**1 Introduction**

**2 Methods**

*2.1 Data collection and preprocessing*

We collected satellite GPS data with altitude readings from 2020–2024 using 4–7 g PinPoint GPS transmitters (Lotek Wireless Inc., Newmarket, Ontario, CA) 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). Transmitters were deployed by 42 collaborators across the eastern portion of the woodcock’s range and were programmed to collect locations primarily during fall and spring migration. In addition to recording diurnal altitudes, transmitters would record nocturnal altitudes at either 0000 or 0100 hours Eastern Time at varying schedules during the migratory season. We subset these readings to only include high quality altitude fixes, and excluded any locations in which the bird’s migratory or non-migratory state was unknown (Chp. 2). We used ArcGIS Pro 3.2.1 to extract the difference between the recorded altitude and orthometric elevation for each location, providing a measurement of height above ground level for each point (cite tk). We normalized height above ground level measurements to between -1 and 1 based on the maximum observed altitude in the dataset (2183m). We then identified locations that were collected at night during each woodcock’s individually-delineated migration (Chp. 2). Locations which met these requirements were designated as possible flight locations, while other locations were designated as definitive non-flight locations for further analysis.

*2.2 Modeling altitude distributions*

Our model of woodcock flight altitudes included both possible flight locations and definitive non-flight locations, with each class of data informing a different aspect of the model. Definitive non-flight locations were assumed to always have a true altitude of 0m, making their recorded altitudes solely attributable to measurement error ( = ). As such, definitive non-flight locations could be used to estimate the error terms of the model. Possible flight locations had either a true altitude of 0m, in which case = , or some flight altitude , in which case = + . Thus, possible flight locations could be used to jointly estimate their own non-flight/flight state (represented as binomial variable , with 0 indicating a ground location and 1 indicating a flight location) and the distribution from which was drawn. The model we used to do so was structured as follows

Equation 1

with set to a known value of 0 for all definitive non-flight locations and used as an estimable parameter for all possible flight locations. When was not known, we provided an informed prior of *p = 0.33*, based on … The measurement bias in the data, , was given an uninformative normal prior with mean 0 and standard deviation 1, while the standard deviation of the measurement error, , was given a half-normal prior with standard deviation 1. The distribution of was modeled using a gamma distribution with shape parameter and rate parameter . We gave and semi-informative priors to restrict their possible values to those that might sensibly describe a distribution scaled between 0 and 1 (McElreath 2018). After simulating possible distributions, we chose to give a half-normal prior with standard derivation 5 and a half-normal prior with standard derivation 10.

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

Equation 2

where the and parameters were dependent on the season or age class associated with any given altitude observation. This model structure allowed the distribution of flight altitudes to be estimated for each season and age class separately, but with shared inference of error terms and .

We implemented these models using Bayesian Markov Chain Monte Carlo in program JAGS (Plummer 2003) running 4 chains at 200 000 iterations with 10 000 iterations burn-in and no sample thinning. All models described above were checked for convergence using trace plots and reported R-hat values < 1.1. A fourth model, with sex used as the group variable, was tested but did not converge, and so the results are not included below. We ran these models using the transformed height above ground level estimates for , and back-transformed all parameter estimates into meters afterwards for evaluation. We described the posteriors of flight altitude distributions by simulating a gamma distribution for each posterior value of and , and sampling the mean and standard deviation of each simulated distribution. We designated locations with a posterior probability density of >0.5 for = 1 as likely flight locations for the purpose of calculating sample sizes.

*2.3 Comparison of flight altitudes to other metrics*

We measured how often woodcock flight altitudes occurred in height intervals associated with NEXRAD minimum detectable altitudes and several airspace obstacles. We estimated the minimum detectable flight altitude of NEXRAD based on the minimum altitude recorded in Horton et al. (2016; tk m), and estimated the proportion of woodcock flight locations (represented by the posterior of ) which fell below this threshold. As low-rise buildings (defined as residential buildings 4–11 stories and non-residential buildings ≤11 stories) result in the majority of window collision mortalities in the United States (est. 339 million per annum; Loss et al. 2014), we also estimated the proportion of locations which were at an altitude below that of an 11-story low-rise building (47m). Wind turbines also result in substantial avian mortality during migration (est. 234 thousand per annum; Loss et al. 2013), so we estimated the proportion of woodcock flight locations which fell within the rotor sweep of the average land-based wind turbine installed in 2022 (32–164m; U.S. Department of Energy 2023). Finally, we measured the proportion of woodcock flight locations which fell below the height of a 244m communication tower, as these towers are responsible for 5–70x as many collisions as shorter towers (total communication tower mortality: 4–5 million birds per annum; Gehring et al. 2011).

