Modeling the power of acoustic monitoring to predict bat fatalities at wind turbines

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Abstract
Large numbers of bats are killed at wind turbines worldwide. To formulate mitigation measures such as curtailment, recent approaches relate the acoustic activity of bats around reference turbines to casualties to extrapolate fatality rates at turbines where only acoustic surveys are conducted. Here, we modeled how sensitive this approach is when spatial distributions of bats vary within the rotor-swept zone, and when the coverage of acoustic monitoring deteriorates, for example, with increasing turbine size. The predictive power of acoustic surveys was high for uniform or random distributions of bats. A concentration of bat passes around the nacelle or at the lower portion of the risk zone caused an overestimation of bat activity when ultrasonic microphones were pointed downwards at the nacelle. Conversely, a concentration of bat passes at the edge or at the top portion of the risk zone caused an underestimation of bat activity. These effects increased as the coverage of the acoustic monitoring decreased. Extrapolated fatality rates may not necessarily match with real conditions without knowledge of the spatial distribution of bats, particularly when the risk zone is poorly covered by acoustic monitoring, when spatial distributions are skewed and when turbines are large or frequencies of echolocating bats high. We argue that the predictive power of acoustic surveys is sufficiently strong for nonrandom or nonuniform distributions when validated by carcass searches and by complementary studies on the spatial distribution of bats at turbines.

KEYWORDS
curtailment, green–green dilemma, mitigation, wind energy production, wind farm

1 INTRODUCTION

Energy production from renewable sources, such as wind energy, is an important contribution to combating human-made global warming (Zhou et al., 2012). Energy generation via wind power is inexpensive compared with conventional forms of energy production and also compared with other forms of renewable energy sources (Blanco, 2009; Traber & Kemfert, 2011). Additionally, the carbon dioxide footprint for erecting and operating wind turbines (WT) is quickly compensated after a few months of operation (Dammeier et al., 2019; Jung & Schindler, 2021). Consequently, wind
energy production is accelerating in many countries world-
wide (Global Wind Energy Council (GWEC), 2021). How-
ever, wind energy production is not necessarily ecologically
neutral (Gibson et al., 2017). Many flying animals collide
with and die at WT (e.g., Thaxter et al., 2017; Voigt, 2020).
Among aerial vertebrates, aerial-hawking bats are particu-
larly vulnerable at WT (Arnett et al., 2016). For instance,
estimated annual losses of bats killed by WT may sum up
to several 100,000 bats for Germany or parts of North Amer-
ica (Arnett & Baerwald, 2013; Voigt et al., 2019). Fatality
rates can be reduced by shifting the operation onset (“cut-in
wind speed”) to wind speeds of 6 m/s or higher when bat
activity drastically decreases (Voigt et al., 2015). Such cur-
tailments can reduce fatality rates by more than 80% com-
pared with the unconditional operation of turbines (Adams et al., 2021; Arnett et al., 2011; Brinkmann et al., 2011;
Mäntoiu et al., 2020; Whitby et al., 2021), while causing
monetary losses of only 0.5% to 2% of total annual revenue
to wind energy companies, depending on local conditions
and turbine type (Arnett & Baerwald, 2013; Behr et al., 2015).
The efficacy of these curtailments for protecting
bats and for generating wind energy improves when mul-
tiple environmental conditions are considered (Behr et al., 2017; Rabie et al., 2022; Whitby et al., 2021).

