MIGRATION

A continental system for forecasting bird migration

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Billions of animals cross the globe each year during seasonal migrations, but efforts to monitor them are hampered by the unpredictability of their movements. We developed a bird migration forecast system at a continental scale by leveraging 23 years of spring observations to identify associations between atmospheric conditions and bird migration intensity. Our models explained up to 81% of variation in migration intensity across the United States at altitudes of 0 to 3000 meters, and performance remained high in forecasting events 1 to 7 days in advance (62 to 76% of variation was explained). Avian migratory movements across the United States likely exceed 500 million individuals per night during peak passage. Bird migration forecasts will reduce collisions with buildings, airplanes, and wind turbines; inform a variety of monitoring efforts; and engage the public.

Billions of birds migrate between distant breeding and wintering sites each year, through landscapes and airspaces increasingly transformed by humans. Hundreds of millions die annually from collisions with buildings, automobiles, and energy installations (*1*), and light pollution exacerbates these effects (*2*). Pulses of intense migration interspersed with periods of low activity characterize birds' movements aloft (*3*, *4*), and efforts to reduce negative effects on migrants (e.g., turning off lights and wind turbines at strategic times) (*5*) would be most effective if they targeted the few nights with intense migratory pulses. However, bird movements are challenging to predict days or even hours in advance.

For decades, scientists have studied the drivers of avian migration. Winds, temperature, barometric pressure, and precipitation play key roles (*6*–*8*). However, such general relationships have not produced migration forecasts accurate at both broad continental extents and fine spatial and temporal resolutions (*9*, *10*). Local topography, regional geography, and time of season modify relationships between conditions and migration intensity, and hundreds of species with diverse behaviors frequently pass over a single location during migration. The complex interactions between environmental conditions and animal behavior make predicting bird migration at the assemblage level a challenge.

One major difficulty has been amassing behavioral data that appropriately characterize bird migration at a continental scale. Radar, used globally as a tool to study animal migration (*3*, *11*–*14*), offers a realistic solution to monitor hundreds of species (*15*). In the continental United States, the Next Generation Weather Radar (NEXRAD) network comprises 143 weather surveillance radars (*16*) and an archive with more than two decades of data. Although designed for meteorological applications, these radars measure energy reflected by a diversity of aerial targets, including birds. Only recently have advances in computational methods [e.g., (*17*)] facilitated the use of the entire radar archive for longitudinal studies of bird migration at continental scales.

Using the NEXRAD archive, we quantified 23 years (1995 to 2017) of spring nocturnal bird migration across the United States (Fig. 1). We developed a classifier to eliminate radar scans contaminated with precipitation. We then trained gradient-boosted trees (*18*) to predict bird migration intensity from atmospheric conditions reported by the North American Regional Reanalysis (*19*). Our model used 12 predictors, including winds, air temperature, barometric pressure, and relative humidity (fig. S1), which we used to predict a cube-root-transformed index of migration intensity (expressed in square centimeters per cubic kilometer). The cube-root transform reduces skewness but is less extreme than a log transformation, which would have given considerable weight to biologically unimportant differences between small values. We measured migration intensity in 100-m altitude bins up to 3 km to model the three-dimensional distribution of migrating birds over the continent. To express migration intensities in numbers of birds, we assumed a radar cross section per bird of 11 cm^2. The radar cross section is a measure of reflected energy; this value is typical of medium-sized songbirds and representative of migratory species (*12*).

Our migration forecast model explained 78.9% of variation in migration intensity over the United States (Figs. 2 and 3A). Performance was consistent across years (mean yearly coefficient of determination $R^2 = 0.781 \pm 0.010$ SD). We quantified the importance of each predictor by calculating gain, a measure of how much predictions improve by adding a given variable. Air temperature was most important, with an average gain more than three times that of the second-ranked predictor, date (fig. S2). High temperatures coincided with large migration pulses (Fig. 4 and figs. S3 and S4). As a predictor of bird migration, temperature likely plays a dual role as an index of spring phenology and a short-term signal for movement, as favorable

