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The scope and severity of bat fatalities at US wind energy facilities

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Wind turbines are a major source of bat fatalities in the United States, yet the magnitude and species-specific patterns of these fatalities have remained poorly quantified because monitoring has been site-specific, unstandardized, and not designed for landscape-level synthesis. In the most comprehensive analysis to date, we synthesized 499 postconstruction monitoring reports and developed a multispecies Bayesian hierarchical framework with an adapted N-mixture model to pool information across sites and estimate total fatalities for ten bat species across the conterminous United States from 1981 to 2024. Our analysis predicts approximately 18.7 million bat fatalities over this period, with substantially higher species-specific totals than previously estimated. Our framework provides a landscape-level analysis that can predict fatalities for unmonitored locations and years, identify landscape-level drivers of fatalities, produce a multidecade hindcast of cumulative losses due to wind energy, and map where species-specific risk is highest. Although limitations and uncertainty remain, the magnitude of predicted fatalities may be comparable to total losses from white-nose syndrome, another major threat to North American bat populations. These threats affect largely different species, suggesting their impacts may compound, but updated population-level impact assessments could reveal potential cumulative effects. Our estimates of species-specific covariate relationships with rotor-swept area, ground clearance, land cover, and proximity to rivers, highlight opportunities to help reduce impacts through wind turbine design and siting. This work establishes a generalizable landscape-level framework for evaluating wildlife fatalities at wind energy facilities and highlights how coordinated monitoring, data sharing, and population-level impact assessments could further inform conservation efforts.

bat | biodiversity | fatality | monitoring | wind energy

Significance

Wind turbines cause large numbers of bat fatalities in the United States, but the scope and severity of these fatalities have remained largely unknown because monitoring has been piecemeal and focused on site-level compliance. By synthesizing 499 postconstruction monitoring reports, our analysis can predict fatalities for unmonitored locations and years, identify landscape-level drivers of fatalities, estimate cumulative fatalities across the history of wind energy development, and map where species-specific risk is highest. Our study estimates 18.7 million bat fatalities in the United States from 1981 to 2024, which may be comparable to total losses from white-nose syndrome. Updated population-level impact assessments could reveal potential cumulative effects across species differentially affected by these threats and further inform conservation efforts.

Bats provide essential and economically valuable ecosystem services (1–4), yet scientists have questioned for more than two decades whether their populations can withstand the impacts of disease, habitat change, and anthropogenic disturbances (5–7). The two greatest sources of mass bat fatalities in North America come from collisions with wind turbines and white-nose syndrome (WNS), a disease caused by an invasive fungal pathogen (5). Coincidentally, these threats were first documented only a few years apart, in 2003 and 2006, respectively (8, 9). In both instances, the sheer number of fatalities raised several questions (9, 10): What species were impacted? Were observations at individual sites indicative of broader, unobserved patterns across populations? And have cumulative fatalities threatened population viability?

Answering these questions has been difficult because bats are challenging to study given their cryptic, highly mobile, and nocturnal nature (11). Bats are the world's second-most diverse order of mammals (12), and individual North American species vary widely in population size, trend, distribution, and ecology (13, 14). Further complicating the matter, their comparatively long lifespans (15) and broad distributions (13) pose substantial data requirements for making reliable population-level inferences. For WNS, the severity of the threat motivated a coordinated, cross-jurisdictional effort to assimilate and analyze available but disjointed datasets (16) and implement a shared population monitoring program (13, 17). This cooperation helped answer the aforementioned questions and has supported efforts to assess population status and trends for the affected species (16, 18–20).

In contrast, a similarly cohesive approach has not been implemented to understand the impacts of bat fatalities at wind energy facilities, despite good intent (21). Monitoring

The authors declare no competing interest.

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at wind energy facilities in the United States has been conducted in a piecemeal way, shaped by the need to demonstrate compliance at individual sites rather than by an explicit design to inform a landscape-level understanding of this human-wildlife conflict (22, 23). Under the current framework, if a proposed wind energy facility is likely to harm federally threatened or endangered species with reasonable certainty, developers may apply to the US Fish and Wildlife Service (USFWS) for an incidental take permit (24). To show evidence of compliance with the permit, postconstruction monitoring (PCM) is typically required (24, 25). Some states also require PCM at wind energy facilities independent of a federal permit. PCM reports rely on carcass searches at wind turbines to estimate the total number of fatalities that occurred at the facility after accounting for imperfect detection of carcasses (26–28).

In North America, the design, protocol, data management, and statistical analyses of PCM studies have varied widely across sites, years, and performers, limiting the utility of these data (25, 26). Additionally, PCM data are not centrally reported and many PCM reports are not available to the public. PCM reports may contain confidential business information, so they may be available only to federal or state agencies, and others are not shared at all, especially if the monitoring occurred independent of state or federal requirements. Efforts to assimilate and analyze disparate datasets have been challenging due to severe access restrictions, interoperability challenges, lack of representativeness, and limited statistical approaches.

Due to these challenges, nationwide estimates of bat fatalities due to wind energy have been limited to broad extrapolations proposing hundreds of thousands of bat fatalities occur each year across North America (29, 30). These initial estimates were published in 2013, and the science has not advanced to offer more precision since then. Efforts to aggregate privately held data have resulted in data summaries (31–33), but have not delivered more robust information. The scientific community still lacks species-specific, range-wide estimates of the cumulative impacts of wind energy facilities on bat populations. Robustly estimating the magnitude of these fatalities can help answer the questions that were first posed more than two decades ago regarding species impacts and population viability.

Understanding the magnitude of these fatalities requires quantifying how multiple factors influence risk for each species. Yet most existing studies have relied on overly simplified models. For example, many PCM studies report a species-agnostic "all-bat take rate," initially expressed as bat fatalities per wind turbine (10). However, as wind turbines grew in size, estimates shifted toward using rated capacity to standardize across facilities, expressed as bat fatalities per megawatt. Most studies still treat rated capacity as the primary risk factor, in some cases using it as the sole predictor of bat fatalities at wind facilities across the nation (30, 34, 35). While this approach standardizes fatalities across wind turbines and facilities of varying size, rated capacity represents only the theoretical maximum energy output and does not directly describe wind turbine design or the actual amount of energy produced, which can vary substantially with windspeed, environmental, and operational conditions (36).

Developing a robust landscape-level understanding of the factors associated with bat fatalities at wind energy facilities requires covariate relationships that go beyond rated capacity. A robust model could be designed to account for variation in fatality rates among species according to a variety of environmental, technological, and biological factors. These sources of variation might include local and seasonal weather conditions, changing population abundances, facility layouts, wind turbine design specifications (e.g., hub height, ground clearance, rotor swept area), and operational adjustments, such as the use of increased cut-in speeds to minimize bat fatalities (37–40). Previously, the lack of standardization among PCM surveys (25) has proven to be a substantial roadblock to landscape-level analyses of wildlife fatalities at wind energy facilities. Despite these challenges, advanced statistical modeling using pooled data across monitored facilities could provide more robust cumulative bat fatality estimates and insights into the factors associated with these fatalities (41). To address these limitations, our analytical approach integrates heterogenous data sources into a unified hierarchical modeling framework, allowing us to account for inconsistencies among PCM studies while quantifying how environmental and technological drivers beyond rated capacity affect species-specific fatality patterns.

