proportion (Table 1 in Peters et al. 2020). *Dwp* adjusts for the distribution of bat carcasses around a wind turbine. Bats are more likely to land near the turbine, decreasing with distance away (see the middle column). These numbers in the middle column are "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" (Peters et al. 2020). The right column cumulatively adds the search bin bands (concentric circles) to calculate the proportion of bats likely within a given radius and then used as dwp in the modified Shoenfeld estimator. Because not all studies calculated a *dwp*, Peters et al. (2020) calculated an average from other available studies, which were based on carcass distance from the turbine and influenced by ground cover conditions and which areas were unsearchable. This average was then applied to all of the fatality studies. These *dwp*'s assume that all bats landed within 100 meters of a given turbine and do not take into account effects of wind direction, wind speed, and variation of ground cover and unsearchable areas among individual sites (Peters et al. 2020). Moreover, turbine size is likely correlated with the fall distance of bats from turbines (Choi et al. 2020).

Equation 1. Modified Shoenfeld Estimator (Peters et al. 2020, 14)

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

n = estimated number of fatalities per turbine per study year
c = number of fatalities observed
t = average time of carcass persistence in days
p = proportion of carcasses found by searchers
l = average interval between searches in days
dwp = density-weighted proportion of carcasses that were available for detection during searches

Starting with dwp, the lower the radius is, and the more the fatality estimate need to be adjusted to take into account the carcasses likely missed outside of the plot. For example, if a study plot was only searched within 30 meters, the raw fatality number (c) would be divided by 0.522, which is the same as approximately doubling it, to take into account the carcasses outside of the search plot.

Expression 1.

$$\frac{t \times p}{l}$$

Equation 1 divides the raw fatality number (c) by time of carcass persistence (t) (Expression 1). The shorter a bat persists, the greater the chance a searcher will miss a bat carcass and thus not count it, requiring a larger increase in n to adjust for missed carcasses. It also divides the raw fatality number (c) by the proportion of carcasses found by searchers (p) because the lower the p, the more carcasses the searchers did not account for, necessitating a higher adjustment for n. Equation 1 effectively multiplies by l (due to inverting the divisor); the higher l is, the more likely carcasses were missed in the search and therefore requires an adjustment, increasing n.

Expression 2.

$$\frac{e^{\frac{l}{t}} - 1}{e^{\frac{l}{t}} - 1 + p}$$

Expression 2 is the part of Equation 1 that allows for a non-steady arrival and removal rate of carcasses, as opposed to the previous assumption of an equal arrival and removal rate. With more carcasses found by the searchers (p), the value of the segment decreases, increasing n as a whole. I am not sure why more carcasses being found by the searchers would warrant needing to compensate for more missed carcasses, though. Other researchers have run into difficulties with deriving the Shoenfeld (2004) as well; Bispo (2012) stated, “no clear theoretical background is given and, despite the effort, it was not possible to derive this expression” (Bispo 2012, 16).

Materials & Methods

Study plan

In this study, I reproduce the methods of Peters et al. (2020) to the best of my ability given the information accessible to me. Peters et al. (2020) study the correlation between bat fatalities at wind turbine sites and surrounding land cover. To do this, they compile bat fatality studies, standardize raw fatality counts using a modified Shoenfeld estimator to calculate total bat fatality estimates per sites. They then calculate landscape metrics on the land cover surrounding wind turbines to characterize land cover class configuration. Given bat fatality estimates and landscape metrics at each turbine, Peters et al. (2020) then run statistical analyses to measure whether there is a correlation between particular aspects of land cover configuration and bat fatalities. Finding which aspects of land cover configuration leads to most bat fatalities can then help inform future wind turbine siting.

With a few exceptions, I follow the methodology of Peters et al. (2020) closely, creating models and code that reproduce their methods. I gather bat fatality studies and assess if enough information is reported to be included in a meta-analysis using a modified Shoenfeld estimator to standardize raw fatality counts. In assessing this, I identify gaps in reporting that can act as guidance for what to include in future fatality study reports. Where data are unavailable, I still provide code so Peters et al. (2020) can be easily reproduced in the future when more data are available. In reproducing Peters et al. (2020), I also identify gaps in its reporting, which contributed to uncertainty in how analyses were conducted and led to differences in the methods of my reproduction. However, in providing full, transparent, and detailed reporting in my reproduction of Peters et al. (2020), I decrease barriers to improvement; because R code and QGIS models are easily editable, others can critique my work and easily create updated versions. Providing code and models with detailed documentation will also make future studies with similar methods less laborious, both for other researchers and myself.

Peters et al. (2020) study methods & differences when reproducing

I followed the methods of the Peters et al. (2020) study (Figure 3), focusing on Region 5 as defined by the U.S. Fish and Wildlife Service, as opposed to both Regions 3 and 5 as Peters et al. (2020) did. I audited bat fatality studies in Region 5 from the American Wind Wildlife Information Center (AWWIC) database to assess whether they could be incorporated into a meta-analysis. I then created models in QGIS and R scripts that reproduce the spatial and statistical analyses done by Peters et al. (2020) to measure landscape statistics and their correlations with bat fatalities at 2.5, 5, and 25 km of each turbine studied, in addition to the local facility footprint itself. Data sources for the independent variables (landscape metrics) included the North American Land Change Monitoring System, Natural Earth, the US Census Bureau's TIGER data, the USGS National Hydrography Dataset, and the USGS Wind Turbine Database.

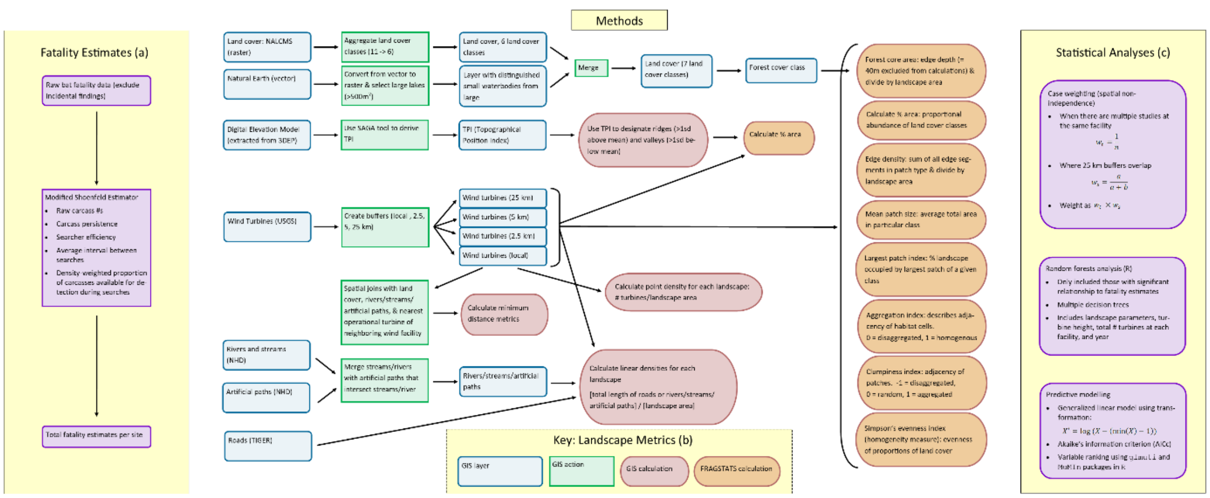

Figure 3. Workflow of Peters et al. (2020) methods, visualized by M. Tango. Panel a: fatality estimates. Panel b: landscape metrics. Panel c: statistical analyses. Link[1] to image

[1] https://github.com/mtango99/thesis/blob/main/results/figures/Workflow_Figure3.png.