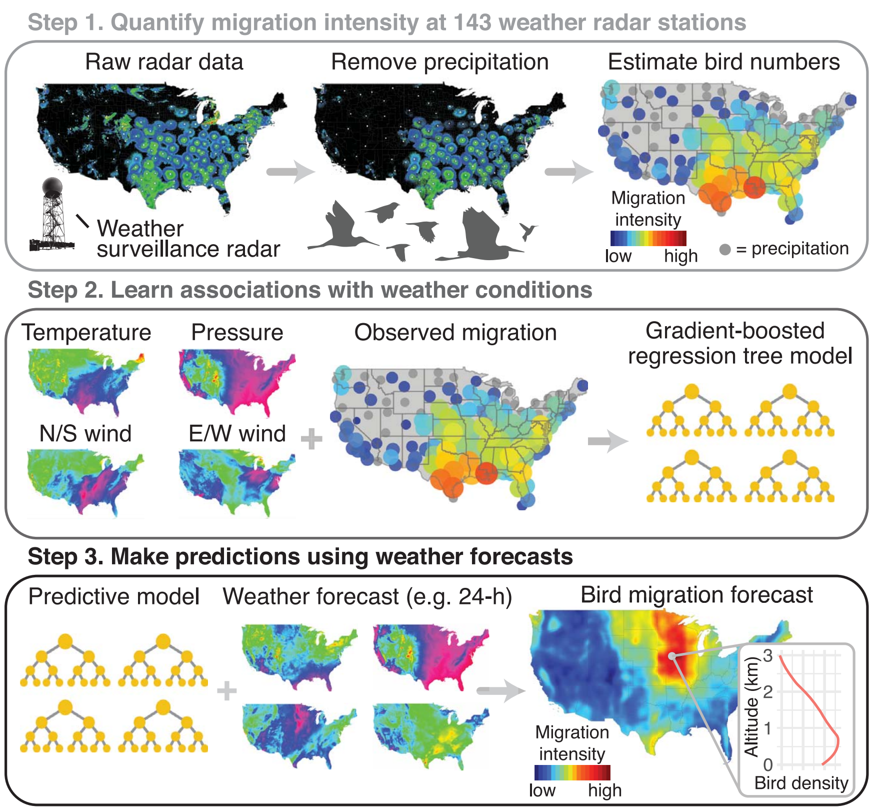

Fig. 1. Methodology for generating migration forecasts. We used weather surveillance radars to quantify 23 years of spring bird migration, modeled migration intensity as a function of observed atmospheric conditions, and used this model to forecast future migration events under predicted weather conditions.

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southerly winds usually accompany warmer air masses. Other important predictors included altitude, longitude, surface pressure, latitude, and wind (fig. S2).

The model provides informative predictions several days in advance. We evaluated its utility as a true forecast system with archived weather forecasts from the North American Mesoscale Forecast System (NAM) and Global Forecast System (GFS). NAM has higher spatial resolution but is a shorter-range forecast (12-km grid, 3-day range) than GFS (0.5° grid, >7-day range). We made predictions up to 3 days in advance with NAM and up to 7 days in advance with GFS, expecting performance to degrade with time because of the decreasing accuracy of longer-range weather forecasts. Predictions on the basis of 24-hour NAM forecasts explained 75% of variation in migration intensity, 3-day NAM forecasts explained 71%, and 7-day GFS forecasts explained 62% (fig. S5).

The model captures patterns of bird migration across the United States with high spatial accuracy, particularly in the central and eastern regions (fig. S6). We evaluated spatial accuracy over areas without radar coverage by iteratively removing the data from each radar station, retraining the model on the remaining data, and testing performance on the withheld station. Median R^2 for withheld stations was 0.72, and R^2 was 0.60 or higher for 75% of stations (fig. S7). Spatial variation in performance likely stems from local influences on migratory behavior (e.g., topography), which our model did not explicitly incorporate.

Previous research suggests that migration behavior and weather conditions in the days immediately preceding a migration event can predict its intensity [e.g., (*10*)]. We found that including atmospheric data from the preceding night and 24-hour changes in conditions did improve performance, but not markedly. A model that included atmospheric conditions 24 hours before an event explained 80.1% of variation in migration intensity, and further including observed migration intensity from the previous night increased R^2 to 81.3%.