One method to estimate WT mortality rates is to search
for carcasses below the WT (Dürr, 2002; Smallwood, 2013;
Trapp et al., 2002). This approach facilitates the identifi-
cation of critical periods, for example, migration, and habi-
tats that correlate with high fatality rates of bats. Yet,
carcasses are often difficult to find because of impaired vis-
bility caused by local topography or vegetation, and also
because scavengers remove carcasses. Accordingly, experimen-
tal trials have to be conducted to account for search
inefficiency and carcass removal (Huso & Dalthorp, 2014;
Huso et al., 2016; Korner-Nievergelt et al., 2013; Simonis et al., 2018), which is labor-intensive and therefore costly.
A complementary approach is to monitor bats acoustically
at the nacelle of WT and then relate the acoustic activity
of bats to expected or observed fatality rates (Behr et al., 2015; Brinkmann et al., 2011; Peterson et al., 2021).
Recent studies confirmed that about 80% of variation in
carcass-based fatality estimates is explained by bat passes
recorded by automated ultrasonic detectors at the nacelle
of WT (Peterson et al., 2021). However, this approach may
be sensitive to biological and technical limitations of
acoustic monitoring at the nacelle of WT (Voigt et al., 2021)
and other factors, which might cause a weak or a complete lack of correlation between bat passes
recorded at the nacelle of turbines and estimated fatality
rates (Bach et al., 2020; Solick et al., 2020). However, it
should be noted that in some of these studies, it is unclear
whether acoustic activity was only measured at those
times when bats were at risk (Peterson et al., 2021).

In some Central European countries, such as
Germany, authorities request developers to monitor bat
activity with ultrasonic detectors at turbine nacelles dur-
ing the first 2 years postconstruction (Fritze et al., 2019).
During this time, turbines operate under a curtailment
scheme defined by authorities, for example, shifted cut-in
speed at night at around 6 m/s, at high ambient tempera-
tures, and mostly during the migration season of bats.
Based on the data from this monitoring period, turbine
operators may then adjust the curtailment scheme for the
successive operation period of the wind turbine after
approval from authorities. This curtailment scheme is
based on a predictive model in which the fatality rates
are extrapolated from a correlational dataset on bat
passes and fatality rates at WT from similar natural
regions (Behr et al., 2015; Brinkmann et al., 2011).
Accordingly, the acoustic monitoring at a given wind tur-
bine does not go along with carcass searches, which saves
time and money for the wind energy developer. Although
this approach is broadly efficient from both a monetary
and conservation perspective, it may be sensitive to dete-
riorating detection volumes of acoustic monitoring at
larger wind turbines (Voigt et al., 2021), and also to the
accuracy and precision of extrapolating patterns for wind
turbines of different types and sizes and across different
landscapes with varying bat assemblages. Since the effi-
ciency of implemented curtailments is rarely if ever con-
trolled, it remains unclear if algorithms prove to be
efficient in protecting bats from colliding with wind tur-
bines. However, some surveys suggest a relatively high
efficacy (Behr et al., 2015).

One of the assumptions for setting critical thresholds
based on acoustic monitoring is that the distribution of
bats within the rotor-swept area is predictable over time
for different types of turbines with different dimensions,
which may also be located in different landscapes, such
as open farmland or forests. This is a critical assumption
because acoustic monitoring at the nacelle of a turbine
covers a relatively small area of the total rotor-swept area,
particularly at new wind turbines with long blades or
when dealing with bat species echolocating at high ultra-
sonic frequencies (Voigt et al., 2021). Until now, the cur-
tailments are defined under the assumption that bats
approaching the turbine aggregate at the nacelle of tur-
bines (Behr et al., 2015). This assumption is violated
when bats concentrate in the periphery of the rotor-swept
area (circumference described by the blade tips) or when
more bats are active in the upper section of the rotor-
swept area than in the lower section or vice versa (Voigt et al., 2021). These different scenarios of spatial distribu-
tions are relevant for several reasons. For example, spa-
tial distributions of bats within the rotor-swept area may
vary between years in which acoustic monitoring is
conducted under a predefined curtailment regime, for example, no operation at all, and subsequent years when other curtailments are practiced (intra-site variation). Further, this scenario is relevant when spatial distributions vary across geographical areas (inter-site variation), because different species occur in the local assemblage of bats. For example, violations may occur when data from reference turbines at inland sites—where nonmigratory bats are suggested to aggregate at the nacelle (Behr et al., 2015)—are used to predict fatality rates at turbines at coastal sites, where migratory bats may show a different spatial distribution within the rotor-swept area.