In this study, we use advanced statistical methods to pool information that was originally collected for site-level reporting into a landscape-level synthesis. Our approach accounts for substantial variation in monitoring efforts while evaluating how wind turbine design specifications and environmental factors are associated with bat fatalities for multiple species. Specifically, we use an adapted N-mixture model to represent total fatalities due to wind energy rather than live population abundance, and we incorporate imperfect detection using informative priors rather than relying on temporal replication (42–44). The latent state represents the total number of fatalities at each facility for a given year, which is identifiable based on shared information from the carcass counts, fatality estimates, and auxiliary detection data in the original PCM reports. Therefore, the model does not rely on assumptions of population closure across temporally replicated counts within or across years.

By pooling data across sites, this approach yields four outputs that no individual PCM study can provide: 1) species-specific fatality predictions supporting inference to locations and years without reported monitoring, 2) inferences about landscape-level drivers of fatalities, 3) hindcasted estimates of cumulative fatalities across the history of US wind energy development, and 4) predictive maps identifying where landscape-level fatality risk is highest for each species. Together, these outputs allow us to quantify the scope and severity of wind energy's impact on bat populations, compare it with other major threats such as WNS, and revisit the largely unanswered questions first posed more than two decades ago. More broadly, our modeling framework is generalizable to other taxa and regions, highlighting additional opportunities to inform siting, mitigation, and long-term conservation planning.

Results

We modeled fatalities for ten bat species observed during carcass searches at wind turbines across the conterminous United States (CONUS) according to 499 PCM reports compiled by the USFWS. The species we modeled included five long-distance migratory tree-roosting bats: the hoary bat (*Lasiurus cinereus*: LACI), eastern red bat (*Lasiurus borealis*: LABO), silver-haired bat (*Lasionycteris noctivagans*: LANO), evening bat (*Nycticeius humeralis*: NYHU), and Seminole bat *Lasiurus seminolus*: LASE); and five cave-hibernating bats: the big brown bat (*Eptesicus fuscus*: EPFU), little brown bat (*Myotis lucifugus*: MYLU), tricolored bat (*Perimyotis subflavus*: PESU), Indiana bat (*Myotis sodalis*: MYSO), and northern long-eared bat (*Myotis septentrionalis*: MYSE). *SI Appendix*, Table S1 describes the total number of carcasses observed across the PCM reports for each species.

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Table 1. Description of the covariates that were considered during the model selection process

Group	Name	Description	Source
Size	Rotor swept area	Average wind turbine rotor swept area (m^2) across the facility.	(45)
	Rated capacity	Average wind turbine rated capacity (MW) across the facility.	
Percent land covers	% forest	Percentage of deciduous, evergreen, and mixed forest NLCD land covers across 9 nearest grid cells.	(46)
	% shrub	Percentage of shrub NLCD land cover across 9 nearest grid cells.	
	% urban	Percentage of open space, low, medium, and high intensity developed NLCD land covers across 9 nearest grid cells.	
	% water	Percentage of open water NLCD land cover across 9 nearest grid cells.	
	% wetland	Percentage of wetland NLCD land cover across 9 nearest grid cells.	
Transformed α-IT land covers	NLCD α-IT 1	α-IT ratio of amount barren, shrub, herbaceous vs. pasture, cultivated NLCD land covers across 9 nearest grid cells.	(46)
	NLCD α-IT 2	α-IT ratio of amount forest vs. barren, shrub, herbaceous, pasture, cultivated NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 3	α-IT ratio of amount pasture vs. cultivated NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 4	α-IT ratio of amount open water, wetland vs. forest, barren, shrub, herbaceous, pasture, cultivated NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 5	α-IT ratio of amount shrub vs. barren NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 6	α-IT ratio of amount herb vs. barren, shrub NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 7	α-IT ratio of amount water, forest, barren, shrub, herb, pasture, cultivated, wetland, vs. open space, low, medium, high intensity developed NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 8	α-IT ratio of amount water vs. wetland NLCD land covers across 9 nearest grid cells.	
	NLCD α-IT 9	α-IT ratio of amount open space, low intensity developed vs. medium, high intensity developed NLCD land covers across 9 nearest grid cells.	
Time	Facility age	Year of PCM minus year of construction.	(45)
	Years since WNS onset	Year of PCM minus year of white-nose syndrome (WNS) onset, constrained nonnegative.	(47)
Wind	Windspeed	Average windspeed (m/s) at wind turbine ground clearance height.	(48)
	Windspeed^2	Quadratic effect for windspeed (above).	
	Windshear	Average wind turbine total height windspeed minus ground clearance windspeed (m/s).	
	Shape index	Unitless ratio of facility perimeter to area.	(45)
	Capacity factor	Average maximum capacity factor for a wind energy facility across the 9 nearest grid cells.	(49)
	Ground clearance	Average height of the lowest wind turbine blade tip above ground across the facility (m).	(45)
	Max cut-in speed	Maximum cut-in speed (m/s) for curtailment used at wind turbines during monitoring.	PCM reports
Climate	Temperature	40-y average daily minimum or maximum temperature (°C) across 9 nearest grid cells. Min or max was selected based on correlations with other covariates.	(50)
	Temperature^2	Quadratic effect for temperature (above).	
	Vapor pressure	40-y average vapor pressure (Pa) across 9 nearest grid cells.	
	Vapor pressure^2	Quadratic effect for vapor pressure (above).	
Habitat	Karst presence	Proportion of 9 nearest grid cells with karst geology.	(51)
	Nighttime brightness	Average nighttime brightness (lumens) across 9 nearest grid cells.	(52)
	Physiographic diversity	Average physiographic diversity index across 9 nearest grid cells.	(53)
	Lake distance	Average distance to nearest lake (m) across 9 nearest grid cells.	(54)
	River distance	Average distance to nearest river (m) across 9 nearest grid cells.	
	Mine distance	Average distance to nearest mine (m) across 9 nearest grid cells.	(55)
	Species richness	Median number of bat species present across 9 nearest grid cells.	(56)

The table groups covariates by type and provides the name we use to describe each covariate throughout this manuscript, a brief description, and the original data source. NLCD: National Land Cover Database (46) and PCM: Postconstruction monitoring.

We assumed that a variety of covariates could be related to the magnitude of annual bat fatalities at wind energy facilities (Table 1). Refer to *SI Appendix, Covariates* for full descriptions of the covariates and their derivations. Through model selection, we tested several hypotheses: 1) Rotor swept area is a better metric of collision risk than rated capacity. 2) Using the isometric α-transformation (α-IT) to convert land cover percentages to ratios improves model fit. Refer to *SI Appendix, Transformations*, Table 1, and Fig. S1 for more details. 3) Models incorporating wind turbine design specifications, environmental conditions, and operational factors fit better than models based on rotor swept area or rated capacity alone. We compared the fit of 18 models with various combinations of covariates to test these hypotheses (*SI Appendix*, Table S2).

From the model selection results, we used fivefold cross-validation to compare the fit of two top-performing models (*SI Appendix*, Table S3). We selected model E2 as the top-performing model, which included rotor swept area rather than rated capacity as a metric of wind turbine size, the transformed α-IT land cover ratios rather than a subset of the untransformed percentages, and all other covariates except for the temperature and vapor pressure gradients. In general, more complex models outperformed simple models, but including the temperature and vapor pressure gradients seemed to cause overfitting according to the cross-validation results. The α-IT transformation enabled us to include information from all ten land-cover classes in a way that avoided compositional dependence, improving predictive performance even though it is not as straightforward to interpret the ecological effects of the transformed land covers compared to a subset of the untransformed percentages. In *Materials and Methods*, we introduce the dataset, formulate our Bayesian hierarchical mixture model, and describe the prediction steps. In *SI Appendix*, we provide further details, including data processing, descriptions of all covariates, transformations, model fitting, model selection, and validation.