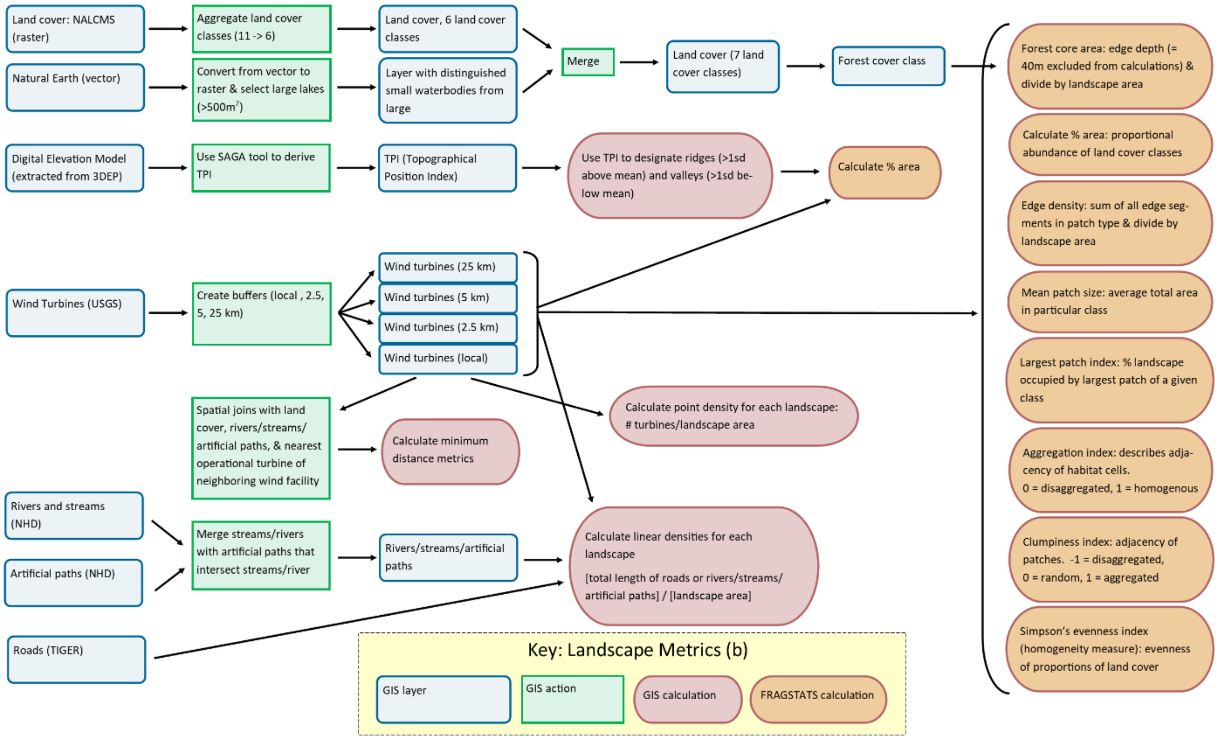

Figure 3b. Workflow of landscape metrics part of Peters et al. (2020) methods.

<u>Bat Fatality Estimates</u>

The Peters et al. (2020) study used 52 studies from the American Wind Wildlife Information Center (AWWIC) database as well as 17 studies from reaching out to individual researchers through the American Wind Wildlife Institute (AWWI). The AWWIC database is unique because it brings together fatality studies, decreasing barriers to doing meta-analyses which otherwise would entail tracking down individual studies. The AWWIC database represents approximately 30% of all onshore operating wind energy in the United States (AWWI 2021). These studies were for both Region 3 and 5 as defined by the US Fish and Wildlife Service. I decided to focus solely on Region 5, finding 32 studies through the AWWIC database with the following criteria: Region 5, Post-Construction Fatality Study, 2006-2015, bats, land-based wind energy (on-shore). Peters et al. (2020) retained studies from 27 wind facilities in Region 5 after assessing each for the following criteria, but did not report how many individual studies they retained (this would be a different number given facilities often have yearly studies):

- *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)*
    - *Raw counts of hoary bat, eastern red bat, and silver-haired bat fatalities observed during PCFM studies (excluding incidental observations)*

(Peters et al. 2020, 11)

Although the AWWIC database is certainly the most centralized, comprehensive resource for wind-wildlife data in the United States, it certainly has gaps as it only represents approximately 30% of onshore wind sites in the United States (AWWI 2021). One small example of a gap is that two of the three sets of data on bat fatalities I received from the Vermont Agency of Natural Resources were not in the AWWIC database (Vermont recently started to require fatality monitoring studies to be shared; Bennett 2020). The USGS Turbine Database provides locations of all turbines, but not all sites perform fatality studies as the USFWS wind energy guidelines (WEGs) are solely recommendations (Figure 1, USFWS 2012). There may also be bias to the data released given likely hesitancy to release incriminating data, particularly for endangered bats, for which it is illegal to kill or harm. This is particularly relevant for states in which it is not required to release fatality monitoring studies. While the hoary bat, eastern red bat, and silver-haired bat (migratory tree bats) are not listed as endangered, white-nose syndrome has led to endangerment for many cave-dwelling bats. The Indiana bat and the Virginia big-eared bat are federally listed as endangered, and the northern long-eared bat is federally listed as threatened (ECOS 2021). Vermont has also listed the little brown bat, northern long-eared bat, small-footed bat, and tricolored bat (cave-dwelling bats) as endangered (VT FWS, n.d., Williams 2006). While cave-dwelling bats are at less risk of wind turbine collisions, they are still sometimes found during fatality studies (e.g,. a few little brown bats at PA-1). Even if not many endangered bats are killed, even a few may deter wind turbine operators from releasing data. Numbers of cave-dwelling bat fatalities may therefore be even more suppressed than currently thought.

I reached out to Ian Evans, one of the co-authors of the Peters et al. (2020) study, who said that there is a non-disclosure agreement between DNV GL (the consulting firm that did the meta-analysis) and the owners of the data (owners of the wind turbines) on the data they used for the meta-analysis (Evans 2020, personal communication). Because Peters et al. (2020) did not report which specific studies they used, the studies that I used in my analysis for Region 5 are likely different from those used by Peters et al. (2020).

Of the 32 studies that matched my search criteria in the AWWIC database, 20 had raw bat fatality data outputs. For each of these 20 studies, I identified whether they reported fully enough to be included in a modified Shoenfeld estimator by searching for the following criteria: raw bat fatality data from between July 15-October 15, average time of carcass persistence in days, proportion of carcasses found by searchers (searcher efficiency), average interval between searches in days, and search plot radius in meters (Figure 3a). Search plot radius was used to calculate density-weighted proportion (*dwp*) of carcasses that were available for detection, which was then used in the modified Shoenfeld estimator (see Table 1 for conversion from radius to *dwp*). Turbine height in meters was also necessary for the random forests analysis, and I used the USGS Wind Turbine Database to assist in finding these heights if not reported in the bat fatality studies themselves. I did not include incidental carcass findings in raw bat fatality counts.

I created a spreadsheet[2] with data from each study, finding that 13 of the 20 studies met all criteria, though 9 of these 13 studies required assumptions and estimations for the search plot radius, as many reported rectangular as opposed to circular search plots, and some reported a range of plot sizes. This left 4 studies that met all criteria strictly.

