Flight characteristics forecast entry by eagles into rotor-swept zones of wind turbines

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Operators of wind power facilities can mitigate wildlife mortality by slowing or stopping wind turbines (hereafter ‘curtail’) when birds are at an increased risk of collision. Some facility operators curtail when individual birds have flight characteristics (e.g. altitude, distance or relative bearing of a bird’s flight path) that exceed some threshold value, but thresholds currently in use have not been empirically evaluated. Overly restrictive thresholds can cause turbine curtailment for birds that never enter rotor-swept zones, thereby resulting in excess power loss. We evaluated the probability that birds, specifically eagles, entered the rotor-swept zone (hereafter ‘entry probability’) in response to their flight characteristics. We used an automated monitoring system to classify individuals as eagles or non-eagles and record flight paths of purported eagles at a wind facility in Wyoming, USA. We used logistic regression with occupancy dynamics and a distance-dependent colonization process to model entry probability. As a result, this model allowed entry probability to decrease with horizontal distance to the nearest turbine. The probability of entry varied with distance to the nearest turbine and approached zero when that distance was more than 202 m. Entry probability peaked when eagles flew 89 m above ground, corresponding to hub heights of turbines (80 m), and decreased to near-zero at altitudes of 189 m or more. Entry probabilities were greatest when flight paths were near the rotor-swept zone and when eagles flew slowly toward the nearest turbine. Compass bearing of a flight path was not associated with entry probability. Our model accurately forecasted entry probability in Wyoming (area under the curve (AUC) = 0.96) and was transferable to another facility in California, USA (AUC = 0.97); therefore, our results may be applicable across a variety of settings. Curtailment criteria can be based on flight path characteristics to forecast entry into rotor-swept zones. The use of distance and altitude thresholds when making curtailment decisions is justified. However, this analysis suggests alteration of the time to collision threshold, with curtailment initiated at greater distances as the speed of the bird decreases. Our novel modelling method and our results can inform curtailment criteria in any situation where curtailment decisions are made in real-time.

Keywords: curtailment, eagle, rotor-swept zone, wildlife collision, wind energy, wind turbine.

Wind power provides renewable energy, yet wind turbines may negatively impact wildlife (Kunz et al. 2007, Loss et al. 2013). Informed curtailment of turbines (Allison et al. 2017) is a
promising technique that attempts to minimize wildlife collisions by slowing or stopping wind turbines while animals are at risk of collision (BirdLife International 2015, Allison et al. 2017). Informed curtailment coupled with automated monitoring systems could be effective at reducing collisions because these monitoring systems are capable of detecting more birds compared with human observers (McClure et al. 2018).

Developing techniques to minimize wildlife fatalities and maximize energy production at wind facilities is a research priority (Marques et al. 2014). This is particularly true for eagles (i.e. Bald and Golden Eagles, Haliaeetus leucocephalus and Aquila chrysaetos, respectively), because collision (with wind turbines but also with vehicles and powerlines) is an important anthropogenic constraint on some of their populations (Millsap et al. 2022). Implementing informed curtailment for eagles with an automated monitoring system has decreased fatalities at Top of the World Wind Power Facility (hereafter TW), but also substantially increased the number of curtailments (McClure et al. 2021b). Of more than 10 000 instances of eagles approaching within 150 m of a wind turbine and thus triggering curtailment at TW, roughly 70% were unnecessary because the eagle never entered the rotor-swept zone (McClure et al. 2021a). These additional curtailments result in less energy production and less revenue for turbine operators; therefore, decreasing the number of unnecessary curtailments is of considerable interest.

Some automated monitoring systems used for informed curtailment can categorize and track flying birds in three-dimensional space. Once a bird is tracked, it can be difficult to forecast the probability that it will enter the rotor-swept zone and be at risk of collision. Balancing collision risk with power generation therefore presents challenges. At TW, the original curtailment prescription assumed that entry into rotor-swept zones could be predicted using distance, altitude and relative bearing of an eagle’s flight path. However, this assumption has not been formally tested and the large number of unnecessary curtailments (McClure et al. 2021a) suggests that models of entry probability could be refined. Here, we developed a modelling framework to identify features of flight paths that best predict entry into the rotor-swept zone, as a tool to inform and improve curtailment prescriptions. To illustrate the utility of our framework, we subsequently applied it to eagle track data collected by an identical monitoring system at a different location.