Cross-validation allowed us to evaluate whether pooling information across sites produced fatality estimates consistent with the original site-level reports. The cross-validation results for the top-performing model indicated that there were minimal differences between the original PCM report fatality estimates

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and our predictions. Across all species, the model had a residual median of −0.015 bats per wind turbine compared to the original reports (*SI Appendix*, Table S3). The differences were also minimal when measured for each species; eastern red bats had the largest difference with a residual median of −0.332 bats per wind turbine (*SI Appendix*, Table S3). The species-specific results for each fold (*SI Appendix*, Fig. S2) showed the middle 50% of the residuals between the reported and predicted per wind turbine fatalities usually fell within +/−5 bats per wind turbine for the most common species: big brown bat, eastern red bat, hoary bat, and silver-haired bat. The middle 50% of the residuals fell within +/−1 bat per wind turbine or less for the other species.

For model validation, we compared estimates from the original PCM reports to our model predictions, both of which included uncertainty, so the tails for these residuals were large. Since the true numbers of fatalities are unknown, it was difficult to determine the true predictive accuracy of our model compared to the original PCM estimates (*SI Appendix*, Fig. S2 and Table S3). This limitation is inherent to all PCM studies because the true number of fatalities cannot be observed directly. However, we used the median fatalities for our predictions, which we have shown had minimal differences compared to the estimates from the original PCM reports, and our predictions accounted for a variety of covariate relationships and site-level random effects likely to improve their accuracy and reduce uncertainty by borrowing information across reports. The goal of our model is to provide the most robust and powerful predictions of bat fatalities at wind energy facilities currently possible while propagating uncertainty across heterogenous PCM datasets.

As described in *Materials and Methods*, the β_s coefficients in the model represented the mean annual fatalities per wind turbine of species s after marginalizing across all other covariates. Therefore, the species-specific intercepts represented the mean annual fatalities at an "average" wind turbine. For *SI Appendix*, Table S4, we calculated the average wind turbine design specifications according to our model. Based on the final model (E2), hoary bat had the highest annual fatality rate at 5.8034 bats per wind turbine (*SI Appendix*, Table S5), followed by eastern red bat (5.0274), silver-haired bat (3.4631), and big brown bat (1.1519) (*SI Appendix*, Table S5). All other species had less than 0.25 annual fatalities per wind turbine, with some species being especially rare, such as Indiana bat (0.0067) and northern long-eared bat (0.0018), likely related to low population abundance.

However, there was considerable variation in fatalities based on covariate relationships. Fig. 1 shows the hypermean covariate relationships across all species. Three of the α-IT land cover ratios had credible effects (i.e., the 95% credible interval did not include a zero effect). In addition, there were credible negative effects for shape index, ground clearance, and river distance, as well as credible positive effects for physiographic diversity and species richness. The quadratic relationship for windspeed was credibly negative by default because we constrained the coefficient to be negative based on ecological evidence that indicates bat fatalities at wind turbines decline as windspeed increases (57). Under this constraint, we prevent the model from fitting a positive quadratic term that could cause biologically unrealistic increases in predicted fatalities at high windspeeds, which could interfere with accurate estimates.

Covariate relationships varied further by species (Fig. 2). Rotor swept area had credible evidence of a positive effect for five species, including big brown bat and all of the long-distance migratory tree-roosting species except Seminole bat. The land cover effects varied in credibility among species, perhaps because these helped

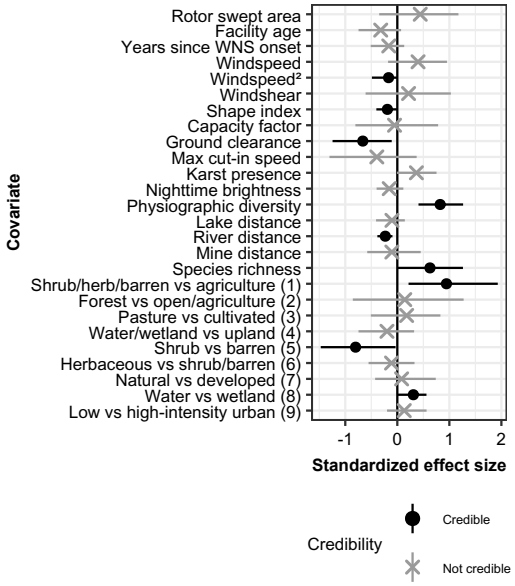


Fig. 1. Hypermean coefficient estimates showing covariate relationships across all species, with 95% credible intervals. The National Land Cover Database (NLCD) α-IT land cover covariates are labeled using concise shorthand descriptions followed by a number in parentheses (e.g., "Shrub/herb/barren vs. agriculture (1)" where "vs." is an abbreviation for versus). The numbers in parentheses correspond to the numbered α-IT ratios described in Table 1, where full covariate descriptions are presented. If the credible interval did not include 0, then the credibility of the effect was "credible," otherwise the effect was "not credible."

account for differences in species-specific abundance across the landscape. Facility age, shape index, ground clearance, nighttime brightness, and mine distance had credible negative effects for some but not all species. River distance had a credible negative effect across all species. Karst presence, physiographic diversity, and species richness had credible positive effects for some but not all species. Maximum cut-in speed had credible negative effects for hoary bat, little brown bat, and northern long-eared bat, but a credible positive effect for Indiana bat.

We used our model to predict median total bat fatalities across all analyzed wind energy facilities in CONUS from 1981 to 2024. The predictions exceeded 1.5 million total fatalities per year starting in 2021 (*SI Appendix*, Table S6). For individual species, our model predicted fatalities of hoary bats, eastern red bats, silver-haired bats, and big brown bats reached approximately 175,000 to 545,000 fatalities annually by 2024 (Fig. 3 and *SI Appendix*, Tables S7 and S8). Fatalities of the additional six species fell between approximately 100 to 55,000 bats per year by 2024. Cumulatively, our model predicted that approximately 6.7 million hoary bats and 5.8 million eastern red bats have been killed across the analyzed wind energy facilities (Table 2 and *SI Appendix*, Fig. S3). Cumulative fatalities for the other species were lower, but our model predicted approximately 3.4 million silver-haired bat fatalities, and approximately 1.5 million big brown bat fatalities have occurred. Predictions for the other six species were substantially smaller (Table 2). In total, our model predicted a median of 18,696,140 bat fatalities (95% credible interval: 13,294,354 to 25,699,968) among these ten bat species across CONUS from 1981 to 2024.

We also used our model to map relative bat fatality potential according to environmental covariates across CONUS (Fig. 4), providing spatial layers to help inform future siting decisions. We calculated the median multiplicative effect on the mean annual fatalities per species across the landscape. For Fig. 4, we truncated