Here, we asked how sensitive the predictive power of acoustic monitoring is for extrapolating the expected number of casualties when the density of bat passes within the rotor-swept area is variable. Additionally, we asked how sensitive this approach is when turbines vary in size, that is, in blade length, or when the recording of bats is impaired by reduced detection distances of high-frequency echolocating bats. We hypothesized that the predictive power of acoustic monitoring at the nacelle deteriorates when spatial distributions vary and when acoustic monitoring covers only a small part of the rotor-swept area, such as when blade length increases or when the detection distance of ultrasonic detectors is impaired by heavily attenuated high-frequency echolocation calls of bats (Voigt et al., 2021). The ultimate goal of our study is not to question acoustic surveys at wind turbines, but rather to improve the current practice of acoustic monitoring at WT by identifying relevant factors which might constrain the outcome. Ultimately, this should help to improve the predictive power of models based on acoustic information by integrating relevant additional parameters, such as the spatial distribution of bats. This is important because of two reasons: (1) novel turbines, particularly large-sized turbines, challenge previous surveying techniques, and (2) the global expansion of wind energy productions calls for standardized methods of acoustic monitoring in the light of different bat species affected by WT operations.

2 | MATERIALS AND METHODS

We simulated the number of bat passes (hereafter abbreviated as \( n_{\text{passes}} \)) based on several theoretical two-dimensional distribution patterns within the rotor-swept area (Figure 1). We acknowledge that while bats are killed within the two-dimensional rotor-swept zone, the detection space of ultrasonic detectors at the nacelle is three-dimensional. Here, we assume that the spatial patterns used in our model translate in a similar way to the...
three-dimensional space of the detection space. All distributions except the uniform scenario were generated with the `rpoint()` and `disc()` functions from the R package spatstat (Baddeley et al., 2015) by defining custom probability density functions.

We refer to a bat pass as a sequence of echolocation calls from a single bat recorded by an ultrasonic detector at the nacelle of a WT (see Table 1 for a complete list of variables and parameters used and Figure 2 for a scheme of our modeling approach). We estimated the number of detected bat passes (hereafter \( n_{\text{monitored}} \)) for the different spatial distributions and based on the proportion of the rotor-swept area covered by acoustic monitoring (\( \text{prop}_{\text{monitored}} \)). We assumed that the maximum area covered by acoustic monitoring equaled 50% of the rotor-swept area, since usually a single ultrasonic detector is used per wind turbine either on top or at the bottom of the nacelle. In Europe, ultrasonic detectors are most often installed at the bottom of nacelles, and therefore, detectors do not cover the upper 50% of the rotor-swept area, or if installed on top vice versa the lower 50%, specifically the acoustic shadow of the nacelle (Figure 3; Voigt et al., 2021). Further, we simplified our simulated spatial distributions by including the inner area of the risk zone encompassing the nacelle diameter. This area is also not covered by acoustic monitoring and bats might not be at risk in this area.

For this simulation, we assumed that the rotor-swept area is unitless. Accordingly, we used different numbers of bat passes to simulate rotor-swept areas of varying sizes. That said, it is important to remember that the number of bat passes may as well vary for a given rotor-swept area due to, for example, geographical and seasonal variation in bat activity. The relative area covered by acoustic monitoring \( \text{prop}_{\text{monitored}} \) may vary for several reasons such as the length of the blades, the call frequency of echolocating bats, the sensitivity of used ultrasonic detectors, and the approach angle of bats (Voigt et al., 2021).