Studies with sufficient reporting could then be included in a modified Shoenfeld estimator to standardize raw bat fatality counts across space and methodologies (Figure 3a). However, I determined that 13 studies did not comprise a sufficient sample size, given Peters et al. (2020) states they used studies from 27 sites. I was therefore unable to reproduce this part of the study.

Spatial Analysis and Landscape Metrics

Peters et al. (2020) then calculated landscape metrics using land cover, wind turbine, rivers/streams/artificial paths, roads, and elevation inputs (Figure 3b). They used ArcGIS 10.3.1 to calculate point and line densities as well as minimum distance metrics (ESRI 2014). I used QGIS 3.16.4 instead as it is a free and open source software, whereas ArcGIS is proprietary. To derive a topographical position index (TPI) from the digital elevation model (DEM), Peters et al. (2020) used a SAGA tool accessed through QGIS 3.4, and in my case 3.16.4 (Conrad et al. 2015). I made a model that calculates these values (point density, line density, minimum distance metrics, TPI) one site at a time, developed using the Beech Ridge wind site in West Virginia (WV-2). I also made a model that preprocesses the land cover layer to aggregate based on type of land cover. To calculate percent area of land cover, percent land cover of ridges and valleys, forest core area, edge density of land cover types, mean patch size, largest patch index, aggregation index, clumpiness index, and Simpson's evenness index, Peters et al. (2020) used FRAGSTATS 4.2.1, whereas I used the R package equivalent of FRAGSTATS, `landscapemetrics`, in RStudio 1.3.1056 and R version 4.0.2, creating a script that can be used by anyone (Hesselbarth et al. 2019, McGarigal et al. 2012, R Core Team 2021, RStudio Team 2020). See Figure 3b and the landscape metrics R script[3] for more information on these landscape statistics. For more specifics on the model, see Appendix A, where I included detailed documentation and instructions about how to use the models and code together.

[2] https://github.com/mtango99/thesis/blob/main/results/FatalitiesStudyAudit.xlsx
[3] https://github.com/mtango99/thesis/blob/main/procedure/code/Thesis_R2.R

The QGIS model operates using 6 land cover classes (wetland, cropland, urban, water, forest, open cover), as opposed to 7 (water splitting into two classes: large lakes and small lakes, as Peters et al. (2020) did), because the Beech Ridge (WV-2) site I used to develop this model does not have any lakes within 25 km according to a Natural Earth 1:10m physical vector lakes layer I downloaded (Natural Earth 2021). To test the model, though, I created a vector layer of arbitrary polygons to represent lakes, both large (>500 m^2) and small (>500 m^2), in the region. However, I was unable to retain the small lakes when rasterizing the layer to a 30x30m raster grid. It is unclear how Peters et al. (2020) retained lakes smaller than their reported cell size.

Peters et al. (2020) state that they created a streams and rivers layer "by merging all 'StreamRiver' NHDFlowlines with all 'ArtificialPath' NHDFlowlines that spatially intersected 'StreamRiver' NHDAreas" (26). However, when I downloaded the National Hydrography Dataset (NHD) data, my NHDFlowlines were not differentiated between artificial paths and streams/rivers. On one page of the USGS website, it states that NHDFlowline layers contain both stream/river and artificial path vector features (USGS, n.d.); however, on another page, only "StreamRivers" NHDAreas are mentioned (not NHDFlowline) as layers that contain artificial paths (artificial paths are defined as "a surrogate for general flow direction in NHDWaterbodies and NHDAreas"; NHD, n.d.). Therefore, there may be differences between my river/stream data and those used by Peters et al. (2020), but my assumption is that the NHDFlowline layers I used do contain artificial paths.

Moreover, I was unable to find the exact data that Peters et al. (2020) used due to not being able to find data from the same year. Peters et al. (2020) did not specify which year the NHD nor TIGER data were from, adding uncertainty in their data and making it difficult to compare results. I used NHD data from 9/1/20 and TIGER data from 2018. For the NALCMS data, I used data from 2015 instead of 2010. For the USGS wind turbines, I used data from July 2020, though the data used by Peters et al. (2020) were from 2019. For the 3DEP layers, Peters et al. (2020) used data from 2017. I downloaded 3DEP files from ScienceBase on 10/1/20, but the links to metadata have since broken so I am not sure when the data were last updated. For more information on metadata, visit the data folder[4] in my GitHub repository.

Peters et al. (2020) report that they used spatial joins to calculate minimum distance metrics. Instead of using spatial joins, I created proximity rasters to calculate minimum distances

[4] https://github.com/mtango99/thesis/tree/main/data

from land class types. To calculate turbines' distance to rivers/streams, I created a proximity raster where each pixel stored distance from rivers/streams (Figure 4). To calculate turbines from NALCMS land cover types, I created a proximity raster where each pixel stored distance from rasterized turbines, (Figure 5). I used the local buffer around the turbines to calculate the minimum distance to the turbine of a nearby facility.

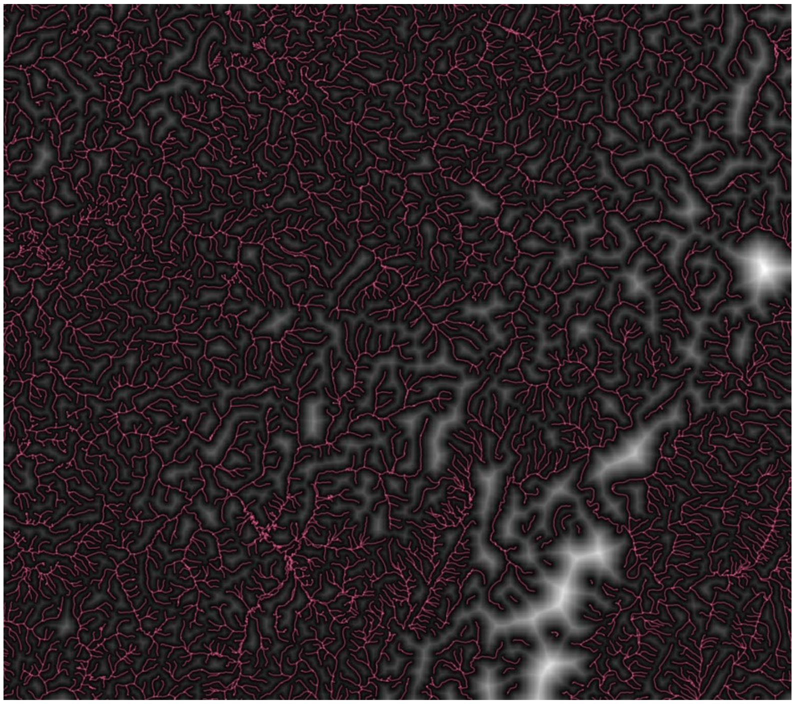

Figure 4. Example of a proximity map from flowlines. Colors range from black being closest to white being farthest from flowlines (red). Each pixel in the proximity map raster shows distance from nearest flowline pixel. This comes from the WV-2 site.

