Materials and Methods

Doppler radar

We used the NEXRAD network operated by the National Oceanic and Atmospheric Administration to characterize spring migratory movements (March 1st to May 31st) from 1995 to 2017. These radars scan 360° at multiple elevation angles (e.g. 0.5°, 1.5°… 4.5°), fully sampling the airspace every 5 to 10 minutes. We downloaded radar scans from Amazon Web Services (https://s3.amazonaws.com/noaa-nexrad-level2/index.html), selecting those in a 30-minute window centered on three hours after local sunset. We chose this time window because it approximates the time of peak nocturnal migration across the United States (e.g., *3*, *25*). However, there is spatial variation in the time of peak nocturnal migration (e.g., stations along the Gulf of Mexico experience peak migration earlier in the night, *26*), so in some areas our predicted totals will be conservative. We processed scans using the WSRLIB weather surveillance radar package for MATLAB (*27*). To characterize migration intensity, we used radar reflectivity factor, a measure of reflectance to the radar. To sample the airspace from 0-3 km above ground level, we extracted radar reflectivity factor values 5-37.5km from each radar (*28*) and cast them into vertical profiles with 100-m altitudinal resolution. We converted radar reflectivity factor (dBZ) to radar reflectivity (dBη) using the equation $\eta[dB] = Z[dBZ] + \beta$, where $\beta = 10\log_{10}(10^3\pi^5|K_m|^2/\lambda^4)$. We set the radar wavelength (λ) to 10.71 cm, the average for NEXRAD radars (*16*) and set the refractive index ($|K_m|^2$) to 0.93 for liquid water. This yielded $\beta = 13.35$. We converted dBη to η using the equation $\eta = 10^{dB\eta/10}$, yielding units of $cm^2 km^{-3}$. To estimate numbers of birds from η, we divided η by a radar cross-section of 11 cm^2. This resulted in units of birds km^{-3}.

To mitigate the influence of time-invariant clutter (e.g., buildings, terrain, wind turbines), we applied binary clutter masks to each low elevation scan prior to the construction of the vertical profile of migration intensity. Masks were generated by summing a minimum of 100 low elevation scans (0.5° elevation), starting on January 1st (16:00 UTC to 18:00 UTC) and continuing to January 15th. This time window falls well outside typical migration periods. If 100 samples were not tallied by January 15th, the window of selection was expanded until the threshold was met. We classified any pixel above the 85th percentile of the summed reflectivity as clutter and masked it from our calculation of migration intensity.

To discriminate radar scans contaminated with precipitation from those containing only clear air or bird-dominated signal (hereafter termed "clear"), we created a random forest classifier using the package "randomForest" (*29*). We trained the classifier on 157,279 manually classified nocturnal scans (generated every 5-10 minutes) selected from a 3-hour period on March 15th, April 15th, and May 15th for every radar and every year in the training set (fig. S8). We designed this sampling to capture any geographic, seasonal, or longitudinal patterns in the data. We extracted derived predictor variables from profiles of radar reflectivity, groundspeed, and summaries of the number of density values above 35 dBZ (extreme densities characteristic of intense precipitation). We generated 1,000 trees and set the minimum terminal node size to 50. Overall, the model showed a 5.6% classification error. We used the algorithm to classify a total of 979,326 scans. As an additional step to reduce the inclusion of precipitation incorrectly classified as clear, we used only scans with a probability of being clear >70% (rather than a majority rule, i.e. >50%).

Identifying and removing flying insects from weather surveillance radar data has been a long-standing challenge for ornithologists. The standard method of ameliorating insect