**METHODS**

**Study sites**

Top of the World Wind Power Facility is located in Converse County, Wyoming, USA, and is operated by Duke Energy Renewables. The facility contains 44 Siemens 2.3-MW, 101-m rotor diameter wind turbines and 66 General Electric 1.5-MW, 77-m rotor diameter turbines (the facility is mapped in fig. 1 of McClure et al. 2021a). Both models of turbines have hub heights of 80 m above ground. During our study, 47 IdentiFlight (IdentiFlight International, Louisville, CO, USA) units were deployed throughout TW in a configuration that provides visual coverage for all turbines (see fig. 1 in McClure et al. 2021b). At TW, IdentiFlight units collected data from 18 May 2018 to 31 March 2019. Both Bald and Golden Eagles occur at TW, although Golden Eagles are substantially more abundant.

The Manzana Wind Power Project (Manzana) is operated by Avangrid Renewables and contains 126 General Electric 1.5-MW, 77-m rotor diameter turbines with hub heights of 65 m. Two IdentiFlight units were commissioned in June 2018 at this site providing at least partial coverage for 21 turbines. At Manzana, IdentiFlight units collected data from 1 June 2018 to 28 March 2020. Manzana is located in Kern County, California, USA. Bald Eagles rarely, if ever, occur at Manzana.

**Automated monitoring system and curtailment**

An IdentiFlight unit included eight cameras arranged in an outward-facing ring directly beneath a stereoscopic camera and mounted on a single pan and tilt unit, and these components were connected to a computer system. IdentiFlight units were placed on towers approximately 10-m tall. Computer vision software used the ring of cameras to detect moving objects, then aimed stereoscopic cameras toward moving objects and recorded tracked movements in three-dimensional space. The IdentiFlight system identified objects as eagles or non-eagles using a
classification algorithm. Hereafter, we refer to birds classified as eagles simply as ‘eagles’. Eagles are particularly managed at TW because they are protected in the USA by law (Bald and Golden Eagle Protection Act 1940). Curtailments are not ordered for birds classified as non-eagles. Past work at TW demonstrated that IdentiFlight detects more than 500% more birds compared with human observers, and when classifying eagles has a false-negative rate of 6% and a false-positive rate of 28% (McClure et al. 2018). The median distance from an IdentiFlight unit of birds classified as eagles was 793 m (McClure et al. 2018). Recordings consisted of images and associated data (e.g. flight path attributes) collected at 1-s intervals. See McClure et al. (2018, 2021a) for more details of the classification algorithm, visual coverage, curtailment prescription, accuracy of IdentiFlight and flight path attributes.

Curtailment of turbines at TW was always ordered when IdentiFlight estimated eagle locations to be within an imaginary cylinder surrounding a turbine (see fig. 2 in McClure et al. 2021a); however, the size of this cylinder varied during data collection for our study. Initially, this cylinder was set to a 200-m height and 200-m radius from turbines, but the radius was reduced to 150 m in August 2018. For eagles detected beyond the cylinder, other criteria including distance to turbine, time to collision, an eagle’s relative bearing in relation to turbines and confidence that the bird was an eagle were used to determine whether curtailment was implemented. Once curtailment is ordered, the time until turbine blades completely stop ranges from 20 s to 1 min.

**Occupancy data and explanatory variables**

We used IdentiFlight data collected at TW from 18 May 2018 to 31 March 2019 (Data S1). Hereafter, we used the term ‘flight path’ to describe a continuously monitored movement path of an eagle through the study area. We used the term ‘segment’ to describe discrete segments of flight paths that we binned into 5-s time intervals. We used spatial data of flight paths collected by IdentiFlight units to determine whether segments had entered the ‘rotor-swept zone’. We defined the rotor-swept zone as an imaginary three-dimensional cylinder centred on the turbine, with a radius that corresponded to the size of the Siemens turbine blades (50.5 m) and a height of 130.5 m, extending from 29.5 m above the ground.

We examined only those flight path data within 1000 m of any rotor-swept zone that eventually caused curtailment of turbines. We omitted data that suggested instrument or estimation error, usually when there were improbable values for flight speed. With a monitoring system such as IdentiFlight, extremely large estimates of speed can result from small errors in location estimates of birds that are monitored over very short time steps; therefore, we assumed speed was improbable when it was greater than that of a Peregrine Falcon in a stoop (> 88.9 m s⁻¹, White et al. 2020). Following this protocol, we omitted 6490 of 385 811 data entries at TW and 3202 of 275 499 data entries at Manzana. Additionally, we excluded data when flight paths lingered for abnormally long periods (> 1260 s), omitting 119 data entries at TW and zero data entries at Manzana. Omitting these entries reduced the size of data matrices because the vast majority of these data (a matrix having dimensions of the number of flight paths by the number of segments) included missing values for the segments of other flight paths. These missing values represented segments after an eagle had moved beyond the range of detection by IdentiFlight. We also omitted data for flight paths less than 10 s in duration (1909 of 15 328 flight paths at TW and 2340 of 11 778 flight paths at Manzana) because entry into the rotor-swept zone (i.e. colonization) cannot be estimated without at least two consecutive segments.