We calculated the difference between the predicted number of bat passes (\( \text{n}_{\text{predicted}} = \frac{n_{\text{monitored}}}{\text{prop}_{\text{monitored}}} \)) and the true number of bat passes \( (n_{\text{passes}}) \) based on 200 repetitions (Figure 1). Importantly, for predicting the total number of bat passes based on \( n_{\text{monitored}} \), we assumed a homogeneous spatial distribution of bat passes, since the predictor is ignorant about the true spatial distribution. In our simulation, the proportion of the rotor-swept area monitored ranged from 5% (low coverage) to 50% (high coverage). The number of bat passes ranged from 100 to

| Variable name | Description | Realistic values | Model input |
|---------------|-------------|-----------------|-------------|
| radius_rotor  | Length of rotor blades | 33 m, 60 m | Constant as 1 |
| area_rotor    | Rotor-swept area | \( \pi \times \text{radius}_\text{rotor}^2 = 3.14 \) | |
| prop_monitored| Relative area covered by acoustic monitoring | 4% (high-frequency) 50% (low-frequency) | 5–50% in steps of 5% plus 4% |
| area_monitored| Area of acoustic monitoring | area_rotor \( \times \text{prop}_{\text{monitored}} \) | |
| radius_monitored| Radius to detect bat passes | \( \sqrt{\frac{\text{area}_{\text{monitored}}}{\pi}} \) | |
| n_passes      | Number of bat passes | 100–3200 | 100, 200, 400, 800, 1600, 3200 |
| distribution  | Circular distribution of bat passes | uniform random | inner > outer (2 levels) outer > inner (2 levels) bottom > top (2 levels) top > bottom (2 levels) |
| prop_fatality | Proportion of passes leading to fatal injuries | 1% of (estimated) bat passes | constant: 0.01 variable: N (0.01, 0.005) |
| n_monitored   | Number of bat passes within the monitored area | | |
| n_predicted   | Predicted number of bat passes extrapolated to the rotor-swept area | \( \text{n}_{\text{monitored}}/\text{prop}_{\text{monitored}} \) | |
| n_fatality    | Predicted number of bats that get fatally injured | \( \text{n}_{\text{predicted}} \times \text{prop}_{\text{fatality}} \) | |
3200, doubling at each step (100, 200, 400, 800, 1600, and 3200).

Furthermore, we estimated the number of fatalities \( (n_{\text{fatality}}) \) by assuming a rate with a mean 1% of bat passes leading to one fatality \((prop_{\text{fatality}})\) and a standard deviation of 0.005 \((N[0.01, 0.005])\) with negative values set to zero. We assumed that the spatial distribution of fatality events is uniform, that is, the probability for a collision with the blades is the same for all bat passes independent of the two-dimensional position of a virtual bat. Consequently, the spatial distribution of bat fatalities follows the spatial distribution of bat passes.

For illustration, we selected two contrasting scenarios to highlight the relevant effects of coverage by acoustic monitoring on the accuracy of predicted fatality rates (Voigt et al., 2021). The first scenario is based on an assumed coverage of 4% of the rotor-swept area, that is, mimicking a large wind turbine with a blade length of about 60 m and a bat calling at high frequencies (Figure 3). The second scenario is based on an assumed coverage of 50% of the rotor-swept area, simulating a small wind turbine (e.g., 30 m blade length) and/or a low frequency and loud calling bat such as an open-space foraging bat (Voigt et al., 2021; Figure 3).

We plotted the predicted fatality rates in relation to the predicted and observed number of bat passes. We compared the match between these two correlations using Wald \( t \)-test. We assumed a level of significance of 5% and used two-tailed testing. For the simulation and analysis, we used the statistical software of R (R Core team, 2021). Data were prepared and visualized with the tidyverse R package collection (Wickham et al., 2019).
and statistical tests were performed with the R package broom (Robinson et al., 2022).

3 | RESULTS

3.1 | Predicting bat passes based on acoustic monitoring at the nacelle of wind turbines

Our simulation shows that the number of bat passes—as estimated by acoustic monitoring at the nacelle—reflects accurately the true number of bat passes if the bats are uniformly or randomly distributed within the rotor-swept zone (Figure 4a,b). This was true for different numbers of bat passes and varying proportions of the rotor-swept area covered by the acoustic monitoring at the nacelle of WT. Further, the variance around mean values (indicated by the standard deviation in Figure 4) decreased with increasing total number of bat passes surveyed.