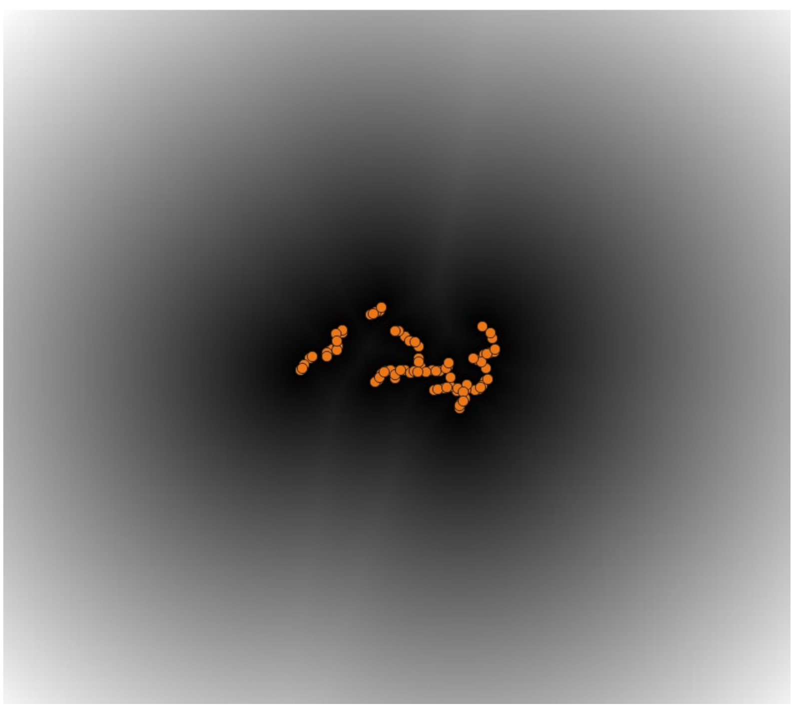

Figure 5. Example of a proximity map from turbines. Each pixel in the proximity map raster shows distance from nearest turbine pixel, with black being closest to the turbines and white being farthest away. This comes from the WV-2 site.

Statistical Analysis to Determine Fatality Risk

Peters et al. (2020) then case weighted the studies for spatial non-independence, where there were multiple studies done at the same site or where sites were within 25 kilometers of each other. They then ran a random forests analysis in R but did not provide the code. Due to the high uncertainty in my data due to such few bat fatality studies that proved suitable for incorporation in a meta-analysis, I did not use my own data to run the random forests analysis and generalized linear model. However, I provide an R script created by Professor David Allen to run the random forests analysis (using the `randomForest` package) and a generalized linear regression with variable ranking using Akaike's information criterion adjusted for small sample size (AICc; using the `MuMIn` package) on simulated data (Barton 2020, Liaw & Wiener 2002). This code can be referenced for when more bat fatality data become available. However, the code does not completely reproduce the methods of Peters et al. (2020) as they also weighted studies based on spatial overlap and if there were multiple studies per site. Peters et al. (2020) also used the `glmulti` package in addition to the `MuMIn` package in R, whereas I incorporated only the `MuMIn` package in R script (Barton 2020, Calcagno 2019).

Models and code can be found on GitHub here.[5]

[5] https://github.com/mtango99/thesis/tree/main/procedure/code

Results

Bat fatality study reporting

Of the 32 papers I downloaded from the AWWIC database, I originally retained 26 papers at 19 wind facilities to enter into QGIS because one study was not publicly accessible (NA-4), one site was not in the USGS Wind Turbine Database (presumably it was never built) (NA-2), one study was a duplicate of another (WV-3a & NA-12), one study was focused on Pennsylvania in general (NA-5), one was a manual, not a study (NA-6) one was a study plan for a project that didn't end up getting built (NA-7) (Table 2).

Four of these remaining 26 papers did not have bat fatality data (NA-1, NA-8, NA-9, NA-10), and two only provided fatality estimates (using a "modified estimation method from Shoenfeld (2004) and Erickson et al. (2003)", and for NA-11 the estimation method was Erickson et al. (2004)) (NA-3, NA-11). This left 20 papers with proper carcass data.

Of these 20, one did not report carcass persistence and searcher efficiency (necessary for the Shoenfeld estimator) (NJ-1), and one combined bird and bat data for searcher efficiency and may have also combined for carcass persistence (DE-1).

Of the remaining 18, sixteen studies did not report a usable search area radius (one did not report (ME-1)), some reported a range (DE-1, WV-1a, WV-1b, MD-1a, MD-1b, ME-1, WV-3a, WV-3b), and some reported rectangular plots (NY-1a, NY-1b, PA-1, ME-2, NY-2, NY-3, VT-1). Six of these studies also included dates outside of July 15-October 15 and did not provide enough information to split data into sub-dates (PA-1, DE-1, WV-1a, WV-1b, NY-1a, NY-1b). Although all but one (NJ-1) provided an average interval between searches, many studies had a mixture of daily and weekly searches which presumably would require weighting for non-independence.

This left 4 studies at 3 sites with enough data to confidently calculate a modified Shoenfeld Estimate, and an additional 9 studies at 7 sites with enough data after assumptions and estimations (Table 2).

Peters et al. (2020) stated that they made assumptions and approximations when including fatality studies in the modified Shoenfeld estimator, which is likely why they were able to include more studies in their analysis. However, Kimberly Peters, the lead author of the paper, did not respond to inquiries about what specific assumptions and approximations they made.

Reference	Carcass persistence	Searcher efficiency	Plot radius	Average interval between searches	Data available for July-October date range?
NJ-1	N	N	N	N	Y
DE-1	U	C	U	Y	N
NY-1a	Y	Y	R	Y	N
NY-1b	Y	Y	R	Y	N
PA-1	Y	Y	R	Y	N
WV-1a	Y	Y	U	Y	N
WV-1b	Y	Y	U	Y	N
MD-1a	Y	Y	U	Y	Y
MD-1b	Y	Y	U	Y	Y
ME-1	Y	Y	U	Y	Y
ME-2	Y	Y	R	Y	Y
NY-2	Y	Y	R	Y	Y
NY-3	Y	Y	R	Y	Y
VT-1	Y	Y	R	Y	Y
WV-3a	Y	Y	U	Y	Y
WV-3b	Y	Y	U	Y	Y
ME-3a	Y	Y	Y	Y	Y
ME-3b	Y	Y	Y	Y	Y
ME-4	Y	Y	Y	Y	Y
WV-2	Y	Y	Y	Y	Y
	U = unclear if combined birds & bats or just bats	C = combined bats and birds	R = rectangle plot N = none U = unclear/range		

Table 2. Relevant gaps in bat fatality study reporting. Studies without bat fatality data (Reference: NA-1-12) were not included in the table. Red indicates data reporting gaps; light orange indicates an assumption or estimation is necessary. See Appendix B for citations of the papers to which the reference codes refer, including NA-XX studies. Turbine heights are available from the USGS Turbine Database, so it did not matter if they were reported in the studies.

Reproducibility of landscape metrics & statistical analyses

I was successfully able to create models and R scripts that together mostly reproduce Peters et al. (2020)'s calculations of landscape metrics and statistical analyses to identify a correlation between land cover and bat fatalities. However, I could not apply these to the study sites I found through the AWWIC database, because too few fatality studies provided enough information to standardize fatalities using the modified Shoenfeld estimator. This means that I am unable to check to see if my results are the same. In addition to not having access to enough data to run the statistical analysis, I was not able to fully reproduce the methods of the statistical analysis due lack of information about how Peters et al. (2020) incorporated weighted studies into their random forests analysis and generalized linear regression.

