contamination is to filter data by airspeed values, because samples with large average airspeeds must be dominated by strong flyers (*30*, *31*). One downside to this approach is that it may also remove samples containing slow-flying birds or a mix of birds and insects. Here, we filter vertical profiles by removing altitude bins with mean airspeeds of 5 m s^{-1} or less (*3*, *22*, *32*), a cutoff value chosen to remove the majority of insects (*30*, *33*). Slow-flying samples represented 16% of total summed reflectivity. We examined the sensitivity of our analysis to this step by comparing model predictions with and without insect filtering (fig. S9).

Weather reanalysis

The North American Regional Reanalysis, or NARR (*19*), compiles data from numerous observational data sources to produce a best estimate of weather conditions that occurred in North America. The reanalysis is published in 3-hour intervals across a 32-km grid. We downloaded NARR data for 1995-2017 and extracted the following parameters: air temperature (ºC), geopotential height (m), zonal and meridional wind components (m s^{-1}), surface pressure (Pa), relative humidity (%), visibility (m), vertical velocity (Pa s^{-1}), mean sea level pressure (Pa), total cloud cover (%), albedo (%), total precipitation (kg m^{-2}), convective available potential energy (J kg^{-1}), and snow cover (%). For variables available at multiple pressure levels, we extracted data from the surface to 300 mb. To match weather data to radar stations, we averaged data within 37.5 km of each radar station. We then calculated altitude above ground level by subtracting surface geopotential height from the geopotential height at each pressure level, and we used linear interpolation to calculate vertical profiles of weather data at 100-m altitude bins from 0-3000 m. Finally, we matched radar profiles to weather profiles by taking the observation closest in time for each radar station. Pairwise correlations among predictor variables were generally low (fig. S1).

Weather forecasts

The North American Mesoscale Forecast System, or NAM (https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-mesoscale-forecast-system-nam), generates weather forecasts out to 84 hours; forecasts are hourly from 1-36 hours and subsequently every 3 hours until hour 84. Forecast models are run every 6 hours. NAM predictions are made on a 12-km grid. We downloaded 0Z NAM forecast data for 2008-2017, extracted the same parameters as for NARR, and matched NAM data to radar stations in the same manner as for NARR.

In addition to NAM, we used the Global Forecast System, or GFS (https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs) to generate longer-range migration forecasts. GFS forecasts with 0.5º spatial resolution currently extend out to 384 hours at 3-hour increments, but this range has improved with time; in 2010, the range was 180 hours. We downloaded 0Z GFS forecast data for 2010-2017 and extracted weather predictions up to 7 days (168 h) in advance.

Supervised learning

We used gradient boosted trees to predict bird migration from weather data (Fig. 1). We used the R implementation of XGBoost (*18*, *34*), a highly efficient and scalable gradient boosting framework. The algorithm automatically detects nonlinear effects and complex interactions among predictors, and it is not hindered by predictor collinearity. We trained an XGBoost model on NARR weather data, with the cube root of bird density as our response variable.