Deviations from a uniform or random spatial distribution of bat passes within the rotor-swept area yielded variable results (Figure 4b–j). An aggregation of bats around the nacelle (“inner” distribution; Figure 4c,d) led to an increasing overestimation of bat passes with decreasing proportion covered, whereas a density distribution where more bats were present in the lower than in the top section of the rotor-swept area (“bottom”; Figure 4g,h) led to an increasing overestimation of bat passes with increasing proportion covered. For the more skewed scenario (“bottom–strong” skew; Figure 4h), a high monitoring coverage caused an overestimation and a low coverage an underestimation of bat passes predicted for the total rotor-swept area.

Contrasting density patterns, that is, an aggregation of bats toward the edge of the rotor-swept area (“outer”; Figure 4e,f), and a distribution where more bats were present in the top than in the lower section (“top”; Figure 4i,j) led to an underestimation of bat passes. The extent of underestimation increased with increasing skewness and coverage of the nacelle monitoring (Figure 4e,i compared to Figure 4f,j). In general, the observed effects were stronger for distributions with higher skewness (referred to as “strong” in

Figure 3 Conceptual overview of the two hypothetical scenarios used for illustration of extreme situations: Low coverage scenario at large wind turbines and when encountering high-frequency echolocating bat species (top row) and high coverage scenario at small wind turbines and with low-frequency echolocating bat species (lower row). The number of bat passes depends on the blade length (the longer the blades, the more bat passes in the same time period) while both, the length of the rotor blades as well as the frequency of the bat calls determine the area covered by automated ultrasonic detectors (orange half circle; areas based on Voigt et al., 2021). Fatalities (indicated as X) are sampled as 1% of bat passes and distributed following the spatial distribution of bat passes within the rotor-swept area. Note that the exact location of fatalities, that is, inside or outside the monitored area, is irrelevant for the purpose of our evaluation.
In the following, we present results for the two focal scenarios related to the relative coverage of the acoustic monitoring in relation to the total rotor-swept area: (1) low coverage scenario caused by large rotors and high-frequency calling bats, or (2) high coverage scenario caused by small rotors and low-frequency calling bats (Figure 3). Both control distributions (“uniform”; Figure 5a; “random”; Figure 5b) showed no large deviation between predicted and true bat passes, yet the random distribution yielded for both scenarios a higher variance compared to the uniform distribution as indicated by the larger whiskers of box plots and the large variation of simulated data (Figure 5a,b). In general, over- and underestimation of predicted bat passes varied largely under the two coverage scenarios (low and high) and across the various spatial distributions, some yielding no deviations and others generating deviations of up to 250% on average (e.g., “inner–strong”, low coverage; Figure 5d). Accordingly, in a low coverage scenario and an inner distribution, 400 monitored bat passes will lead to an overestimate of on average 400 bat passes (1 × 400 bat passes) for a weak skewness (Figure 5c) and of 1.000 bat passes (2.5 × 400 bat passes) for a strong skewness (Figure 5d). For most other distributions, numbers of bat passes were underestimated (Figure 5 e,f,h,j), mostly for the high coverage scenarios (except for “bottom” distribution; Figure 5h,g). For the high-coverage scenario, the effects were less pronounced. For ‘bottom’ distributions, bat passes were overestimated by about 50% when weakly skewed (Figure 5g) and overestimated by 100% when strongly skewed (Figure 5h).