We calculated occupancy (i.e. whether or not a purported eagle occupied the rotor-swept zone) for each 5-s segment as whether an eagle occupied the rotor-swept zone during that segment. Binning at 5-s time intervals allowed us to improve computational efficiency. Occupancy data were a matrix \( z_{i,t} \) with each row representing a flight path \( i \) and each column representing a 5-s time step \( t \). When the 5-s segment of a flight path occupied the rotor-swept zone, \( z_{i,t} = 1 \), otherwise \( z_{i,t} = 0 \).

We included a total of five explanatory variables (Table 1) as covariates in models, each averaged over a single 5-s segment. Two of these were the flight altitude (ALTITUDE) and horizontal speed (SPEED) of the eagles. IdentiFlight calculated values for ALTITUDE as ‘height above ground’, and IdentiFlight provided spatial locations of eagles used to calculate SPEED.
We decomposed relative and compass bearings for regression using standard methods for including circular data as explanatory variables (e.g. pp. 709–711, Crawley, 2007). We decomposed the relative bearing of flight segments toward the nearest turbine monopole into one explanatory variable (hereafter APPROACH). APPROACH was a continuous variable that measured how much an eagle was flying toward the nearest turbine in two-dimensional space (Fig. 1) as follows. To calculate APPROACH, a flight segment can be viewed from above and assigned a relative bearing of zero degrees to the nearest turbine monopole. We then calculated the relative bearing of each flight segment in relation to that turbine monopole (0–359°). We converted the relative bearing from degrees to radians (0–2π) and calculated APPROACH as the cosine of these radians. When an eagle’s flight segment was directed perfectly toward the nearest turbine monopole, regardless of compass direction or the orientation of the turbine blades, APPROACH equaled 1, the maximum possible value. When an eagle’s flight segment was perfectly away from the nearest turbine monopole, APPROACH equaled −1, the minimum possible value. APPROACH equaled 0 when an eagle flew directly tangential to the turbine monopole.

We decomposed the compass bearing of flight paths into two components (NORTH and EAST) for inclusion as covariates in models. We calculated NORTH from the compass bearing of eagle flight paths relative to north, in radians, where NORTH was the cosine of the compass bearing. NORTH indicated how much a flight path was directed northward (NORTH = 1 as the maximum value) or southward (NORTH = −1 as the minimum value). We calculated EAST from the compass bearing of eagle flight segments relative to north, in radians, where EAST was the sine of the compass bearing. EAST indicated how much a flight path was directed eastward (EAST = 1 as the maximum value) or westward (EAST = −1 as the minimum value).

**Modelling framework**

Our primary modelling objective was to use flight characteristics from observed 5-s flight segments to forecast the probability that eagles would enter the rotor-swept zone during subsequent segments. Our modelling framework combined a hierarchical logistic regression with occupancy dynamics and a distance-dependent colonization process (e.g. Sutherland *et al.* 2014, Chandler *et al.* 2015).

We began with the occupancy data that described whether each flight segment of eagles occupied the rotor-swept zone. Occupancy of the rotor-swept zone was serially autocorrelated within the flight paths of individuals. That is, the time series data of occupancy within each flight path...
were dependent on previous occupancy states. Generalized linear models require independent data for robust inference (Breslow 1996), and autocorrelation within time series data violates this assumption (Cochrane & Orcutt 1949). To account for autocorrelation between time steps, we used a first-order Markov process, where occupancy dynamics enabled each occupancy state to be autoregressive and dependent on the previous occupancy state, thereby explicitly accounting for serial autocorrelation.

We estimated the probability that segments within a given path would enter the rotor-swept zone by combining a hierarchical logistic regression with occupancy dynamics (MacKenzie et al. 2003, Royle & Kéry 2007). Occupancy dynamics for the logistic regression model included parameters describing the probabilities of ‘colonization’ and ‘persistence’. This colonization process is equivalent to the probability that an eagle will enter the rotor-swept zone, because when the rotor-swept zone of a turbine is unoccupied by an eagle, the site will either remain unoccupied or the site will become occupied (i.e. colonized) during the subsequent time step. Therefore, our focal parameter, the probability of an eagle entering the rotor-swept zone (hereafter the entry probability), can be estimated as the probability of site colonization using occupancy dynamics (MacKenzie et al. 2003). Persistence is the probability that an eagle will continue to occupy the rotor-swept zone after entry during the next segment.