Finally, we used model predictions to estimate the total number of birds actively migrating each night across the United States. Summing predictions countrywide, we infer that nightly movements frequently exceed 200 million birds (Fig. 3B). Peak passage occurred in the first half of May, when the median predicted movement size was 422 million birds per night. Although our model tended to underpredict the largest observed movements (Fig. 3A), a conservative forecast system

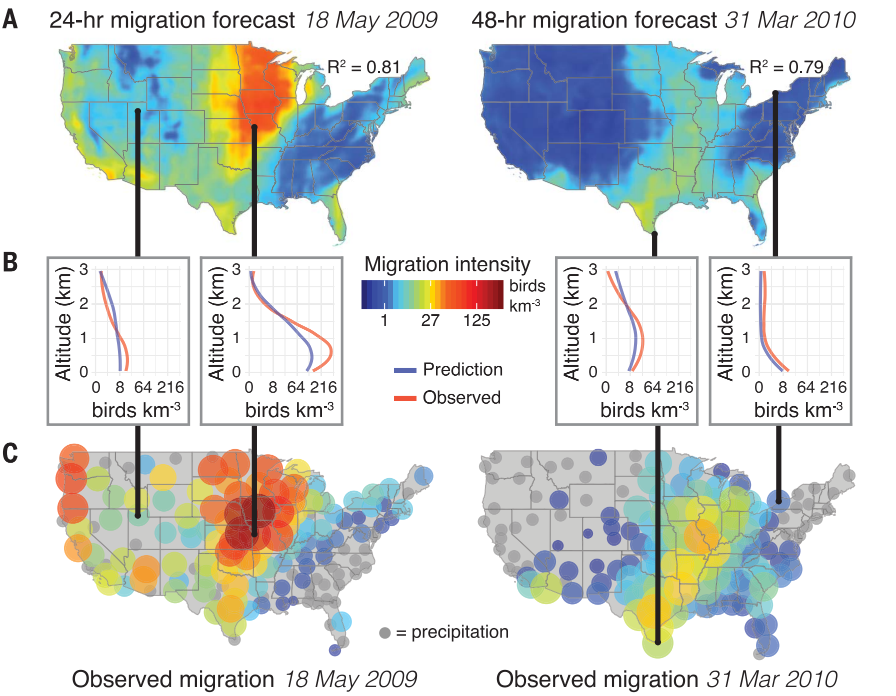

Fig. 2. Migration forecasts and corresponding observed migration. (**A**) Countrywide migration forecast surfaces showing predicted mean migration intensity across altitudes. (**B**) Altitudinal profiles at four stations, showing predicted and observed intensity values. (**C**) Mean migration intensity observed at all radar stations. Gray circles indicate stations where migration intensity could not be measured because of precipitation.

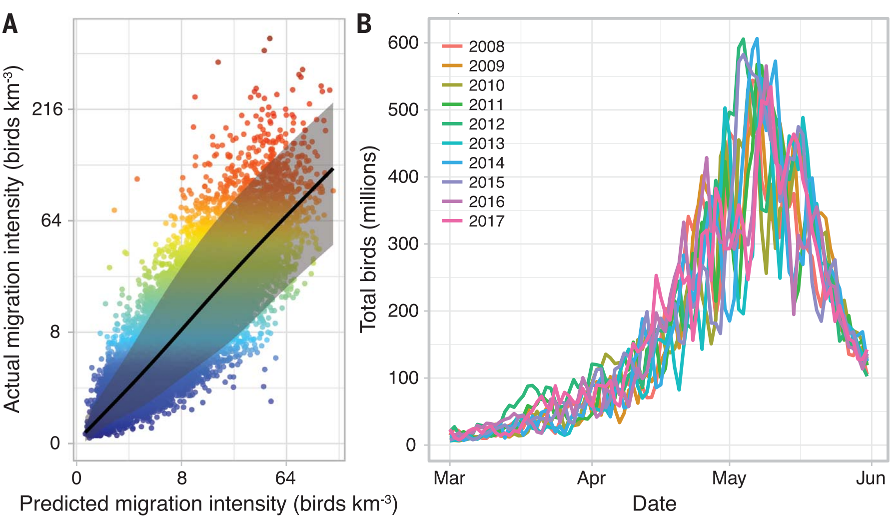

Fig. 3. Accuracy of forecasts and nightly continental predictions. (**A**) Mean predicted and observed migration intensities for test data, with points colored by observed migration intensity (*y* axis). The scatterplot shows values after averaging across altitudes. Shading shows empirical 90% prediction intervals, which covered 90.5% of observed values. (**B**) Nightly peak migration magnitude estimated across the continental United States for 2008 to 2017. The size of migratory movements varied markedly from night to night during the peak of the migration season.