While I was unable to calculate fatality risk by site due to the lack of information reported for inclusion in the modified Shoenfeld estimator, I was able to calculate landscape statistics and did so at the Beech Ridge (WV-2) site. This required downloading data layers from a variety of sources (Figure 3b). Because Peters et al. (2020) did not provide original data layers and for a few layers did not specify which date they were from, I was unable to find some layers they used and instead substituted with different years.

Although I could have used the general linear model coefficients reported by Peters et al. (2020) to assess bat fatality risk based on landscape metrics, some landscape metric variables would have required a transformation dependent on surrounding sites (Equation 2). This transformation applies to 9 of the variables (Table A1). Therefore, using these coefficients would have required downloading layers for and running the landscape metrics model on each site, and renders Peters et al. (2020)'s methods less accessible for those interested only in bat fatality risk at a particular site. Moreover, Peters et al. (2020) did not publish which specific sites they used, so their regression coefficients may not be accurate for the data sample I have access to.

Equation 2. Transformation necessary for 9 variables (Table A1), from Peters et al. (2020).

$$X' = \log (X - (\min(X) - 1))$$

I used QGIS and R to create the models and scripts because ArcGIS is a proprietary software and FRAGSTATS is less accessible than R. I also departed from Peters et al. (2020)'s methods by not including small lakes because I was not confident about how they included them. Moreover, because Peters et al. (2020) did not report how spatial joins would calculate minimum distance metrics, I used proximity rasters instead.

Report analyzing landscape metrics at 25 km buffer for Beech Ridge (WV-2) site

This is an example of the metrics outputted by using the models and landscape metrics R script when run at a 25 km spatial scale at the Beech Ridge (WV-2) site.

This region is mostly forest (76.5%) with some open cover (9.88%) and cropland (8.47%) (Figure 6, Table 3, Table 4). Therefore, it makes sense that the edge density, mean patch size, and largest patch index are highest for the forest class (Table 4). All positive clumpiness indices show that patches tend to be aggregated, with cropland and wetland having the highest aggregation and urban areas with the lowest aggregation (this is likely because roads are classified as urban areas) (Table 3). This is also supported by the aggregation index for the region as a whole being 90.4 out of 100, showing close to maximum aggregation (Table 4). According to the Simpson's evenness index, the landscape is neither homogenous nor heterogeneous given on a scale from 0 to 1 the measure was 0.476 (Table 4). The forest core area was relatively low at 65.5%, supporting the relative clumpiness of the forest cover (Table 3, Table 4). Ridges and valleys are fairly evenly split, with ridges being 7.7% of the landscape and valleys being 8.34% of the landscape (Table 4).

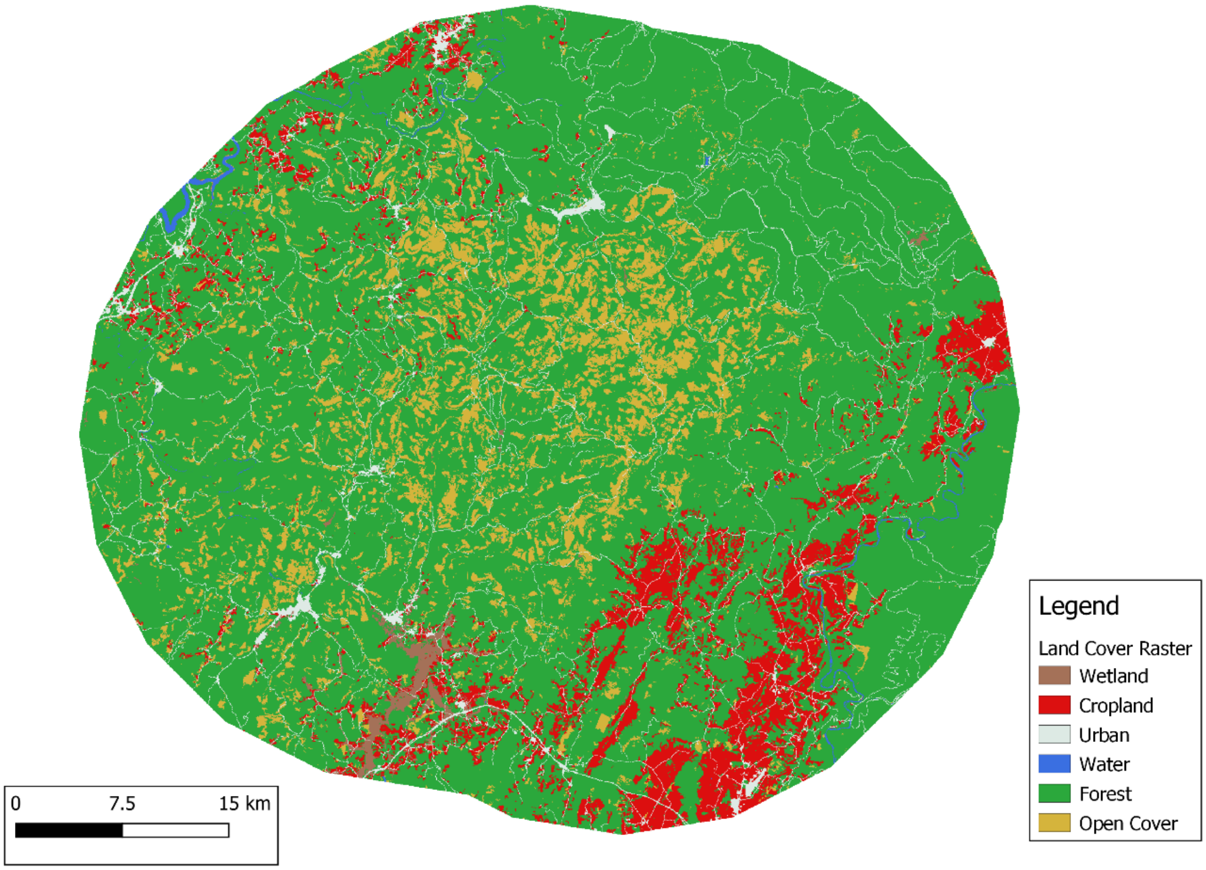

Figure 6. Land cover within 25 km buffer of wind turbines at Beech Ridge, WV site (WV-2), aggregated from original NALCMS layer.

	14- wetland	**15- cropland**	**17- urban**	**20- forest (1,5,6)**	**21- open cover (8,10,16)**
% area (proportional abundance of land cover classes): lsm_c_pland	0.806	8.47	3.98	76.5	9.88
Edge density (sum of all edge segments in patch type & divide by landscape area): lsm_c_ed	2.07	18	23.5	55.3	25.6
Mean patch size (average total area in particular class): lsm_c_area_mn	5.17	11.7	6.71	151	6.58
Largest patch index (% landscape occupied by largest patch of a given class): lsm_c_lpi	0.418	1.69	0.301	74.8	0.388
Clumpiness index (adjacency of patches. -1 = disaggregated, 0 = random, 1 = aggregated): lsm_c_clumpy	0.807	0.825	0.533	0.768	0.782

Table 3. R calculations by land cover class for 25 km metrics at WV-2 site.

