## Data Collection and Preprocessing

We collected woodcock locations with altitude readings from 2020 to 2024 using GPS transmitters as a part of a larger collaborative effort by the Eastern Woodcock Migration Research Cooperative (Blomberg et al. 2023, Clements et al. 2024, Fish et al. 2024). We captured woodcock at 100 sites across the eastern portion of their range, including Alabama, Florida, Georgia, Louisiana, Maine, Maryland, New Jersey, New York, North Carolina, Nova Scotia, Ontario, Pennsylvania, Québec, Rhode Island, South Carolina, Vermont, Virginia, West Virginia, and Wisconsin. We caught woodcock using a combination of spotlighting and mist netting (McAuley et al. 1993). We aged and sexed birds upon capture, where we classified birds undertaking their first fall and spring migrations as juveniles, and all other birds as adults. We then attached 4–7 g PinPoint transmitters (Lotek Wireless Inc., Newmarket, Ontario, CA) using a rump-mounted leg loop harness (Fish et al. 2024).

We programmed transmitters to collect locations every 1–3 days during migration, with locations alternating between diurnal (1300–1500 hours Eastern Time) and nocturnal (0000–0100 hours) times. Transmitters recorded time, latitude, longitude, and GPS-derived altitude above the WGS84 ellipsoid, and transmitted data back to the ARGOS satellite constellation after every third location. We subset these locations to include only those within the migratory classification dataset produced by Berigan (2024). This dataset classified individual locations as migratory or non-migratory based on the assumption that migration starts after the first ≥16.1 km movement and ends after the final ≥16.1 km movement of the season. We used ArcGIS Pro 3.2.1 (ESRI 2024a) to calculate the difference between the altitude and orthometric elevation recorded for each location (ESRI composite elevation layer; ESRI 2024b), providing a measurement of altitude above ground level for each point.

We classified data for our models based on prior descriptions of woodcock activity patterns. Woodcock are ground-feeding birds that rarely fly outside of crepuscular hours (Rabe et al. 1983). When rare diurnal flights do occur, these are generally brief, comprising 1–3% of diurnal time budgets, and close to the ground (McAuley et al. 2020). We therefore made a modeling assumption that all diurnal locations could be treated as though they were known to be recorded on the ground (hereinafter “known ground locations”). As woodcock are nocturnal migrants, we define potential flight locations as all points that were nocturnal, occurred during migration based on the classification in Berigan (2024), and were preceded and followed by >6.68 km steps (defined as lines connecting consecutive locations). The 6.68 km threshold was based on the 99th percentile of step lengths recorded within a stopover site (Berigan 2024). Ensuring that the preceding and following steps were >6.68 km increased the likelihood that the bird had moved away from a stopover site before the point was recorded.

## Modeling Altitude Distributions

Our model of woodcock flight altitudes included both potential flight locations and known ground locations, with each class of data informing a different aspect of the model. Known ground locations were assumed to always have a true altitude of 0 m, making their recorded altitudes Ar solely attributable to measurement error ε by the GPS units. The recorded altitude of a ground location i can be modelled as follows:

|  |  |  |
| --- | --- | --- |
|  | Ari ~ StudentT(νε, με, σε) | Eq. 1 |

where νε represents degrees of freedom, με is the mean error observed across all observations and σε is the scale parameter associated with the error. As such, the known ground locations can be used to directly inform the measurement error term εi, which we assume remains consistent between ground and flight locations. We chose to model εi using a Student’s t-distribution due to the distribution’s flexibility in modeling heavy tails, which are frequently observed in altitudinal measurement error distributions (Péron et al. 2017).

For potential flight locations there are two possible outcomes. They can be recorded on the ground, in which case Ari = εi, or recorded in flight with altitude Af, in which case Ari = Afi + εi. This can be modelled as follows:

|  |  |  |
| --- | --- | --- |
|  | if Flighti = 0:  Ari ~ StudentT(νε, με, σε)  if Flighti = 1:  Ari ~ StudentT(νε, με + Afi, σε) | Eq. 2 |

|  |  |  |
| --- | --- | --- |
|  | Afi ~ Lognormal(μf, σf) | Eq. 3 |

where Af for each location i that is identified in flight (i.e., Flighti = 1) is drawn from a log-normal distribution with location parameter μf and scale parameter σf. We chose a log-normal distribution because it accommodated a heavy right tail, which is a common feature of bird altitude distributions (White et al. 2020). The flight status of the birds is the function of a Bernoulli distribution

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| --- | --- | --- |
|  | Flighti ~ Bernoulli(pf) | Eq. 4 |

where pf is the proportion of true flight locations among all potential flight locations. As the programming language we used (i.e., Stan) does not support sampling discrete parameters, we expressed Eq. 4 through a latent discrete parameterization described in Stan Development Team (2024).