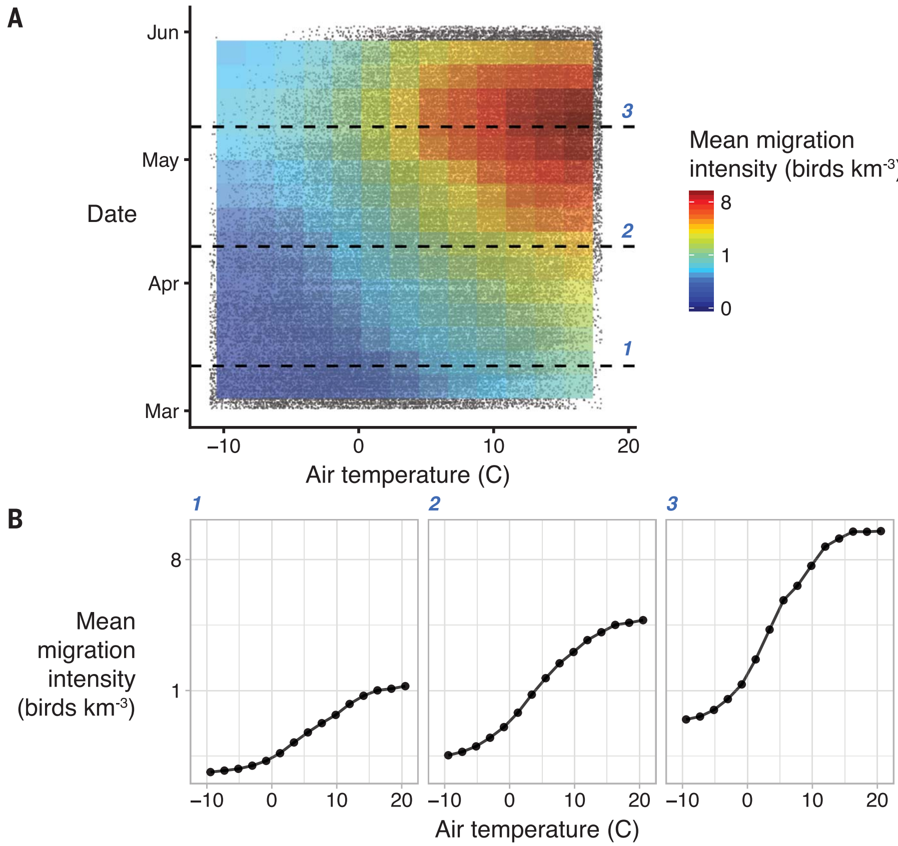

Fig. 4. Migration intensity predictions by air temperature and date. (**A**) Heat map colors show migration intensity predictions for dates and air temperature values. Each data point on the scatterplot behind the heat map represents data for one night from one radar. Only well-supported predictions and corresponding data points are shown (the outer 10% of temperature and date values are excluded). Temperature values correspond to air temperatures at altitudes up to 3000 m. (**B**) Cross sections of model predictions for three spring dates. For a given date, the model predicts migration intensity to vary closely with temperature. Fewer observations correspond to cold temperatures later in the season.

decreases the risk of taking unneeded mitigation action. More accurately predicting the largest migration events may require explicit modeling of migrant flow across the continent, including responses to topographical features (*20*).

Migration forecasts will further ecological research while aiding monitoring and mortality mitigation efforts. Accurate predictions can inform decisions to temporarily shut down lights and wind turbines, halt gas flares, choose airplane flight paths, and take other actions to prevent human and avian mortality (*10*, *21*). Global health workers monitoring avian-borne diseases can use migration forecasts to anticipate bird movements. Further integration of large citizen science datasets with radar observations will provide the means to study species-specific patterns of behavior at a large scale (*22*), and studying local variation in migratory behavior will lead to more accurate models of atmospheric bird distributions (*23*). Migration forecast systems have great potential to aid environmental monitoring and conservation efforts; fully realizing this potential will require the cooperation not just of scientists but also of governments and agencies that produce and disseminate radar products (*21*).

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SUPPLEMENTARY MATERIALS

www.sciencemag.org/content/361/6407/1115/suppl/DC1
Materials and Methods
Figs. S1 to S10
References (*25*–*37*)

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