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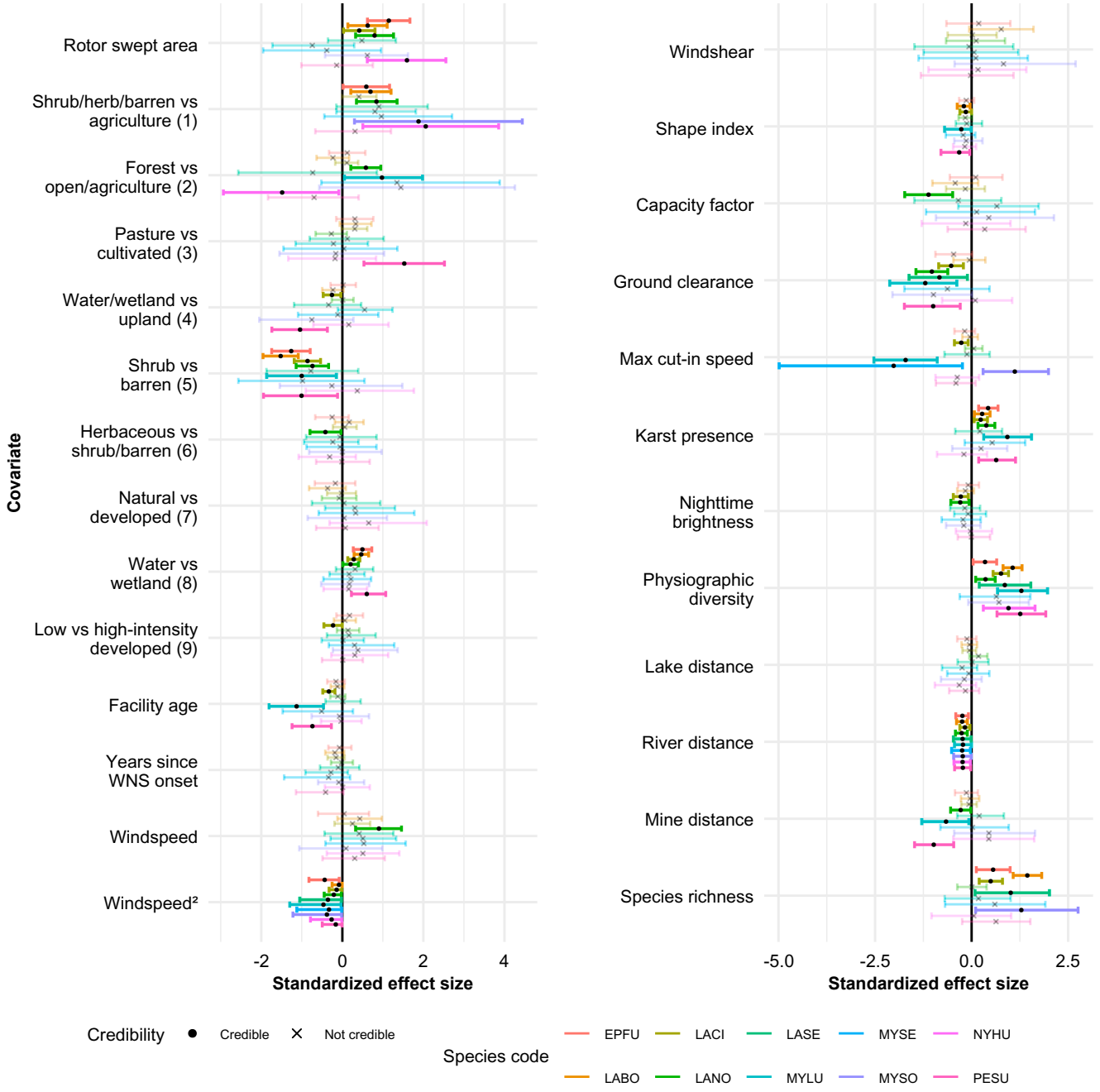


Fig. 2. Species-specific coefficient estimates showing covariate relationships with 95% credible intervals for ten species including: big brown bat (*Eptesicus fuscus*: EPFU), eastern red bat (*Lasiurus borealis*: LABO), hoary bat (*Lasiurus cinereus*: LACI), silver-haired bat (*Lasionycteris noctivagans*: LANO), Seminole bat (*Lasiurus seminolus*: LASE), little brown bat (*Myotis lucifugus*: MYLU), northern long-eared bat (*Myotis septentrionalis*: MYSE), Indiana bat (*Myotis sodalis*: MYSO), evening bat (*Nycticeius humeralis*: NYHU), and tricolored bat (*Perimyotis subflavus*: PESU). The National Land Cover Database (NLCD) α-IT land cover contrasts are labeled using concise shorthand descriptions followed by a number in parentheses (e.g., "Shrub/herb/barren vs. agriculture (1)" where "vs." is an abbreviation for versus). The numbers in parentheses correspond to the numbered α-IT ratios described in Table 1, where full covariate descriptions are presented. If the credible interval did not include 0, then the strength of the effect was "credible," otherwise the effect was "not credible."

the multiplicative effect at a factor of 100 in both directions to keep the effect comparable across species. Relative fatality potential across the nation varied by species, which could help identify locations where collision risk is highest for each species. Silver-haired bat, eastern red bat, little brown bat, tricolored bat, and Indiana bat had some locations with extremely high fatality potential, whereas some of the other species, particularly hoary bat, had less geographically variable values. In *SI Appendix*, we also included 95% credible intervals of these maps for each species (*SI Appendix*, Figs. S4–S13).

Discussion

In the most comprehensive analysis of bat fatalities at wind energy facilities to date, we predicted approximately 18.7 million bat fatalities among ten species across CONUS from 1981 to 2024, revealing an impact that has not previously been recognized on this scale even though PCM data have been collected for more than two decades. By pooling data originally collected for site-level reporting into a landscape-level analysis, we overcame long-standing data limitations and expanded the

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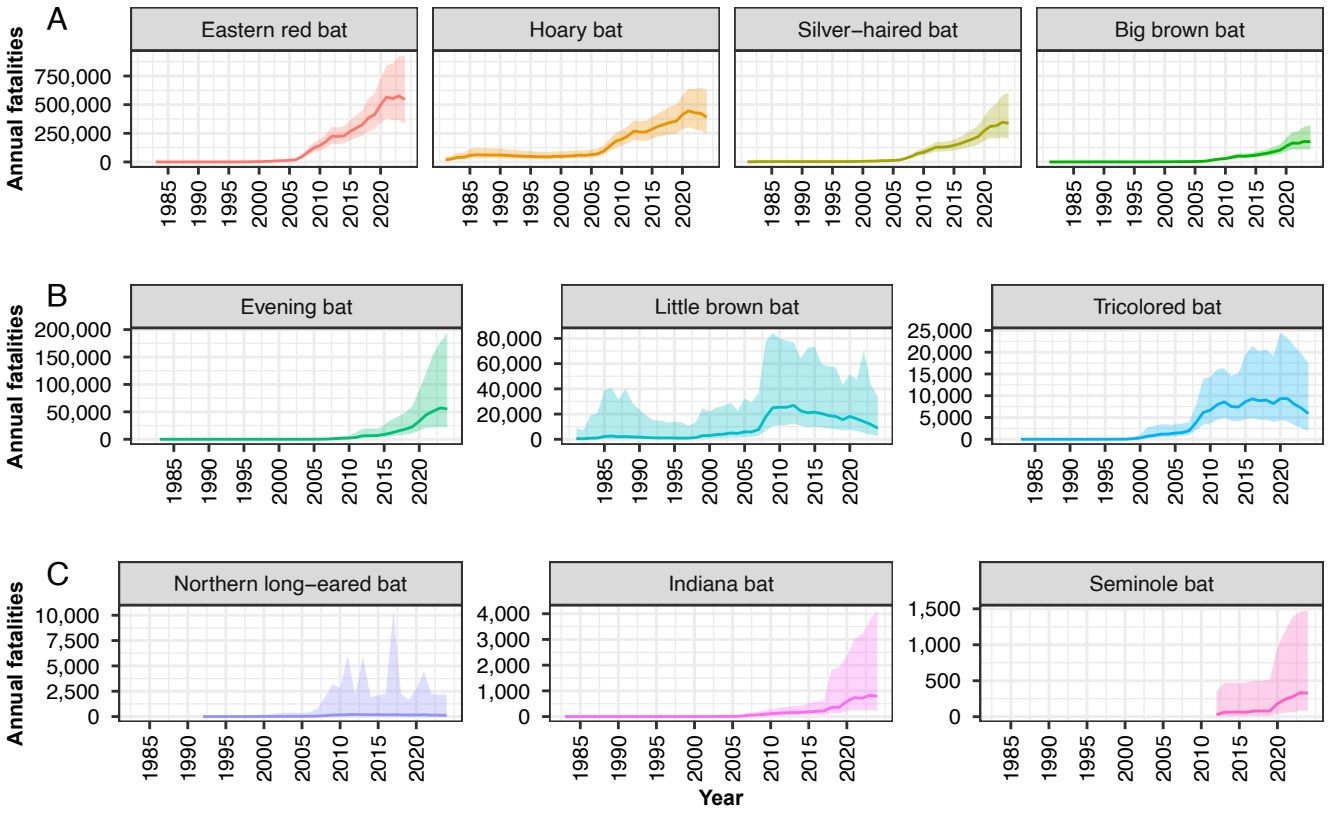