All parameters in the model received vague priors. The measurement bias in the data, με, and location parameter for the flight distribution, μf both received normal priors with mean 0 and standard deviation 1. The standard deviation of the measurement error, σε, and the scale parameter for the flight distribution, σf, both received half-normal priors with mean 0 and standard deviation 1. The proportion of true flight locations among all potential flight locations, pf, received a beta distribution prior where both the α and β shape parameters were set to 2. The degrees of freedom in the measurement error distribution, νε, received a gamma distribution prior with an α of 2 and a β of 0.1, following suggestions for vague priors of ν in Juárez and Steel (2010).

Season, age, and sex models received a similar formulation to the base model, with the only difference being the use of group-specific (g) μf, σf, and pf parameters

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| --- | --- | --- |
|  | Afi ~ Lognormal(μfg, σfg) | Eq. 5 |

|  |  |  |
| --- | --- | --- |
|  | Flighti ~ Bernoulli(pfg) | Eq. 6 |

where the μfg, σfg, and pfg parameters were dependent on the season, age, or sex class associated with any given altitude observation. This model structure allowed the distribution of flight altitudes to be estimated for each season, age, and sex class separately, but with shared inference of error terms με and σε as we had no *a priori* reason to believe that GPS measurement error would change as a function of these classes.

We implemented these models in a Bayesian framework using package *rstan* (Stan Development Team 2024) in R version 4.4.1 (R Core Team 2024) running 4 chains at 15,000 iterations with 7,500 warmup iterations. We checked all models for convergence using trace plots and ensured that potential scale reduction values were <1.1 (Brooks and Gelman 1998). As Bayesian models often perform better with scaled variables, we scaled our estimated flight altitudes between 0 and 1 for modeling, and back-transformed all parameter estimates into meters above ground level for evaluation. We described the posteriors of flight altitude distribution parameters by simulating a log-normal distribution for each posterior value of μf and σf, and sampling the mean, median, standard deviation, and skewness of each simulated distribution. We estimated the number of flight locations from the base, season, age, and sex models by multiplying posterior values of pf by the number of potential flight locations in each dataset. We summarized posteriors for all parameters using median values and highest density credible intervals (CRI) since they allow for more conservative estimates when posterior densities are skewed (Kruschke 2014, Makowski et al. 2019). We also calculated the probability of superiority, or the likelihood of one group having a higher parameter value than another group, for season, age, and sex models following Ruscio (2008).

## Comparison of Flight Altitudes to Weather Radar and Airspace Obstacles

We used derived metrics from our model to assess how often woodcock flight altitudes occurred in the altitude range typically detected by ground-based radar and how they coincided with height intervals associated with common airspace obstacles that pose collision risk. We calculated these metrics by simulating a log-normal distribution for each posterior value of μf and σf, and measuring the proportion of each simulated distribution that fell below or within the given height interval. We compared woodcock flight altitudes to the minimum altitude (120 m) detected by Horton et al. (2016) using the Next Generation Weather Radar (NEXRAD) system, a weather radar system in the USA frequently used to study bird migration (DeMott et al. 2022, Horton et al. 2023). We quantified the proportion of simulated flight altitudes that fell below a 120-m threshold, representing the proportion of locations that would not be detectable by weather radar. As low-rise buildings (defined as residential buildings 4–11 stories and non-residential buildings ≤11 stories) result in the highest number of window collision mortalities in the United States (Loss et al. 2014), we also quantified the proportion of simulated flight altitudes below the height of an 11-story building (47 m). We estimated the proportion of simulated flight altitudes that fell within the rotor-swept zone of the average land-based wind turbine installed in 2022 (32–164 m; Wiser et al. 2023). Finally, we measured the proportion of simulated flight altitudes that fell below the height of a 305-m communication tower, as these towers are responsible for 5–70x as many collisions as shorter towers (Gehring et al. 2011).

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