We allowed the entry probability to decrease with greater distances from the rotor-swept zone. Briefly, if we assume equal conditions, eagles that are near turbines will have a greater entry probability compared with those that are farther away. That is, colonization of the rotor-swept zone is more likely if the animal is closer to the turbine. Distance could also be useful for refining

Figure 1. An overhead two-dimensional map depicting the relative bearing of an eagle’s flight path in relation to the nearest turbine. Relative bearing was converted into a covariate (APPROACH) for use in hierarchical logistic regression models with occupancy dynamics. An eagle flying directly toward the nearest turbine monopole had a relative bearing equal to zero degrees, which converts to an APPROACH equal to 1, whereas an eagle flying directly away from the nearest turbine monopole had a relative bearing equal to −1. Grey dashed arrows depict axes for hypothetical flight path vectors while grey text specifies relative bearing, covariate values and equations used for calculations. APPROACH varied along the vertical y-axis in this depiction.
curtailment, because curtailment criteria included measures of distance from an eagle to the rotor-swept zone (see the Automated monitoring system and curtailment section). When an eagle entered the rotor-swept zone it could persist or leave the rotor-swept zone and this model parameter, the probability of persistence, accounted for additional autocorrelation. Although persistence provides important information that could inform the cessation of curtailment, persistence was of lesser interest to our study because we focused on when flight paths triggered curtailment.

Model formulation

The model estimated initial occupancy during \( t = 1 \) as \( z_{i1} \) Bernoulli\((\psi)\) where the model-estimated parameter \( \psi \) was the mean probability that a flight segment occupied the rotor-swept zone during the first 5-s time step. The maximum duration \((T)\) of observation for each flight path was a vector, and we input these data into the model to account for differing numbers of segments for each flight path. Occupancy during subsequent time segments \( t = \{2, 3, \ldots T_i\} \) was dependent on model-estimated dynamics that included the entry probability (i.e. probability of colonization \( \gamma \), our focal parameter), the probability of remaining occupied after entry (i.e. probability of persistence \( \phi \)) and the previous discrete occupancy state \((z_{i,t-1}, \text{Royle and Kéry 2007})\) of a flight path as a first-order Markov process.

\[
\begin{align*}
z_{i,t} \mid z_{i,t-1} & \text{ Bernoulli}(\gamma_{i,t-1}(1-z_{i,t-1}) + \phi z_{i,t-1}) \\
& (1)
\end{align*}
\]

To account for the effect from proximity of a flight segment to the rotor-swept zone on the entry probability, we specified the future entry probability as a function of minimum Euclidean distance \((x_{i,t-1})\) to the nearest turbine for each segment of a flight path during the previous time step. We used a Gaussian kernel to specify the decrease in entry probability with greater distance (Clobert et al. 2012) because it describes a gradual and monotonic decrease in dispersal probability with distance. This Gaussian kernel was similar to a normal distribution truncated at zero to exclude negative numbers, where \( \rho \) described the apex entry probability at zero distance, also termed the y-intercept. The distance scale parameter \((\sigma_D)\) was analogous to the error term of a zero-truncated normal distribution and described the flatness of the decrease in the entry (i.e. small values decrease steeply and large values are relatively flat) probability with greater distance.

\[
\gamma_{i,t-1} = \rho_{i,t-1}e^{-x_{i,t-1}^2/\sigma_D^2}
\]

We included covariates for the distance scale parameter by constraining it to an estimated mean \((\delta_0)\) and some number of covariates and their interactions \((N = 3\) here). \( A \) was a matrix of covariates and their interactions during the previous time step \((t-1)\) expressed as

\[
\log(\sigma_{D,i,t-1}) = \log(\delta_0) + \sum_{j=1}^{N}\delta_{1,N}A.
\]

The global model included the covariates SPEED and APPROACH from the previous segment, and an interaction between the two.