**3 Results**

We collected 12 558 GPS locations with altitude recordings, of which 428 could potentially be flight locations based on time of day and migratory classification. The model predicted that tk of these locations were most likely recorded when the bird was in flight (fall: tk locations, spring: tk; adult: tk, juvenile tk). Woodcock have an estimated median flight altitude of 262m and a mean flight altitude of 364m (Table 1). Woodcock fly at mean altitudes of 312m in fall and 428m in spring, with no overlap in the 50% credible intervals of those seasons (Fig. 1). Adult woodcock fly at mean altitudes of 400m, while juveniles fly at altitudes of 344m, with some overlap in the 50% credible intervals of those age classes (Fig. 2). Almost half of woodcock flight locations were at altitudes <244m, posing potential risks for collisions with low-rise buildings, wind turbines, and communications towers (Fig. 3).

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Estimate | 50% Credible Interval | 95% Credible Interval |
| **Median Flight Altitude** | **262m** | **239–285m** | **195–332m** |
| *Fall* | 225m | 196–252m | 148–312m |
| *Spring* | 319m | 282–355m | 216–427m |
| *Adult* | 294m | 254–333m | 185–408m |
| *Juvenile* | 260m | 231–288m | 182–345m |
| **Mean Flight Altitude** | **364m** | **341–386m** | **300–432m** |
| *Fall* | 312m | 284–338m | 239–398m |
| *Spring* | 428m | 392–463m | 326–539m |
| *Adult* | 400m | 360–437m | 301–516m |
| *Juvenile* | 344m | 316–370m | 270–430m |
| **% of observations below NEXRAD detection altitude** | **33%** | **29–36%** | **23–43%** |
| *Fall* | 37% | 32–42% | 23–51% |
| *Spring* | 26% | 21–31% | 14–41% |
| *Adult* | 29% | 23–34% | 15–45% |
| *Juvenile* | 31% | 26–36% | 18–45% |
| **% of observations below height of low-rise buildings (47m)** | **10%** | **8–13%** | **4–19%** |
| *Fall* | 12% | 8–16% | 4–25% |
| *Spring* | 8% | 5–10% | 2–18% |
| *Adult* | 9% | 5–12% | 2–22% |
| *Juvenile* | 9% | 5–12% | 2–19% |
| **% of observations within sweep of land-based wind turbines (32–164m)** | **27%** | **25–29%** | **21–32%** |
| *Fall* | 30% | 28–33% | 22–36% |
| *Spring* | 23% | 22–36% | 14–30% |
| *Adult* | 24% | 21–27% | 15–31% |
| *Juvenile* | 27% | 25–30% | 18–34% |
| **% of observations below height of large communication towers (244m)** | **47%** | **44–51%** | **37–57%** |
| *Fall* | 53% | 49–58% | 39–65% |
| *Spring* | 40% | 35–45% | 26–54% |
| *Adult* | 43% | 38–48% | 28–58% |
| *Juvenile* | 47% | 43–52% | 34–60% |