Fig. 3. Annual species-specific bat fatalities predicted for ten species across all analyzed wind energy facilities from 1981 to 2024. The shaded regions indicate approximate 95% credible intervals for each annual prediction. Panel (*A*) includes eastern red bat (*Lasiurus borealis*), hoary bat (*Lasiurus cinereus*), silver-haired bat (*Lasionycteris noctivagans*), and big brown bat (*Eptesicus fuscus*) with shared y-axes across the four species. Panel (*B*) includes evening bat (*Nycticeius humeralis*), little brown bat (*Myotis lucifugus*), and tricolored bat (*Perimyotis subflavus*) with an independent y-axis for each species. Panel (*C*) includes northern long-eared bat (*Myotis septentrionalis*), Indiana bat (*Myotis sodalis*), and Seminole bat (*Lasiurus seminolus*) with an independent y-axis for each species.

spatial and temporal coverage of data available to analyze. Our analysis offers four key advancements: 1) species-specific fatality predictions that support inference to locations and years without reported monitoring, 2) inferences about landscape-level drivers of fatalities, 3) hindcasted estimates of cumulative fatalities across the history of US wind energy development, and 4) predictive maps identifying where risk is highest for each species. Our framework moves beyond simple predictors of fatalities, such as rated capacity, by incorporating wind turbine design specifications, land cover, wind resource, and other environmental conditions as covariate effects. All covariate effects in this study represent correlative, hypothesis-generating relationships rather than causative relationships due to the observational nature of the data and potential for confounding factors. While these covariates likely do not explain all the variation in bat fatalities nationwide, this study offers further insight than has previously been available.

Although prior studies have used rated capacity to explain variation in bat fatalities at wind energy facilities (29, 30), we suggest rotor swept area is more appropriate because it directly measures the airspace where bats could collide with rotating wind turbine blades. A previous study demonstrated that relative energy production explains wildlife fatalities better than wind turbine size or rated capacity (36), so we also attempted to explore the effect of energy production on bat fatalities. Because we lacked access to data describing actual energy production, we used capacity factor estimates as a proxy for relative energy production,

Table 2. Species-specific median cumulative fatalities predicted across all analyzed wind energy facilities across the conterminous United States from 1981 to 2024 and 95% credible intervals across the aggregated predictions

Common name	Scientific name	Species code	Predicted cumulative fatalities	95% credible interval
Hoary bat	*Lasiurus cinereus*	LACI	6,745,440	4,608,094 to 9,782,493
Eastern red bat	*Lasiurus borealis*	LABO	5,775,252	4,044,024 to 8,192,655
Silver-haired bat	*Lasionycteris noctivagans*	LANO	3,383,448	2,348,230 to 4,855,458
Big brown bat	*Eptesicus fuscus*	EPFU	1,544,236	1,067,619 to 2,288,842
Little brown bat	*Myotis lucifugus*	MYLU	486,806	266,597 to 1,044,726
Evening bat	*Nycticeius humeralis*	NYHU	366,461	187,571 to 900,777
Tricolored bat	*Perimyotis subflavus*	PESU	147,452	84,507 to 278,440
Indiana bat	*Myotis sodalis*	MYSO	6,168	2,381 to 22,830
Northern long-eared bat	*Myotis septentrionalis*	MYSE	5,931	663 to 50,900
Seminole bat	*Lasiurus seminolus*	LASE	1,974	483 to 9,517

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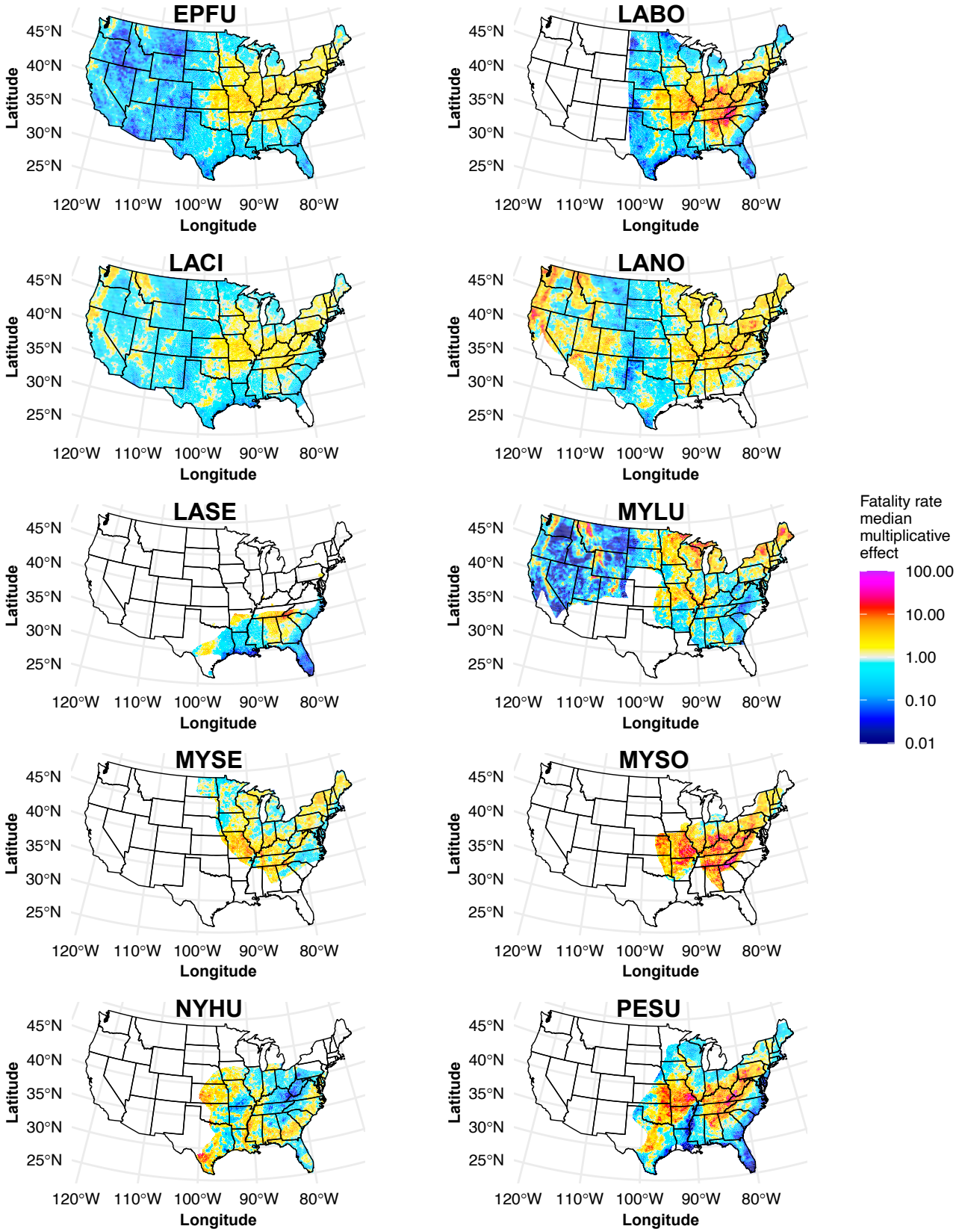


Fig. 4. Median multiplicative effect of relative bat fatality potential across the conterminous United States for ten bat species including hoary bat (*Lasiurus cinereus*: LACI), silver-haired bat (*Lasionycteris noctivagans*: LANO), eastern red bat (*Lasiurus borealis*: LABO), big brown bat (*Eptesicus fuscus*: EPFU), little brown bat (*Myotis lucifugus*: MYLU), tricolored bat (*Perimyotis subflavus*: PESU), evening bat (*Nycticeius humeralis*: NYHU), Seminole bat (*Lasiurus seminolus*: LASE), Indiana bat (*Myotis sodalis*: MYSO), and northern long-eared bat (*Myotis septentrionalis*: MYSE) clipped to their published species range (56).