### 3.2 Relationship between simulated fatality rates and predicted bat passes

The relationship between simulated fatality rates and predicted bat passes did not deviate from those expected for the uniform and random spatial distributions (Table 2; Figure S3). Yet, most other conditions of spatial distributions and levels of skewness yielded strong deviations (Table 2, Figure S3). A few conditions resulted in a close match between predicted and observed bat passes and thus led to accurate predictions for fatality rates, such as the “bottom” distribution (weak skew) for 4% and 5% coverage, and the “inner” distribution (strong skew) for 45%...
coverage. In addition, when coverage of acoustic monitoring was maximal (50%), predicted bat passes matched with observed bat passes, and thus, simulated fatality rates were correct, for “inner” distribution (weak skew) and “outer” distributions (for both levels of skewness). Most scenarios resulted in a mismatch between predicted and observed bat passes, which resulted as a consequence in false fatality estimates.

For the low coverage scenario (4% of rotor-swept area) and high coverage scenario (50% of rotor-swept area), the number of predicted bat passes matched those of observed bat passes in case of a “uniform” or “random” spatial distribution of bat passes (Figures 6a,b and 7a,b; Table 2). It should be noted, however, that the variance of fatality rates was high.

For the low coverage scenario, predicted fatality rates were correct for a “bottom” distribution with weak skewness because the number of predicted bat passes fell close to the real scenario (Figure 6g). Predicted bat passes were underestimated for the given fatality rates in case of “inner” distributions (both levels of skewness). In contrast, predicted bat passes were underestimated in case of “outer” and “top” distribution (both levels of skewness; Figure 6e,f,i,j) and “bottom” distribution for the given fatality rates (strong skewness; Figure 6h, Table 2). Predicting fatality rates based on underestimated bat passes, for example, “outer” distribution, will yield an overly high number of assumed casualties at wind turbines, while predicting fatality rates based on overestimated bat passes, for example, “inner” distribution, will lead to an underestimation of casualties.

For the high coverage scenario, predicted fatality rates were correct for the “uniform,” “random,” and “outer” distributions (both levels of skewness) and for the “inner” distribution (weak skewness). Predicted bat passes were underestimated for the given fatality rates in case of the “top” distribution (both levels of skewness), while they were overestimated for given fatality rates for the “bottom” distribution (both levels of skewness). Accordingly, underestimated bat passes will lead to overly high estimates of casualties, whereas overestimated bat passes will lead to underestimates of casualties.
4 | DISCUSSION

We asked how sensitive the predictive power of acoustic monitoring is for extrapolating the expected number of bat casualties at wind turbines when the spatial distribution of bat passes within the rotor-swept area is unknown. In particular, we were interested to shed light on the question how sensitive the extrapolation is when...
turbines vary in size, that is, in rotor diameter, or when the recording of bats is impaired by limited detection distances (Voigt et al., 2021). We confirmed that the power of predicting the exact number of bat passes based on acoustic surveys, and also the true number of fatalities, is high for uniform or random distributions of bat passes in the rotor-swept area. Also, we observed that a high coverage of acoustic monitoring of the total rotor-swept area improved the predictive power of models. However, we noted that even a high coverage, that is, a relatively large proportion of the rotor-swept area covered by acoustic monitoring, may lead to overestimates of bat activities in the rotor-swept area, for example, when bat passes occur at the bottom of the rotor-swept area, or underestimates of bat activity, for example, when bat passes occur mostly at the top of the rotor-swept area. The strength of observed effects varied with the skewness in the nonuniform/nonrandom distributions.

Our focal scenarios of low (4% of rotor-swept area covered) and high coverage (50%) illustrated interesting patterns. For example, in the low coverage scenario extrapolating fatality rates based on underestimated bat passes, for example, “inner” distribution, will lead to an underestimate of casualty numbers. This highlights how sensitive the acoustic monitoring is for predicting total bat passes and exact casualty numbers in the absence of information on the spatial distribution of bats. We derive two important conclusions from this: An underestimated number of fatality rates, for example, in case of a concentration of bat passes at the circumference of the rotor-swept area may generate poor curtailment schemes. Specifically, applied curtailments may be not strict enough to protect bats within the rotor-swept area because the presence of bats is underestimated. Second, an overestimate in the number of fatality rates may involve overly strict curtailments, which may protect bats efficiently but may come at the cost of significant reductions of the energy yield of wind turbines, and thus involve monetary losses for the wind energy company. Both scenarios are undesired considering that the protection of bats at wind turbines and the contribution of wind to renewable energy production is equally important.