<table>
<tr><td colspan="2">Aggregation index (describes adjacency of habitat cells: 0 = maximally disaggregated, 100 = maximally aggregated classes): lsm_l_ai</td><td>90.4</td></tr>
<tr><td colspan="2">Simpson's evenness index (evenness of proportions of land cover; homogeneity measure: "Equals SIEI = 0 when only one patch is present and approaches SIEI = 1 when the number of class types increases while the proportions are equally distributed" [source: R help documentation]): lsm_l_siei</td><td>0.476</td></tr>
<tr><td rowspan="2">Forest core area % (core area percentage of landscape; edge depth was 1.3114): lsm_c_cpland</td><td>0 (not forested)</td><td>13.9</td></tr>
<tr><td>1 (forested)</td><td>65.5</td></tr>
<tr><td rowspan="3">TPI % area (percentage of landscape of class): lsm_c_pland</td><td>Valleys (<-1)</td><td>8.34</td></tr>
<tr><td>Neither (-1:1)</td><td>84</td></tr>
<tr><td>Ridges (>1)</td><td>7.7</td></tr>
</table>

Table 4. R calculations of landscape area for 25 km metrics at WV-2 site.

Discussion

Bat fatality study reporting

Given only 13 studies of the original 20 with reported carcass data reported data in a way in which it was possible (with some estimations and assumptions) to include in a meta-analysis— namely, to calculate a modified Shoenfeld estimate—there is clearly an opportunity for improvement in the way that data are reported.

Most importantly, raw data should be included in reports with the dates of searches included so that estimates can be calculated for particular times of the year. In this meta-analysis, only studies from July 15-October 15 were included as it is the fall migratory period where bat fatalities are highest. Some studies did not include raw data making it impossible to sort out fatalities by date.

The wind energy guidelines (WEGs) describe in detail the protocol for conducting post-construction fatality studies, but do not give a straightforward way to report results (Tier IV; USFWS 2012). It would be helpful to have all the information necessary to calculate the modified Shoenfeld estimate on one page to decrease the amount of time it takes to calculate the estimate. This information includes number of fatalities observed, average time of carcass persistence in days, proportion of carcasses found by searchers, average interval between searches in days, and search plot radius which was used to calculate the density-weighted proportion (*dwp*) of carcasses that were available for detection during searches using radius using Peters et al. (2020)'s own internal metric.

This also means that search plots should be circular, which was not always the case among the AWWIC studies included in this analysis. It is unclear to what extent differences in plot shape affect estimator calculations, but regardless, consistency would increase accuracy. Another improvement for field study methodology would be establishing a consistent temporal interval between searches, which many studies did do but some did not. This would help decrease confidence intervals around fatality estimates.

Carcass persistence should be calculated for bats, as opposed to combined with bats and birds; in one study, this was not clearly defined (DE-1). The methodologies for carcass persistence and searcher efficiency trials also ranged, adding uncertainty to the total estimated fatalities; trials used carcasses ranging from freshly killed bats (PA-1) to frozen bird carcasses (DE-1) to brown mouse and juvenile quail carcasses (WV-1b).

Another source of bias is that likely studies in the AWWIC database do not accurately represent fatalities as they are contingent on operators releasing data; this could either mean an overestimation given high-risk facilities are more likely to be forced to release data for permitting reasons, or an underestimate given facilities with more fatalities will likely be more hesitant to publish their data (Peters et al. 2020). This also leads to an inaccurate representation of the spatial distribution of wind turbines (Figure 1).

This study was using the modified Shoenfeld estimator as a comparison tool, rather than for the purpose quantifying bat fatality estimates themselves (Peters et al. 2020). However, the Shoenfeld estimator is not consistent in its bias, so even as a comparison tool it may not be as useful as Peters et al. (2020) suggest (Huso 2021, personal communication).

Newer and more accurate estimators like GenEst could allow for a greater insight into bat risk patterns. More accurate measures of uncertainty for detection probability could also be calculated using GenEst or using parametric bootstrapping, which was not possible for the Peters et al. (2020) study due to data limitations (Madsen et al. 2019, Peters et al. 2020). Therefore, it is important that post-construction fatality monitoring studies are written with more transparency and detail, including ground cover conditions and carcass persistence distribution (Simonis et al. 2018).

Additionally, with wind turbines increasing in size, fatality surveys will also need to adjust protocols by increasing study plot areas to accommodate greater fall distances (Choi et al. 2020). GenEst's user guide lists input files as searcher efficiency, carcass persistence, search schedule, density weighted proportion, and observed fatalities, so it seems like new variables have not been introduced but likely will in the future (Simonis et al. 2018).

Data privatization

The largest barrier to using non-academic reports in studies is data privatization. Unless by endangerment or permitting laws, post-construction fatality study data are owned by turbine operators. There is a fear of litigation for having accidentally killed birds or bats, although in recent years operators have been more open to sharing data for research purposes as a path to finding solutions (Hale 2020, personal communication). The AWWIC database is the most centralized, accessible resource for bat fatality data and has created more incentive to release data. There are, however, still a lot of data sitting in boxes (Hale 2020, personal communication), in addition to data owners forgetting to add their data to the database or not knowing the database exists. Additionally, lawyers are frequently involved in data sharing negotiations to protect operators from liability (Diffendorfer 2020). However, when there are critical species to protect, there is more motivation to release data, such as recently in the case of the California condor when diverse stakeholders rallied around protecting the species (Diffendorfer 2020). On the other hand, the fear of future regulation of operations due to species endangerment can encourage preventative measures that may include releasing data for research. Some states have policies that require wind turbine operators to release data, including Vermont. Upon request, and with lawyers to help negotiate, operators may also release data to researchers, as did the operators involved in the NDA for the Peters et al. (2020) study. Over time, operators seem to have become more open to releasing data as their priorities have moved from fear of litigation to openness to help solve the bat collision problem (Hale 2020, personal communication).

In the case of the Peters et al. (2020) study, it is unclear whether or not the original data were used in this study, as the raw numbers of the Peters et al. (2020) meta-analysis are sealed under a non-disclosure agreement (NDA). This NDA, and the hesitancy of wind operators to release their post-construction fatality monitoring studies, is understandable as voluntarily admitting to having accidentally killed bats or birds can be risky. However, this barrier to knowledge about bat risk is only slowing down solutions by adding uncertainty to data and making it very difficult to quantify the problem.

Applications for Peters et al. (2020) study

In addition to improvements on post-construction fatality monitoring studies themselves, the Peters et al. (2020) meta-analysis could also have benefitted from transparency, particularly in how the data prepared. Examples include explanations for how rectangular study plots were treated when calculating radii, if fatality summary statistics over larger time frames than the July to October focus period were used, and how studies with multiple search frequencies or forms (with and without dogs) were treated. It would have been helpful for reproducibility purposes to include a raw data file or data sources, or even just the names of the studies they used, though this was protected under the non-disclosure agreement. It would have also been helpful if they had included code and/or a model with all of their analytical steps. Even a visualization of their results, such as a bat fatality risk map, would be helpful to compare results in future reproductions when bat fatality data are more available.

There is a fairly large discrepancy between the number of studies I could successfully incorporate into a meta-analysis following the criteria necessary (13 studies with flexible criteria) and those that Peters et al. (2020) used (27 sites, so at least that many studies). This may partially have to do with the fact that they also used studies from outside the AWWIC database, but it is likely I am still missing something about how they pulled data from studies to end up with so many. The 17 studies they used from outside the AWWIC database were split between Regions 3 and 5, so it is likely I am missing at least a few studies from within the AWWIC database that they did use. The fact that Peters et al. (2020) primarily used the AWWIC database meant I could have some confidence that I used similar studies to theirs, but there is no way of knowing how closely my dataset matched with theirs. It would also make reporting which studies researchers used easier if the AWWIC database were to create a straightforward labelling system for the studies, perhaps similar to the way I labelled them for myself (Appendix B).