The y-intercept included the aforementioned covariates that were also included as covariates for the distance scale parameter. Additionally, we included ALTITUDE and ALTITUDE SQUARED from the previous segment as explanatory variables to allow a quadratic response by the entry probability. We also included the covariates NORTH and EAST and their interaction, thereby including a total of eight covariates \((L = 8)\). \( B \) was a matrix of these covariates and their interactions during the previous time step \((t-1)\). The y-intercept was specified as

\[
\logit(\rho_{i,t-1}) = \beta_0 + \sum_{j=1}^{L}\beta_{1,j}B + c_{i,t-1} + \eta_{i,t}.
\]

We included a random intercept \((c)\) that allowed entry probability to vary by turbine to account for differences among turbines that could be caused by landscape position or numerous other factors: \( c_{i,t-1}\text{Normal(mean} = 0, \text{sd} = \sigma_C)\). We included an additional random intercept \((\eta_{i,t})\) to account for seasonal differences by month: \( \eta_{i,t}\text{Normal(mean} = 0, \text{sd} = \sigma_M)\) that have been previously documented (McClure et al. 2021a).

Interpretation of modelled parameters

Interpretation of model parameters requires some nuance. The y-intercept \((\rho)\) is the probability that an eagle will enter the rotor-swept zone when distance nears zero during the previous segment. Hereafter, we refer to the mean y-intercept \((\beta_0)\) as
‘apex entry’, because it represents the greatest entry probability while ignoring random effects for turbine. Covariates affect the entry probability through their relationship with apex entry or the distance scale parameter \((\sigma_D)\) of the Gaussian distance kernel. Hereafter, we refer to the mean intercept \((\delta_0)\) of the distance scale parameter as ‘flatness’, because this parameter is inversely related to the slope of decrease. Flatness values were constrained by priors to have values between zero and 3000, and the entry probability decreased steeply with greater distance when flatness values were small (e.g. 0–100). Conversely, the entry probability decreased more gradually with distance when flatness values were greater (e.g. 500–3000).

Model implementation

We used R (R Core Team 2021) with the NIMBLE package (NIMBLE Development Team 2019) to implement Bayesian Markov chain Monte Carlo methods and estimate model parameters. We archived code for model implementation online at https://github.com/The-Peregrine-Fund/IdentifiFlight-flight-paths. We used three chains with 25 000 burn-in iterations and 25 000 posterior iterations with a thinning interval of 25 iterations, resulting in a posterior distribution that contained 1000 iterations from each chain, thereby obtaining a total of 3000 posterior draws. We assessed convergence of chains using traceplots and the Gelman–Rubin diagnostic (R, Gelman & Rubin 1992), and we assigned adequate convergence when traceplots of parameters did not visually appear to drift and \(R \geq 1.1\).

We implemented the global model that included all covariates considered and designated covariates to be important when 95% credible intervals did not intersect zero. For the quadratic term \((\text{ALTITUDE}^2)\) and interactions, we considered covariates important when 95% credible intervals of the highest order polynomial excluded zero (p. 453, Zar 1999). We implemented a final reduced covariate model that only retained important covariates so that we could assess the predictive accuracy of occupancy estimates using cross-validation.

Model validation

We randomly sampled data by flight path at TW to implement 10-fold cross-validation (Bergmeir et al. 2018) and assess the predictive accuracy of occupancy estimates from models using R and the ROCR package (Sing et al. 2005). We chose this approach because cross-validation is a robust model selection technique for time series (Bergmeir & Benítez 2012). We blocked data by flight path to allow predictive accuracy measures to correspond to flight paths that were tracked for more than one segment, and we used occupancy data from the first segment to predict subsequent occupancy of segments within a flight path (Bergmeir & Benítez 2012).

We estimated the average true-positive rates and average false-positive rates for occupancy of the rotor-swept zone. We plotted these rates using receiver operator characteristic (ROC) curves and used the area under those curves (hereafter AUC) as assessments of predictive accuracy. We considered AUC values greater than 0.7 as useful, greater than 0.8 as good and greater than 0.9 as excellent for prediction (Pearce & Ferrier 2000). For each of the folds (10 total), we used 90% of flight paths as training data and 10% as test data. Our study is primarily focused on forecasting entry probability after an eagle’s path was detected so that curtailment could be made in response to flight characteristics; therefore, we did not assess the predictive accuracy of the model for occupancy during the first 5-s time step \((t = 1)\) of each flight path.

We also tested the transferability of the model from TW by estimating predictive accuracy at a new site, Manzana, using 10-fold cross-validation. We trained models by inputting data from TW. We used parameter estimates from these models to predict the probabilities of entry at Manzana while using flight characteristics from Manzana as covariates. We compared these model predictions with observed occupancy of the rotor-swept zone at Manzana. Otherwise, we used identical methods to those described above.