We envisage that the easiest solution to solve this problem is to ground-truth fatality rates by carcass searches or establish a solid knowledge about what factors may cause spatial distributions of bats within the rotor-swept area to deviate from a uniform or random distribution (Cryan et al., 2014; Goldenberg et al., 2021; Hochradel et al., 2015).

**FIGURE 7** Individual simulation outcomes are shown for the high coverage scenario and spatial distribution patterns as opaque points with predicted bat passes on the x-axis and predicted fatality rates on the y-axis. The red line gives the correlation. The gray dashed line denotes the true correlation between bat passes and fatality rates. Fatalities were simulated as 1% of all bat passes with a standard deviation of 0.005 (scattering along the y-axis). The clustering of observations (scattering along the x-axis) is the result of the varying number of simulated bat passes.
Unfortunately, our current understanding of the spatial distribution of bats within the rotor-swept area is limited to a few qualitative studies. For example, Cryan and colleagues quantified the flight behavior of bats at three wind turbines (82 m rotor diameter, 41 m blade length) in the US with thermal imaging. They reported that 30% of bats approached the turbine nacelle, 13% of bats the monopole, and 6% of bats the blades, suggesting a concentration of bats around the nacelle ("inner" distribution in our simulation; Cryan et al., 2014). However, the field of view (55 m × 40 m = 2200 m²) covered less than 50% of the total rotor-swept area (5278 m²), which prevents an accurate representation of the spatial distribution of bats around the wind turbines. A second thermal imaging survey showed similar trends for four wind turbines (70 m rotor diameter, 35 m blade length) in Germany (Hochradel et al., 2015), which also suggests an aggregation effect of bats around the turbine nacelle, most likely because of bats inspecting the nacelle structure. However, Hochradel and colleagues were unable to monitor the top half of the rotor-swept area so that it is impossible to draw a comprehensive picture of the spatial distribution of bats in the rotor-swept area. A third study by Goldenberg et al. (2021) at one wind turbine (77 m rotor diameter, 38.5 blade length) showed a higher activity at the monopole (~50%) and similar levels of approaches to the nacelle and blade (15% and 11%, respectively) as well as nonfocal passes (17%). The authors also showed seasonal and nightly changes in activities, which is also confirmed by studies with other surveying techniques (e.g., Goldenberg et al., 2021; Mântoiu et al., 2020; Peterson et al., 2021; Roemer et al., 2019; Wellig et al., 2018). In all studies with videogrammetry, the number of wind turbines and the number of nights surveyed were severely limited due to the time-consuming analysis of the video material. Further, the focal wind turbines do not necessarily reflect the size of turbines (>120 m rotor diameter, >60 m blade length) which are currently installed. At this stage, the lack of more quantitative and thus more representative studies prevents us from drawing larger inferences on the spatial distribution of bats in the risk zone of WT. We recommend establishing a more comprehensive knowledge of what factors may influence the spatial distribution of bats within the rotor-swept area. This knowledge is an important addition to the valuable information obtained from automated ultrasonic detectors that record the acoustic activity of bats within the rotor-swept zone.