Reproducibility of landscape metrics & statistical analyses

Because I cannot compare my results to Peters et al. (2020)'s, it is difficult to know how differences in methodology and software affected the results. Peters et al. (2020) did not report which specific ArcGIS tools they used, and even if they did, tools may differ between ArcGIS and QGIS and it is difficult to know in what ways because ArcGIS tools are not open source.

I do not think that using proximity rasters instead of spatial joins to calculate minimum distance metrics would have meaningfully affected the results, though there may have been slight differences due to the way values were calculated as a result of using rasters at a 30m scale instead of vectors. Although lakes were not present at the site I studied (WV-2), the removal of small lakes from the analysis due to raster resolution may affect results at other sites.

Peters et al. (2020) did not provide full information about the land cover layers they used, so I am not confident I used the same data. In future studies, original datasets, or at least full reporting on their metadata so researchers can download the datasets from the source themselves, should be provided.

Because I was not able to figure out how to incorporate case-weighted data into the random forests analysis, there would likely be differences in results given the same original data as well. Peters et al. (2020) neither provided a model for calculating landscape metrics, nor code for calculating the random forests analysis or generalized linear model, so my methods may differ.

Applications of reproduction

Creating models and R scripts with the methods I was able to reproduce, even if not fully, will help provide a framework for doing similar analyses in the future, particularly when fatality estimators become more consistent and comparable, when fatality studies are more available, and when more fatality studies report fully enough to be included in a meta-analysis normalizing raw fatality data using an estimator. My work also creates an example case for how others may want to reproduce or replicate other studies in a way that is itself reproducible. Namely, I provided a detailed record of my methods via written explanations, in addition to the models and scripts themselves, which I made publicly available on GitHub[6] for others to learn from and use, both within and outside the context of bat fatalities at wind turbines. These contexts can be very different, given the methods use a dependent variable at points and independent variables across space. For example, with a way to standardize public observations (e.g., iNaturalist or eBird data using a standardizing estimator), we could compare populations in relation to other variables across space.

Applications for bats: wind turbine siting

Given the number of variables one must consider when siting to build new wind turbines (e.g., favorable wind patterns, low environmental impacts, public acceptance, radar considerations, transmission line access, cost, military airspace, wildlife habitat, and of course, bird and bat fatality risk) and the shrinking ideal space that meet these criteria, siting by bat risk may not even be possible at this point (Lantz 2020, Renz 2020, Rodman & Meentemeyer 2006). Future studies should include other important variables, such as known migration patterns and weather, into bat fatality analyses.

[6] https://github.com/mtango99/thesis

However, many researchers now agree that bats are everywhere and that they are perhaps even attracted to wind turbines, making it difficult use siting alone as a sufficient mitigation measure (Amanda Hale 2020, Dowling 2020). At this point, researchers are beginning to instead assume bats will always be at risk, particularly given the scale at which wind developers are planning to build-out to slow the effects of climate change, and are focusing on deterrents, as opposed to trying to build where bats are not.

Nevertheless, if strong correlations between landscape factors and bat risk were to be found, it would be an important factor to consider to influence siting, as well as being prepared with curtailment and deterrence methods in place to mitigate bat risk (Dowling 2020, personal communication). Therefore, gaining a better understanding of the methodology behind this meta-analysis is useful for both its results and also to improve future meta-analyses, which could then help target sites where mitigation efforts are most needed. Knowledge about bat population impacts could also increase pressure and therefore funding for research on the efficacy of mitigation methods including curtailment (i.e., stopping blades during high-risk times or increasing cut-in speeds), acoustic and visual deterrents, and possible new methods.

Moreover, estimation standardization will prove important to quantify and communicate the scale of risk to decision-makers when it increases with the wind infrastructure build-out. While wind-wildlife scientists have accepted bat risk, even if quantifying it is uncertain, in order to instead focus on solutions, decision-makers often need more of a reason to take action.

Even though the three migratory bats (eastern red bat, hoary bat, and silver-haired bat) studied in this paper are not currently listed as endangered, it is important to study them as much as possible to prevent from being listed. Moreover, once listed, there are many regulations and red tape which can make it difficult to study the particular species and would also slow down necessary build-out of wind energy.

At the same time, federal regulation of wind energy development could promote research if written with such a purpose. Regulation could also require the use of curtailment or deterrence methods, which would not otherwise be economically favorable, in areas with high bat fatality risk.

Geography and ecology integration

The interplay between geography and biology in this study allows the knowledge from the two fields, often seen as completely separate frameworks of understanding, to create a more valuable, holistic understanding of the ways geographic tools can inform species conservation. Geographic tools, when used properly, can give great insight into phenomena over space, and ecological theory is necessary to guide an analysis by using relevant variables. Understanding both fields' contexts and relevance can decrease uncertainty in analyses by ensuring construct validity.

Conclusion

This study attempted to replicate a meta-analysis to identify reporting gaps in both the meta-analysis itself and the studies from which it took its data, finding that variations in post-construction fatality study methods and reporting made inclusion in a meta-analysis difficult to achieve, particularly without specific guidance about how the study treated the studies from which it extracted raw bat fatality data. However, with greater transparency, reporting improvements, and more interactions between researchers (i.e., responding to inquiries about methods), analyses like these could provide a powerful tool to study not just bat fatality risk, but any other question that requires the standardization of a dependent variable and inclusion in a meta-analysis to be answered. With more collaboration among data owners, more accurate meta-analyses could also explore collision risk to birds or target particular areas to focus deterrence mechanisms. Moreover, a more accurate estimation of fatalities could help push for funding and necessary legislation to continue wind-wildlife research and prevent extinctions as wind energy build-out becomes a reality.

I also made QGIS models and R scripts that reproduce the Peters et al. (2020) methods the most accurately possible given the information provided in the study. These methods are available to the public on GitHub[7] and only require free and open source software (QGIS and R) to run. They can be used to reproduce my work or be applied to another context. The consistency and transparency of these methods should be standard and required for future geographic studies as it allows for more confidence in methods and makes knowledge acquisition more efficient, helping the field along as a whole in an age when time is not on our side.

[7] https://github.com/mtango99/thesis

Appendices

Appendix A: Model info sheet (https://github.com/mtango99/thesis/blob/main/procedure/protocols/Model_InfoSheet.pdf): here you'll find more detailed explanations of the models and R scripts.

Appendix B: Study citations and code names.

Study citations and code names, non-NA studies ordered in consonance with Table 2. Reference code with "NA" means there was no bat fatality data in the study. All other reference codes use state abbreviation. If there is a lowercase letter it means there are multiple studies at the same location, e.g., ME-3a and ME-3b are two studies at the same location in Maine.

Table B1: Study citations and code names.