RESULTS

After filtering for incomplete or improbable covariate data at TW, we retained data that included 13 419 flight paths, of which 2364 (18%) entered the rotor-swept zone. IdentiFlight recorded a mean of 7.1 segments (median=5, range=2–248) for each retained flight path. In total, flight paths included 95 182 segments for analysis, of which 5828 (16%) occupied the rotor-swept zone. Segments of eagle flight paths entered the rotor-swept zone...
1457 times; persisted within the three-dimensional cylinders representing rotor-swept zones 3105 times; and occupied the rotor-swept zone during the first segment 870 times.

Model diagnostics indicated good convergence among chains for all parameters except the random intercept for month \( (\eta_i) \); therefore, we omitted this parameter during analyses. Overall, the mean entry probability into the rotor-swept zone for a flight segment was influenced by an eagle’s flight altitude (ALTITUDE and ALTITUDE\(^2\)), flight speed (SPEED) and relative bearing (APPROACH) in the previous segment. However, compass directions of flight (i.e. NORTH and EAST) were not important predictors of entry into the rotor-swept zone.

Flight altitude of eagles had a quadratic relationship with the entry probability and influenced apex entry (the \( y \)-intercept). When an eagle was flying at average speed near the rotor-swept zone with a relative bearing toward a turbine, the mean entry probability by eagles increased as flight altitude increased, peaking at 0.18 at altitudes of 89 m, then decreased to near zero (mean entry probability \( \leq 0.01 \)) when altitudes were 189 m or more (Fig. 2a, Table 2).

An eagle’s relative bearing (Fig. 2b, Table 2) and flight speed (Fig. 2b, Table 2) interacted to influence apex entry (the \( y \)-intercept). This resulted in large mean entry probabilities for slow flying eagles, and low probabilities of entry for fast flying eagles. The greatest mean entry probabilities corresponded with eagles that flew slowly (i.e. slow SPEED) and directly toward the nearest turbine (i.e. greater APPROACH), and the entry probabilities decreased with greater distance from the rotor-swept zone nearing zero (mean entry probability \( \leq 0.01 \)) after 202 m. The lowest mean probabilities of entry corresponded with eagles that flew fast and had relative bearings directed toward the nearest turbine (i.e. greater APPROACH); all probabilities in this scenario were 0.01 or less. Notably, the interaction between APPROACH and SPEED resulted in low

![Figure 2](image-url)

*Figure 2.* Predicted mean entry probabilities for eagles during one future time step (5-s intervals) from logistic regression models with occupancy dynamics and distance-dependent entry into the rotor-swept zone applied to data from Top of the World, Wyoming, USA. Important predictors are depicted for the eagle flight characteristics: (a) a quadratic effect of altitude (ALTITUDE) on apex entry (\( \rho \), the \( y \)-intercept); and (b) an interaction effect between speed (SPEED) and relative bearing to a turbine (APPROACH) on entry with respect to distance from the eagle to turbine (derived from \( \sigma_D \), the distance scale parameter). Shaded polygons depict predicted 95% credible intervals. ‘Lesser’ and ‘slower’ correspond to 2.5 centiles, while ‘greater’ and ‘faster’ correspond to 97.5 centiles of APPROACH (\(-0.98 \) and \(0.96 \)) and SPEED (\(1.47 \) and \(40.69 \text{ m s}^{-1}\)), respectively. In (b), ALTITUDE was set to the maximum entry probability (i.e. ALTITUDE \(= 89 \) m). The \( x \)-axis of (b) that depicts distance from the rotor-swept zone was truncated at 200 m for visibility. Illustrations of eagles provided by Bryce Robinson.
probabilities (< 0.05) of entry when eagles flew fast regardless of flight direction and distance to turbine. Ten-fold cross-validation demonstrated that the model that included important covariates (reduced covariate model) was excellent for forecasting the entry probability at TW (AUC = 0.958; Fig. 3).

At Manzana, we retained 9438 flight paths, of which 1151 (12%) entered the rotor-swept zone. IdentFlight recorded a mean of 6.7 segments (median 5, range 2–52) for each flight path. In total, we included 63,009 segments for analysis, of which 2,947 segments occupied the rotor-swept zone. Segments entered the rotor-swept zone 639 times and persisted within the rotor-swept zone 1,610 times. The model trained using data from TW was excellent at predicting occupancy at the new site, Manzana (AUC = 0.974; Fig. 3).

### Table 2. Model estimates to evaluate the entry probability by eagles during subsequent 5-s time steps at Top of the World, Wyoming, USA.