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which did not have a credible effect on bat fatalities except for silver-haired bat. Relying on annual, facility-wide estimates of capacity factor instead of fine-scale measurements of actual energy production likely obscured any relationship with fatalities after accounting for other wind turbine design specifications. During model selection, rotor swept area slightly outperformed rated capacity when the α-IT land cover ratios were included. However, we found strong evidence that neither rated capacity nor rotor swept area were adequate predictors alone. Including additional technological and environmental covariates produced more robust results.

Wind turbine design covariates previously linked to bat fatalities in smaller-scale studies showed similar patterns in our analysis. For big brown bat and all of the long-distance migratory tree-roosting species except Seminole bat, fatalities increased as rotor swept area increased. Prior research has also identified positive relationships between fatalities and wind turbine hub height or total height, which are both strongly correlated with rotor swept area (40, 58). We observed negative relationships with wind turbine ground clearance for some species, consistent with a previous study (59). Wind turbines have grown substantially over time (45), with most installed since 2020 having rotor swept areas between 10,000 to 20,000 m^2, and some retrofitted wind turbines are receiving larger blades that reduce ground clearance. These trends may elevate bat fatality risk, suggesting wind turbine design choices and mitigation could be considered simultaneously. We also found credible evidence of a negative effect of facility age for some species (hoary bat, little brown bat, and tricolored bat) suggesting fatalities may decline at sites over time, which has been observed previously (60, 61). While potentially confounded with other factors, this relationship may suggest local population declines or behavioral changes, such as avoidance, at sites over time.

Land cover and the presence of, or distance to, bat habitat were associated with bat fatalities, but effects varied by species. River distance, physiographic diversity, and several landcover ratios showed the most consistent patterns. Fatalities increased at sites closer to rivers for all species and generally increased with greater physiographic diversity. However, the multiplicative fatality potential maps show that areas with the highest predicted fatalities varied greatly by species across CONUS. These differences were driven primarily by the environmental and habitat effects that varied among species, including karst presence, nighttime brightness, mine distance, species richness, and the α-IT land cover ratios. Although the individual α-IT ratios are difficult to interpret biologically, they effectively capture multivariate land cover effects and improve the model's ability to predict species-specific bat fatalities across the landscape. Collectively, these results suggest that siting strategies to reduce bat fatalities are possible, but species-specific approaches could be beneficial.

We did not observe strong relationships between bat fatalities and average annual windspeed, and we detected only some patterns weakly consistent with the reductions expected under curtailment (57). For hoary bat, little brown bat, and northern long-eared bat, maximum cut-in speed had a credible negative effect, indicating a decrease in fatalities as maximum cut-in speed increased. In contrast, maximum cut-in speed had a credible positive effect for Indiana bat. However, the Indiana bat has a long-standing history of regulatory considerations due to its endangered status (24), and this history may have confounded the estimate. Wind energy facilities where Indiana bats were present or fatalities were observed may have been more likely to adopt high cut-in speeds to avoid fatalities, which could have produced a spurious positive relationship between maximum cut-in speed and fatalities. The coarse temporal resolution of the current dataset also restricted our ability to evaluate how windspeed and curtailment affect fatalities. Although finer-scale windspeed data exist, we could not incorporate them because of the temporal resolution of the PCM data. Similarly, we could only represent curtailment by the maximum cut-in speed used at a facility over the entire PCM period. As with relative energy production, finer temporal resolution data could substantially improve future analyses. Removing the effects for windspeed^2 and windshear may also help isolate the influence of windspeed alone and produce results more consistent with previous studies.

Despite using modern statistical methods, the state of PCM data remained a limiting factor in our analysis. We collated carcass counts, survey designs, and total estimates from 499 PCM reports, but these details were often only available annually, leaving finer details unavailable for use. We also had carcass counts from several hundred additional reports, but the associated PCM methods lacked sufficient detail to include. For the adequately documented reports, we accounted for variation in the observed carcasses using detection probabilities and search effort correction factors. Even so, the PCM input data were uncertain estimates of true fatalities, as were our predictions. Some PCM reports may have contained biased estimates due to outdated statistical methods, but we lacked the underlying survey data to address this issue. Because the unknown true fatalities cannot be directly compared with our predictions, we included uncertainty from the reported detection probabilities when calculating residuals during cross-validation. As expected, cross-validation indicated substantial uncertainty in site-specific predictions, reflected in long residual tails. The longer positive tails suggest the original PCM reports may have overestimated fatalities more often than our model. Importantly, cross-validation showed that the predicted median fatalities differed little from the original PCM report estimates, indicating the median predictions from this analysis are realistic despite the data limitations.

We predicted approximately 18.7 million bat fatalities among ten bat species due to wind energy development across CONUS from 1981 to 2024. Most of these fatalities came from four species: hoary bat (~6.7 million), eastern red bat (~5.8 million), silver-haired bat (~3.4 million), and big brown bat (~1.5 million). We interpret these predictions as absolute fatality counts rather than relative abundance of fatalities, consistent with the interpretation of fatality estimates from the original PCM reports. Abundance estimates from standard N-mixture models are sensitive to violations of population closure and unmodeled heterogeneity, so estimates are commonly interpreted as relative unless additional information informs detection. In contrast, our adapted method incorporated calibration data on detection probabilities from the original PCM studies to enable separation of detection and abundance without temporal replication consistent with previous work (42–44). Additionally, because each PCM report provides a single observation for a bounded monitoring period, our adapted N-mixture model does not rely on an assumption of population closure across repeated counts (44). Posterior predictive checks for our final model E2 did not reveal evidence of lack-of-fit or overdispersion due to unmodeled heterogeneity (*SI Appendix*, Table S2). Still, unbiased absolute abundance estimates rely on accurate original estimators and the absence of unmodeled heterogeneity or sampling bias. Our sample was nonrandom, and the predictors may not have captured all heterogeneity across the spatial and temporal extent

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of our hindcasted predictions. However, our approach provides the most robust method known to date for estimating the magnitude of bat fatalities due to wind energy in the United States.

This analysis helps address long-standing information gaps about the scope and severity of the threat wind energy poses to bats. We produced species-specific fatality estimates for ten species and identified fatality patterns that enable inference to unobserved locations and years, revealing how observations at individual sites could reflect broader range-wide patterns. Our predictions reveal cumulative fatalities due to wind energy are potentially comparable in magnitude to one rough estimate of total losses from WNS (62). This parity has not previously been recognized because piecemeal, site-level PCM data have not been synthesized at this scale. Wind energy and WNS affect a largely nonoverlapping set of species: the migratory tree-roosting bats bearing the greatest wind energy losses (hoary, eastern red, and silver-haired bats) are not the cave-hibernating species most heavily impacted by WNS. As a result, the two threats may compound across North American bat species rather than concentrating on a shared group of species, potentially broadening the scope and severity of conservation threats to bats.