Citation	Reference
The Louis Berger Group, Inc. and Richard H. Podolsky. "Pre and Post-construction Avian Survey, Monitoring, and Mitigation at the Lempster, New Hampshire Wind Power Project." Prepared for Lempster Wind, LLC and Community Energy, Inc. August 2006.	NA-1
Anderson, K.W. "A Study of the Potential Effects of a Small Wind Turbine on Bird and Bat Mortality at Tom Ridge Environmental Center, Erie, Pennsylvania." December 2008.	NA-2
Efromyson, R.A., R.J. Day, & M.D. Strickland. "A Retrospective Tiered Environmental Assessment of the Mount Storm Wind Energy Facility, West Virginia, USA." November 2012.	NA-3
Reynolds, D.S. "Monitoring the Potential Impact of a Wind Development Site on Bats in the Northeast." Journal of Wildlife Managemnet 70:1219-1227. <http://dx.doi.org/10.2193/0022-541X(2006)70[1219:MTPIOA]2.0.CO;2>	NA-4
Mumma, T.L. & W. Capouillez. "Pennsylvania Game Commission Wind Energy Voluntary Cooperation Agreement: Second Summary Report." March 2011.	NA-5
NJ Department of Environmental Projection. "Technical Manual for Evaluating Wildlife Impacts of Wind Turbines Requiring Coastal Permits." September 2010.	NA-6
Stantec Consulting Services, Inc. "Study Plan for Post-Construction Monitoring Surveys: Wild Meadows Wind Project, Grafton and Merrimac Counties, New Hampshire." Prepared for Atlantic Wind, LLC. October 2013.	NA-7
Stantec Consulting Services, Inc. "2009 Spring, Summer, and Fall Avian and Bat Surveys for the Groton Wind Project in Groton, New Hampshire." Prepared for Groton Wind, LLC. December 2009	NA-8

Stantec Consulting Services, Inc. "Bird and Bat Pre-Construction Surveys for Kingdom Community Wind Project in Lowell, Vermont." Prepared for Green Mountain Power. January 2010.	NA-9
Tidhar, D. & A. Merrill [Western EcoSystems Technology, Inc.]. "Study Plan for Post-construction Fatality Monitoring and Bat Acoustic Monitoring for the Colebrook Wind Resource Area, Litchfield County, Connecticut." Prepared for BNE Energy, Inc. August 2011.	NA-10
Taucher, J., T.L. Mumma, & W. Capouillez. "Pennsylvania Game Commission Wind Energy Voluntary Cooperation Agreement: Third Summary Report." December 2012.	NA-11
Young, D.P., S. Nomani, W.L. Tidhar, & K. Bay [Western EcoSystems Technology, Inc.]. "NedPower Mount Storm Wind Energy Facility Post-Construction Avian and Bat Monitoring." Prepared for NedPower Mount Storm, LLC. February 2011.	NA-12
New Jersey Audubon Society Center for Research and Education. "Post-construction Wildlife Monitoring at the Atlantic County Utilities Authority-Jersey Atlantic Wind Power Facility." Prepared for New Jersey Board of Public Utilities Clean Energy Program. December 2008.	NJ-1
Buler, J., K. Horton, & G. Shriver. "Post-Construction Avian and Bat Impact Assessment of the University of Delaware Wind Turbine in Lewes, DE: Interim Report." 2012.	DE-1
Stantec Consulting Services, Inc. "2013 Bird and Bat Post-Construction Monitoring Report: Report for Laurel Mountain Wind Energy Project in Randolph and Barbour Counties, West Virginia." Prepared for AES Laurel Mountain Wind, LLC. January 2014.	WV-1a
Stantec Consulting Services, Inc. "2014 Bird and Bat Post-Construction Monitoring Report-- Laurel Mountain Wind Energy Project, Randolph and Barbour Counties, West Virginia." Prepared for AES Laurel Mountain Wind, LLC. January 2015.	WV-1b
Jain, A., P. Kerlinger, R. Curry, & L. Slobodnik (Curry and Kerlinger, LLC). "Annual Report for the Maple Ridge Wind Power Project Postconstruction Bird and Bat Fatality Study- 2006." Prepared for PPM Energy, Horizon Energy & Technical Advisory Committee (TAC) for the Maple Ridge Project Study. June 2007.	NY-1a
Jain, A., P. Kerlinger, R. Curry, & M. Lehman. "Annual Report for the Maple Ridge Wind Power Project Postconstruction Bird and Bat Fatality Study- 2008." Prepared for Iberdrola Renewables, Inc., Horizon Energy, & Technical Advisory Committee. May 2009.	NY-1b
Arnett, E.B., M.R. Schirmacher, M.M.P. Huso, & J.P. Hayes. "Patterns of Bat Fatality at the Casselman Wind Project in South-Central Pennsylvania." Prepared for the Bats and Wind Energy Cooperative and the Pennsylvania Game Commission. June 2009.	PA-1
Tetra Tech. "Spruce Mountain Wind Project: Post-Construction Bird and Bat Fatality and Raptor Monitoring- Year 1 Annual Report." Prepared for Patriot Renewables and Spruce Mountain Wind. May 2013.	ME-2

Stantec Consulting Services, Inc. "Post-construction Monitoring at the Munnsvile Wind Farm, New York 2008." Prepared for E.ON Climate and Renewables. January 2009.	NY-2
Stantec Consulting Services, Inc. "Cohocton and Dutch Hill Wind Farms: Year 2 Post-Construction Monitoring Report, 2010." Prepared for Canandaigua Power Partners, LLC. And Canandaigua Power Partners II, LLC. January 2011.	NY-3
Martin, C., E. Arnett, & M. Wallace. "Evaluating Bird and Bat Post-Construction Impacts at the Sheffield Wind Facility, Vermont." Prepared for Bat Conservation International and First Wind. March 2013.	VT-1
Young, D., M. Lout, Z. Courage, S. Nomani, & K. Bay [Western EcoSystems Technology, Inc.]. "2011 Post-Construction Monitoring Study, Criterioin Wind Project, Garrett County, Maryland." Prepared for Criterion Power Partners, LLC. April 2012.	MD-1a
Young, D., C. Nations, M. Lout, & K. Bay [Western EcoSystems Technology, Inc.]. "2012 Post-Construction Monitoring Study, Criterion Wind Project, Garrett County, Maryland." Prepared for Criterion Power Partners, LLC. January 2013.	MD-1b
Stantec Consulting Services, Inc. "Record Hill Wind Project: Post-Construction Monitoring Report, 2012." Prepared for Record Hill Wind LLC c/o Wagner Wind Energy I, LLC. March 2013.	ME-1
Young, D.P., S. Nomani, W.L. Tidhar, & K. Bay [Western EcoSystems Technology, Inc.]. "NedPower Mount Storm Wind Energy Facility Post-Construction Avian and Bat Monitoring." Prepared for NedPower Mount Storm, LLC. February 2011.	WV-3a
Young, D., S. Nomani, Z. Courage, & K. Bay [Western EcoSystems Technology, Inc.]. "NedPower Mount Storm Wind Energy Facility Post-Construction Avian and Bat Monitoring." Prepared for NedPower Mount Storm, LLC. February 2012.	WV-3b
Stantec Consulting Services, Inc. [formerly Woodlot Alternatives, Inc.] "2007 Spring, Summer, and Fall Post-construction Bird and Bat Mortality Study at the Mars Hill Wind Farm, Maine." Prepared for UPC Wind Management, LLC. January 2008.	ME-3a
Stantec Consulting Services, Inc. "Post-construction Monitoring at the Mars Hill Wind Farm, Maine- Year 2." Prepared for First Wind Management, LLC. January 2009.	ME-3b
Stantec Consulting Services, Inc. "Stetson I Mountain Wind Project: Year 1 Post-Construction Monitoring Report, 2009." Prepared for First Wind Management, LLC. January 2009.	ME-4
Tidhar, D., M. Sonnenberg, & D. Young. "2012 Post-construction Carcass Monitoring Study for the Beech Ridge Wind Farm Greenbrier County, West Virginia: Final Report April 1-October 28, 2012." Prepared for Beech Ridge Wind Farm, Beech Ridge Energy, LLC. January 2013.	WV-2

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