<table>
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<tr>
<th>Model</th>
<th>Parameter</th>
<th>Description</th>
<th>Mean</th>
<th>sd</th>
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<th>95% UHPDI</th>
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Estimates are from logistic regression models with occupancy dynamics and distance-dependent entry probability that included all covariates (global model), reduced covariates (reduced) and no covariates (null). Estimates are summarized using means, standard deviations (sd) and 95% highest posterior density intervals (lower as ‘95% LHPDI’ and upper as ‘95% UHPDI’). Importance of covariates was determined using 95% highest posterior density intervals. Covariates considered important are indicated in bold. Colons (:) indicate interactions. ‘Apex entry’ refers to the $y$-intercept parameter ($\rho$) for the entry probability and represents the greatest entry probability while ignoring random effects. The entry probability decreases as distance increases and this probability is a function of the ‘flatness’ parameter ($\delta_0$) where smaller flatness values (e.g. 0–100) indicate that the entry probability decreased steeply with distance, while greater flatness values (e.g. 500–3000) indicate little or no change with distance (i.e. flatter response).
DISCUSSION

Our study illustrates how features of eagle flight paths can be relevant to understanding the probability that an eagle enters the rotor-swept zone of a wind turbine. An eagle’s distance, relative bearing of a flight path, flight speed and altitude all affected the entry probability. These results can inform efforts to reduce risk from wind turbines to eagles and the number of unnecessary curtailments at wind turbines. Our modelling framework may allow customized curtailment algorithms at each wind energy site or turbine while circumventing the need for detailed site-specific ancillary data such as wind characteristics and topography.

Flight characteristics and risk

Distance was useful in forecasting rotor-swept zone entry at our two study sites. Elsewhere, and in a different context, models using distance from raptor (Verreaux’s Eagle, *Aquila verreauxii*) activity centres were useful for informing potential collision risk and the spatial placement of turbines (Murgatroyd *et al.* 2021). Here, eagles that were 202 m or more from the nearest turbine had little risk (mean entry probability < 0.01) of entering the rotor-swept zone during the subsequent 5-s time interval regardless of flight behaviour. Such a low probability at that distance is expected given that an eagle would have to be flying at 40.4 m s$^{-1}$ or faster directly at the turbine to enter within 5 s. Sustained (30-s time intervals) flight speeds of migrating eagles typically range from 10 to 18 m s$^{-1}$ (Duerr *et al.* 2012), speeds that probably explain why birds farther than 100 m from a turbine had a low probability of entering into a rotor-swept zone within the subsequent 5-s segment. Distance therefore can be a major facet of curtailment criteria.

The altitude of an eagle’s flight path is often considered when assessing collision risk (Khosravifard *et al.* 2020), and our empirical results support this. It is logical that eagles are more likely to enter rotor-swept zones when flying near hub height. Such inference might seem obvious; however, both Bald Eagles (Buehler 2020) and Golden Eagles (Katzner *et al.* 2020) will stoop to attack prey. Our results suggest that eagles flying above

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**Figure 3.** Receiver operator characteristic (ROC) plots of occupancy forecasts of the rotor-swept zone for 5-s segments of eagle flight paths. Plots depict average true-positive rates (y-axis) and average false-positive rates (x-axis) of occupancy predictions while varying thresholds of occupancy. We trained models using subsets of data from Top of the World, Wyoming, USA, and we tested model predictions at this site (left panel) and a new site (right panel; Manzana, CA, USA). Thin grey solid lines depict predictions for each fold in 10-fold cross-validation. The thick black line depicts the mean for all 10 folds. The grey dashed line depicts an ROC curve for a model that predicts at random.
wind turbines rarely perform descending flights into the rotor-swept zone. Several other models of collision risk incorporate altitude of a bird (Garthe & Hüppop 2004, Band et al. 2007, Furness et al. 2013). The entry probability in relation to altitude will inevitably depend on the size of turbine blades and hub height (at TW, maximum blade heights of 131 m and 119 m and 80 m hub heights) given the types of turbine that were installed at a site. Here, eagles flying at altitudes of 189 m or more had little risk (mean entry probability ≤ 0.01) of entering the rotor-swept zone during subsequent 5-s time steps. The flight altitude of eagles can also be considered when setting curtailment criteria.

The direction of flight relative to turbines also influenced risk. This is intuitive because, when an eagle is outside the rotor-swept zone and flying away from the turbine, it cannot be at risk of entry into the rotor-swept zone. It was, however, more surprising that flight speed was an indicator of entry probability. At first glance, it seems counter-intuitive that the faster an eagle travels, the lower the likelihood of entry into the rotor-swept zone, because faster speeds could be associated with less time for decision-making. However, this relationship seems more plausible from a behavioural perspective. Migratory eagles flying in a directional and presumably fast manner are known to avoid turbines (Johnston et al. 2013, 2014), probably because they are looking ahead and actively navigating the landscape. In contrast, raptors that are hunting, especially while kiting or hovering, appear to be at greater risk of collision (Hoover & Morison 2005, Smallwood et al. 2009), probably because they constrain their field of view to the area below, where prey may be present, and so may be less likely to avoid turbines (Martin 2011). As such, the slow wandering flight that results in greater entry probability may be associated with specific behaviours that expose birds to risk.