Yet similar magnitudes of fatalities from these two threats do not necessarily imply similar rates of decline because population-level impacts depend on population size, structure, demographic rates, and ecological traits. Empirical data on these components remain largely unavailable for most species, especially migratory tree-roosting bats such as the hoary bat. Despite these uncertainties, previous demographic projection models based on expert opinion have suggested that wind energy could cause population declines of 50 to 90 percent for hoary bats within the next 50 y (34, 35). These projections indicate that, under the most severe demographic scenarios, wind energy could potentially result in population-level impacts that rival the greater than 90 percent declines observed in some species affected by WNS (16).

Interpreting our predictions in the context of these earlier projections highlights the conservation implications raised by our study. The projection models relied on expert-elicited demographic rates, population size assumptions, and an estimated 1.7 hoary bat fatalities per megawatt (30, 34, 35). By broadly extrapolating this fatality rate to total wind energy capacity nationwide, these studies assumed baseline median values of approximately 112,656 hoary bat fatalities in 2012 and 128,469 in 2014. In contrast, our model predicted median estimates of 267,947 hoary bat fatalities in 2012 and 262,235 in 2014, greatly exceeding the assumed fatalities in the projection models (*SI Appendix*, Table S7). These differences when evaluated under the previous demographic assumptions suggest that population-level impacts for hoary bats could be more severe than previously projected in each scenario (34, 35). Future range-wide estimates of population status and trends from the North American Bat Monitoring Program (NABat) could provide empirical information to critically evaluate these scenario assumptions (13, 20, 63) and updated demographic models that incorporate our fatality predictions can provide a clearer understanding of population-level impacts and extinction risk. Additionally, our model predicts eastern red bat fatalities have recently reached over 500,000 per year since 2021, surpassing about 400,000 annual hoary bat fatalities in comparison (*SI Appendix*, Table S7). Our predictions underscore conservation implications for multiple species, although we currently lack wind energy-related projections for any species besides hoary bat. Updated population-level impact assessments incorporating our fatality predictions could reveal potential cumulative effects and inform conservation efforts for species experiencing the greatest losses and for those exposed to both wind energy and WNS.

Although population-level impacts remain uncertain, our model provides predictions of cumulative bat fatalities at wind energy facilities across CONUS and offers a framework adaptable to species-specific assessments for other regions and taxa. The model can also predict total annual fatalities at proposed facilities prior to construction, based on geographic location and wind turbine design specifications, highlighting opportunities to evaluate siting and wind turbine design choices to mitigate site-specific impacts. However, uncertainty remains due to limitations in N-mixture modeling, potential unmodeled heterogeneity, and gaps in the available PCM data. Coarse seasonal and annual aggregation restricted our ability to estimate the effects of windspeed, weather, and curtailment on bat fatalities and limited spatiotemporal representation reduced precision. Higher-resolution PCM data could strengthen inference and further inform mitigation strategies (64). To this end, programs such as NABat demonstrate that coordinated monitoring is feasible despite the broad spatiotemporal windows relevant to these cryptic species (63). An optimized, collaborative, landscape-level monitoring framework that integrates these advances could improve precision, increase return on monitoring investments, and more efficiently evaluate mitigation effectiveness. Ultimately, translating fatality estimates into concrete population-level consequences and effective mitigation can benefit from additional research that includes coordinated demographic studies for the most-impacted species, integration with range-wide monitoring programs such as NABat, and a shift in how future PCM data are collected, shared, and analyzed so that compliance monitoring also serves broader ecological understanding.

Materials and Methods

Postconstruction Monitoring Data. We analyzed data from 499 PCM reports submitted to the USFWS spanning 277 wind energy facilities across the United States that were monitored for one or more years between 1996 and 2024. While our sample was not random nor fully representative of all wind energy facilities across the United States over time, it represented the largest known collection of analyzed monitoring reports at the time of publication. The reports included PCM survey design specifications and species-specific counts of bat carcasses observed during monitoring. Each report included an estimate of the total bat fatalities that occurred during the monitoring period based on a variety of statistical estimators (26–28). Survey effort was not standardized across reports. Monitoring may have lasted for different lengths of time and may not have accounted for carcasses falling outside of the area searched around each wind turbine. We extracted metadata from each report describing survey design to account for differences in search effort and carcass detection probability. Refer to *SI Appendix, Postconstruction Monitoring Data Processing* for more details.

Model. In brief, we developed an adapted N-mixture model (65) in which the latent state N represents total fatalities during a bounded PCM period at a wind energy facility, rather than the abundance of live populations through time. From the original PCM reports, we derived informed beta prior distributions approximating the detection probability p, allowing us to model imperfect detection without requiring temporally replicated surveys. The parameters in the model are identifiable based on shared information from the carcass counts, fatality estimates, and auxiliary detection data in the original PCM reports. This approach parallels previous applications of N-mixture models to study marine animals (42–44), which similarly incorporated calibration study information to allow for abundance estimation without the need for temporally replicated surveys of a closed population. Fatalities from different years are treated as independent realizations of the fatality process rather than repeated sampling of a closed population.

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In the PCM reports included in our analysis, the total number of fatalities N is not directly observed. Instead, each report provides an estimate of N generated using an established mortality estimator [e.g., GenEst, (27), Huso (28), and Shoenfeld (66)], which adjusts the observed carcass count Y based on field-derived estimates of detection probability. Because all fatalities cannot be observed directly, N remains a latent quantity and the PCM-reported values represent noisy estimates rather than ground truth. To incorporate these estimates while acknowledging their uncertainty, we used the PCM-reported fatality estimates and their associated uncertainty bounds to construct informative priors for the detection probabilities. The hierarchical structure then allows information to be shared across species and facilities, enabling the model to adjust based on covariate relationships and observation-level random effects rather than assuming the original PCM estimates are perfectly accurate. This approach propagates uncertainty in N throughout the model and mitigates potential biases inherent in any single PCM report or its original mortality estimator, some of which have been shown to be biased, as we discuss in *SI Appendix*.

Formally, we parameterized an adapted N-mixture model based on the number of carcasses Y_{rs} of species s observed in PCM report r. We let N_{rs} be a random variable representing the total number of fatalities of species s that occurred during the PCM study, and we let p_r be the average probability of detecting those fatalities. The parameter λ_{rs} described the mean annual fatalities for species s according to a Poisson distribution that related N_{rs} to wind turbine/facility design specifications and environmental covariates associated with the wind energy facility studied in PCM report r. A binomial distribution determined the likelihood of observing Y_{rs} carcasses out of N_{rs} total fatalities dependent on detection probability p_r.