Table 1. Caption tk

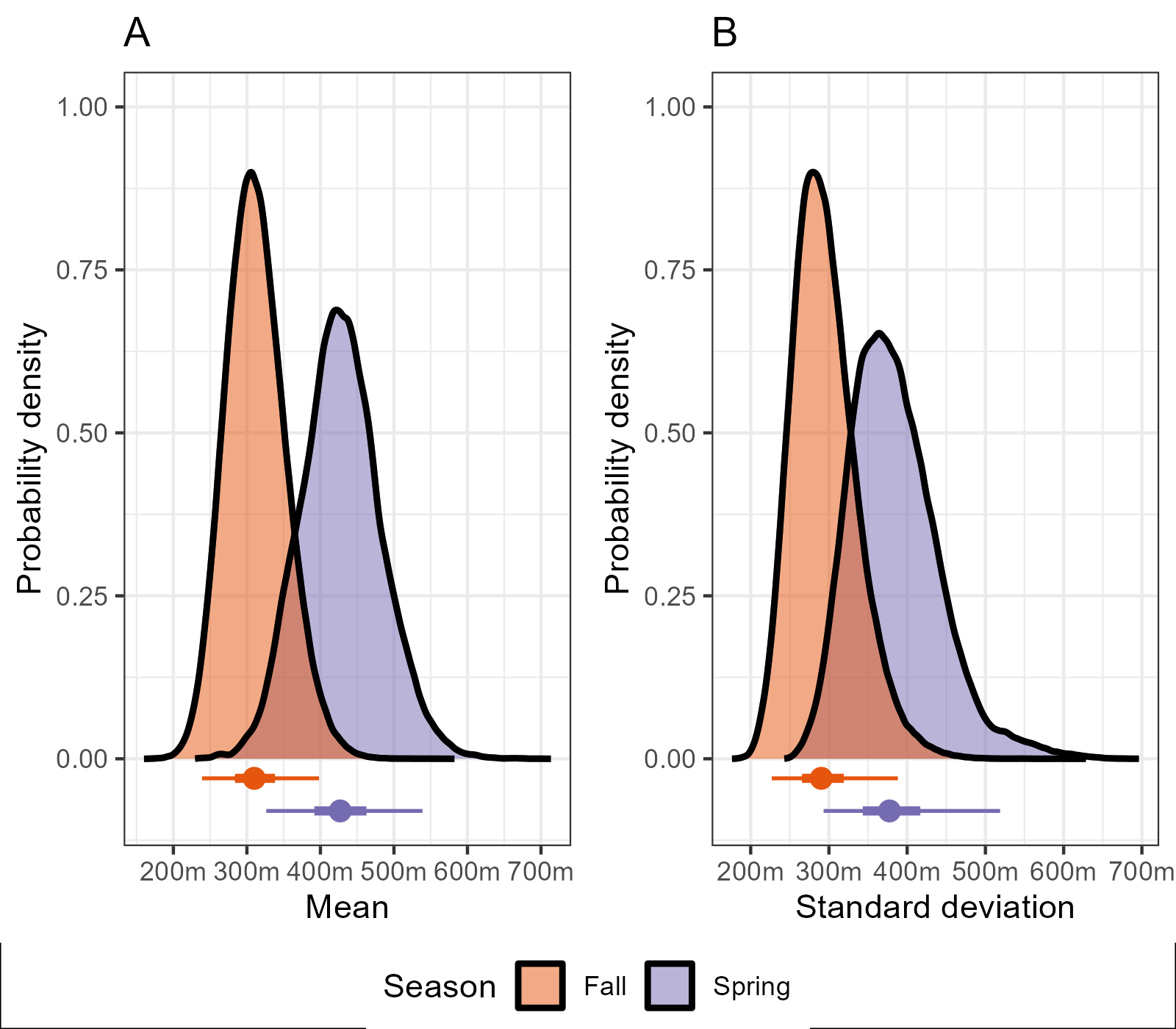


Figure 1. Points represent medians, thick lines represent 50% credible intervals, thin lines represent 95% credible intervals.

A comparison of a normal distribution

Description automatically generated

Figure 2. Points represent medians, thick lines represent 50% credible intervals, thin lines represent 95% credible intervals.

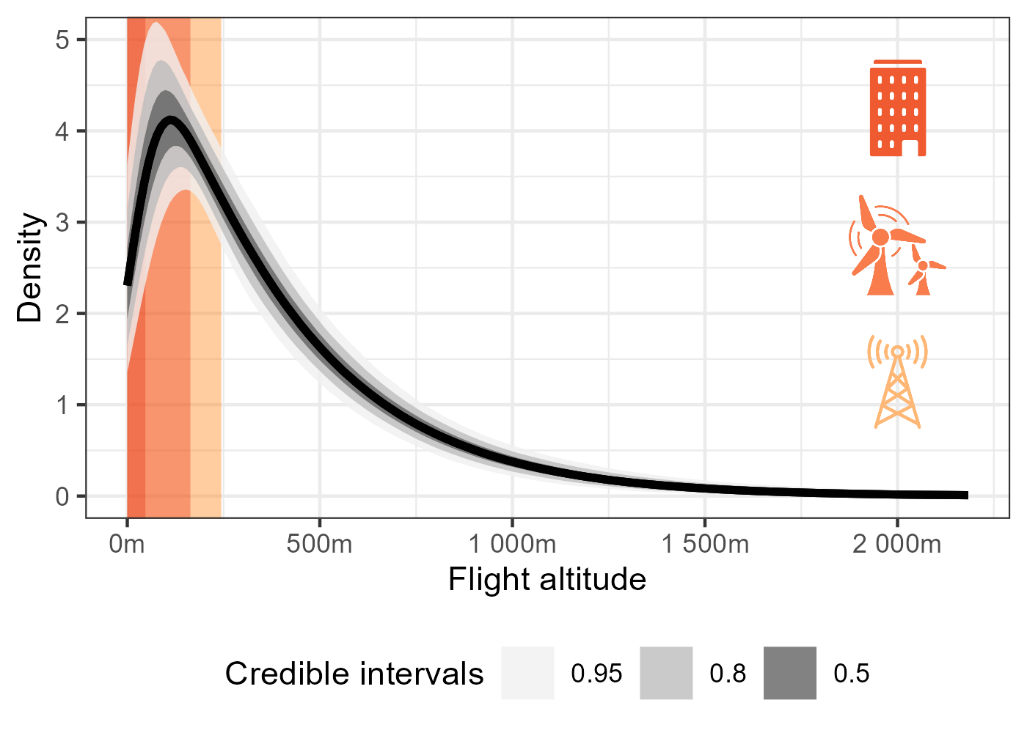


Figure 3. Distribution of woodcock flight altitudes compared to the heights of low-rise buildings (red), land-based wind turbines (orange), and communications towers (yellow).

**4 Discussion**