It is possible that the act of curtailing a wind turbine might change the flight behaviour of birds and so impact whether they enter a rotor-swept zone. We only analysed data from curtailed turbines, so our results might be biased if curtailment affects flight behaviour. Future work could build upon ours by examining whether flight characteristics and entry into a rotor-swept zone are affected by the curtailment of wind turbines.

**Entry into the rotor-swept zone and curtailment decisions**

Our results regarding the interplay between flight path characteristics and rotor-swept zone entry can inform curtailment decisions. The current curtailment prescription at TW mandates turbine curtailment if an eagle is detected within a virtual cylinder above the ground that is 200 m tall and 150 m in radius (see fig. 2 in McClure et al. 2021a). Our results suggest that basing curtailment decisions on altitude and distance is well founded. Beyond 150 m from a given turbine, the curtailment criterion is currently a time to collision threshold where curtailment is triggered if the trajectory of an eagle will place it at the turbine within 10 s (McClure et al. 2021a). This criterion might be reconsidered given that fast moving eagles are unlikely to enter rotor-swept zones. Our results also suggest that curtailment decisions could be based, in part, upon the flight speed of the eagle.

Curtailment criteria also could consider the amount of time required to sufficiently slow turbine blades to prevent collision. We modelled our data at 5-s time intervals because, given our resources, that is the shortest time interval computationally possible. However, ideally, we would analyse data at 1-s intervals and attempt to forecast rotor-swept zone entry within the amount of time needed to slow the turbine blades (20 s to 1 min). Future work might endeavour to perform such forecasting, as computational resources allow.

The current curtailment prescription at TW applies equally across all turbines (McClure et al. 2021a). Our previous work at TW demonstrated that some turbines were more likely to have eagles enter their rotor-swept zones than others; therefore, we suggested that curtailment criteria could be tailored for each turbine (McClure et al. 2021a). In the current study, we also observed variation among turbines (σC = 0.35; Table 2) in entry probability into the rotor-swept zone at TW. Flight path characteristics associated with the entry probability might vary by turbine, and future research could examine whether turbine-specific curtailment criteria would better balance eagle collision risk and power generation.

Our model was excellent at forecasting entry by birds classified as eagles into rotor-swept zones at both TW and Manzana, suggesting high

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transferability of both predictions and inference. Our results could therefore generally inform curtailment criteria for automated curtailment systems to protect eagles. Ideally, our work would be a starting point for an adaptive management process (Köppel et al. 2014) for potentially any species – where curtailment criteria are adjusted over time per species, season and turbine.

The interplay between eagle distance, altitude, relative bearing, speed and entry into rotor-swept zones is complicated and context-dependent. The combination of logistic regression, occupancy dynamics and distance modelling was highly effective for forecasting the entry probability into the rotor-swept zone by eagles. This model and code for implementation can therefore be useful in future studies to advance our knowledge of collision risk and inform curtailment criteria.

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AUTHOR CONTRIBUTIONS

Brian W. Rolek: Data curation (equal); investigation (equal); methodology (lead); formal analysis (lead); writing – original draft (equal).
Melissa A. Braham: Data curation (lead); formal analysis (equal); writing – review and editing (equal).
Tricia A. Miller: Investigation (equal); supervision (equal); writing – review and editing (equal).
Adam E. Duerr: Investigation (equal); writing – review and editing (equal).
Todd E. Katzner: Methodology (equal); supervision (equal); writing – review and editing (equal).
Jennifer D. McCabe: Writing – review and editing (equal).
Leah Dunn: Writing – review and editing (equal).
Christopher J. W. McClure: Investigation (lead); methodology (lead); formal analysis (lead); writing – original draft (equal).

ETHICAL NOTE
None.

REFERENCES


Bald and Golden Eagle Protection Act. 1940. 16 United States Code (USC) § 668–668d. Bald Eagle Protection Act of 1940, June 8, 1940, Chapter 278, § 2, 54 Statute (Stat.) 251; Expanded to include the related species of the golden eagle October 24, 1962, Public Law (P.L.) 87–884, 76 Stat. 1246. As am.


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SUPPORTING INFORMATION

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

Data S1. Metadata and raw data used for analyses.