4.1 Assumptions of our simulation

The interaction of bats with wind turbines is complex and this complexity is difficult to take into account in simplified models. Our simulation was based on several assumptions that we will evaluate in the following. We explicitly chose to use bat passes and not echolocation calls of individual bats as a proxy for the presence of bats. Usually, the acoustic monitoring at turbine nacelles records echolocation calls and it is the expert deciding on whether to use the sequence of echolocation calls or each echolocation call as a relevant parameter to predict the activity of bats at WT. Under a real-world scenario, recorded echolocation calls emitted by a bat would have to be considered as a sequence to avoid pseudo-replication. Second, we set the fatality rate to be fixed at 1% of bat passes (one casualty for every 100 bat passes). We assume that fatality rates at wind turbines will vary considerably under real conditions. For example, the likelihood of bats to interact with WT may vary with the location of WT, season, and type of WT. Possibly, certain spatial positions of bats within the rotor-swept area may be associated with an increased fatality rate. Third, our simulation is based on the assumption that fatality events follow the spatial distribution of bats, which might not be the case under real-world conditions (see above). For example, it is possible, yet unproven that collisions may happen close to the fast-moving tips of blades, since these structures may inflict a lethal impact even at slow rotation speed. A concentration of bats at the nacelle, as suggested in previous studies (Cryan et al., 2014; Goldenberg et al., 2021; Hochradel et al., 2015), might correlate with a lower fatality rate than a concentration of bats at the edge of the area swept by the rotor. It is important to note here that we calculated the risk zone for bats as the rotor-swept area without subtracting the inner radius of the nacelle where fatality events are unlikely to happen. Unfortunately, we are lacking quantitative data on where exactly bats collide and die at wind turbines. Therefore, it is conservative to assume that fatality events follow spatially the distribution of bats within the rotor-swept area. Fourth, our simulation builds on a simplified behavior of an assumed high collision risk species. However, high collision risk species differ in their flight behavior. For example, open-space foraging bats, such as common noctule bats (Nyctalus noctula), use low-frequency echolocation calls and forage mostly beyond vegetation structures, whereas edge-space foraging bats, such as Nathusius’ pipistrelles (Pipistrellus nathusii), use high-frequency echolocation calls and orientate along edge structures (Denzinger & Schnitzler, 2013; Roemer et al., 2017; Wellig et al., 2018). Members of these two guilds may interact with WT differently and their presence at wind turbines is covered differently with ultrasonic detectors (Voigt et al., 2021). This may be problematic if data from a reference WT is used where, for example, an open-space foraging species is most abundant to predict the
fatality rates at another WT where an edge-space foraging bat is most abundant. Open-space foraging bats tend to be also larger and better able to cope with strong winds compared to species of other guilds. For example, migratory common noctule bats (*Nyctalus noctula*) flew relatively high and in a range of airspeeds (7.2–15.9 m/s; O’Mara et al., 2019), at which smaller migratory bats, such as Nathusius’ pipistrelles (*Pipistrellus nathusii*) decrease their flight activity (Voigt et al., 2018). Data from reference wind turbines sites with, for example, predominantly low airspeeds may not be useful in predicting fatality rates at unsurveyed wind turbines where strong winds are prevailing, for example, at coastal sites.

5 | CONCLUSIONS

We infer from our simulation that the predictive power of acoustic monitoring is sensitive to variation in the spatial distribution of bats. Unaccounted variation in the spatial distribution of bats within the rotor-swept zone may impair extrapolations of relationships between fatality rates and acoustic data across turbines of different sizes and types, and also across different locations, for example, from inland areas to coastal areas, or open farmland to forest sites. The strength of the effect is largely defined by the skewness in the spatial distribution of bats and by the relative area of the risk zone covered by the acoustic monitoring. We call for more detailed studies investigating the factors influencing the spatial distribution of bats around WT. Also, we consider validating the efficacy of mitigation measures as mandatory when based on an extrapolative approach. Further, algorithms developed to mitigate the number of bat casualties at wind turbines should be made transparent and raw data made accessible to better understand how to improve curtailment procedures, both from an energy generation and conservation perspective.

AUTHOR CONTRIBUTIONS

Christian C. Voigt and Volker Runkel conceived the idea. Cedric Scherer designed the simulation, analysis, and visualizations. Christian C. Voigt led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST

Volker Runkel declares to own a company producing ultrasonic detectors that are used for monitoring bats at wind turbines. The authors are not aware of competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

DATA AVAILABILITY STATEMENT

Data and codes are accessible at: https://github.com/z3tt/TurbineCollisionDetection.

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**SUPPORTING INFORMATION**

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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