$$Y_{rs} \mid N_{rs},\, p_r \;\sim\; \text{Binomial}(N_{rs},\, p_r)$$

$$N_{rs} \mid \lambda_{rs} \;\sim\; \text{Poisson}(\lambda_{rs})$$

We informed the prior for each detection probability p_r based on the total fatalities observed over all species $Y_r = \sum_s Y_{rs}$ compared to the mean (M_r), upper (U_r), and lower (L_r) bounds of the estimated total bat fatalities described in each report r. Because the PCM fatality estimates themselves are derived from imperfect observations, these priors represented the uncertainty in those estimates rather than treating them as true values of N. The reports used a variety of approaches to estimate upper and lower bounds including 90% or 95% CIs or credible intervals, so we devised a method to inform the detection probability priors agnostic to interval type. We estimated the mean detection probability for each report as $\hat{p}_r = \frac{Y_r}{M_r}$ and an approximate standard deviation for the detection probability as $\hat{\sigma}_r = \frac{Y_r/L_r - Y_r/U_r}{1.35}$. For the derivation of $\hat{\sigma}_r$, we assumed the range of potential detection probabilities based on the upper and lower bounds, U_r and L_r, could roughly approximate the interquartile range (IQR) for a normal distribution on the detection probability (since the IQR is approximately 1.35 times the SD). If any of the values for M_r, U_r, or L_r were missing, then $\hat{p}_r$ and $\hat{\sigma}_r$ were set to the mean values across all reports by estimator type (e.g., Huso, GenEst, Shoenfeld, etc.). Imputing these values by estimator helps to reduce the risk that assumptions from one approach influence the estimates from another, as some estimators have been shown to be biased, which we discuss more fully in *SI Appendix*. Finally, we calculated $\hat{\alpha}_r$ and $\hat{\beta}_r$ using the method of moments to derive an informed prior based on a beta distribution for each p_r as follows:

$$\hat{v}_r = \frac{\hat{p}_r(1-\hat{p}_r)}{\hat{\sigma}_r^2} - 1$$

$$\hat{\alpha}_r = \hat{p}_r \hat{v}_r$$

$$\hat{\beta}_r = (1-\hat{p}_r)\hat{v}_r$$

$$p_r \mid \hat{\alpha}_r,\, \hat{\beta}_r \;\sim\; \text{Beta}(\hat{\alpha}_r,\, \hat{\beta}_r)$$

To standardize the mean annual fatalities λ_{rs} across variable PCM survey designs and covariate relationships, we modeled λ_{rs} with a Bayesian generalized linear mixed model (GLMM) including an offset based on the number of wind turbines t_r monitored during the study.

$$\log(\lambda_{rs}) = \log(t_r) + \beta_s + Z_r\beta_z + \mathbb{I}(r)\frac{\beta_d}{d_r} + X_r\beta_{xs} + \xi_{rs}$$

The offset term $\log(t_r)$ represented the number of wind turbines monitored in PCM report r, scaling mean fatalities per wind turbine by wind turbine count. Each species had a species-specific fixed-effect intercept β_s, which represented the mean number of bats of species s killed per wind turbine annually, after marginalizing across all other covariates. We used a vector of three β_z coefficients adjusted for the total proportion of each spring, summer, and fall season searched for report r as recorded by Z_r. We used an indicator function $\mathbb{I}(r)$ to determine whether an additional adjustment for report r was needed to account for carcasses falling outside of the maximum search distance from the wind turbines. For the reports needing this adjustment, we included an inverse relationship with the maximum search distance d_r and coefficient β_d. With a negative value for β_d, this adjustment on the log-link for abundance can approximate an additional binomial thinning process for sampling exposure (a penalty for shorter maximum search distances) and has a desirable property where the penalty approaches zero as max distance searched approaches infinity (20, 65, 67). A negative value for β_d can be enforced using parameter constraints, or the final solution can be monitored to ensure the bounds of the estimated values are negative.

A vector of species-specific coefficients multiplied by the data values X_r accounted for all other facility-specific design and environmental covariates of interest. A species-specific observation-level random effect ξ_{rs} helped to account for unexplained variation, providing a structure to account for overdispersion similar to a Poisson-normal or negative-binomial variance model. To accommodate potential changes in bat populations or fatalities over time, the model includes temporal covariates such as facility age and years since the onset of white-nose syndrome at each grid cell. Species-specific coefficients for other site-level effects and the observation-level random effects allow the model to capture temporal and spatial variation in fatalities without assuming constant population sizes over the entire multiyear study. The priors used for the parameters and the model selection process are described in *SI Appendix*.

Prediction. We used the best performing model to hindcast bat fatalities based on the historical record of wind energy development in the United States from 1981 to 2024 and forecast relative bat fatality potential across CONUS.

Hindcasting Fatalities from 1981 to 2024 Across Operational Wind Energy Facilities. To account for wind energy development through time, we determined when wind turbines became operational and were decommissioned according to the US Wind Turbine Database and then aggregated wind turbines into annual representations of each facility (45). If the year a wind turbine became operational or was decommissioned was missing, we removed it from the analysis (1,815 wind turbines). For all other specifications, such as rated capacity, hub height, and rotor diameter, we interpolated missing values based on the average of each specification across all other wind turbines constructed within +/− one year. According to this analysis, at least 84,234 wind turbines existed on the landscape across CONUS from 1981 to 2024 for a total of 1,218,598 wind turbine-years (one wind turbine operating for one year is equal to one wind turbine-year).

For each facility phase, we calculated the covariates described in Table 1 and determined the total number of wind turbines in the facility. Using these values and setting all seasonal sampling proportions in matrix Z to 1 and distance adjustments to 0, we predicted standardized species-specific annual fatalities at all wind energy facilities according to the covariate relationships in matrix X. We also accounted for additional uncertainty by simulating values for ξ_{rs} according to hyperparameter estimates for τ_s. In this manner, we calculated species-specific means, medians, and credible intervals estimating total fatalities for each facility through time. We then aggregated these estimates annually, to predict annual and cumulative species-specific fatalities across all wind energy facilities in CONUS from 1981 to 2024.

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Predicting Relative Fatality Potential Across CONUS. We predicted relative bat fatality potential across CONUS for each species by estimating a multiplicative effect on annual fatalities according to the environmental covariate relationships across CONUS and marginalizing across all other covariates. These maps represent a prediction of relative bat fatality risk at a hypothetical wind energy facility in any location across CONUS without regard to whether a wind energy facility has been or could feasibly be installed in that location. We allowed the following covariates to vary across the landscape: years since WNS onset (facility construction year set to 2025), all α-IT land covers, capacity factor, karst presence, nighttime brightness, physiographic diversity, lake distance, river distance, mine distance, and species richness. Based on these covariate relationships, we calculated the species-specific median multiplicative effect on the annual fatalities and 95% credible intervals for each grid cell. We plotted these quantities as maps of relative fatality potential across the United States, which could be used to inform siting of future wind energy facilities. Formally, we used 100 simulations of $M_{gsi} = \exp(\sum_k x_{gk}\beta_{ksi})$ for each grid cell g based on the values of the above covariates x_{gk} for $k \in 1, 2, \ldots, 18$ and 100 MCMC sampled iterations of the species-specific coefficient values β_{ksi} for $i \in 1, 2, \ldots, 100$. The M_{gsi} simulations approximated posterior distributions of the multiplicative effect on mean annual fatalities per species across the landscape. We then approximated the median and 95% credible interval bounds for each grid cell from the simulated posterior distributions.

Data, Materials, and Software Availability. Data have limited availability owing to restrictions. We are prohibited from publicly disclosing postconstruction monitoring data used in this analysis that have been marked as confidential to ensure compliance with the Trade Secrets Act, 18 U.S.C. 1905; refer to 43 C.F.R. 2.36. Please contact C.J.L. or B.R.F. for more information. All data and code approved for public disclosure are available in the associated data release at https://doi.org/10.5066/P13NP5JM (68) and the associated software release at https://doi.org/10.5066/P138DAXS (69). The data release contains tables of annual and cumulative fatality estimates with credible intervals for each species from 1981 to 2024, posterior summary statistics for fitted parameters, and the relative fatality-risk layers as a GeoPackage. The software release includes code to recreate the covariate layers, run the model, and complete the downstream analysis. A demo dataset, consisting of the publicly available subset of PCM reports, is included to demonstrate the workflow, since reproducing the full analysis requires access to the restricted PCM data described above.

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