Towards detailed and interpretable bird migration forecasts

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Take home

A mechanistic movement model can be combined with deep neural networks to account for insufficiently understood dependencies to provide coherent descriptions of the processes under study.

We have used this approach to predict continental-scale bird migration at coarse (Voronoy) as well as fine-scale (hexagonal grid) tessellations. We predict not only aerial movements, but also explicitly capture take-off, flight, and landing dynamics in space and time.

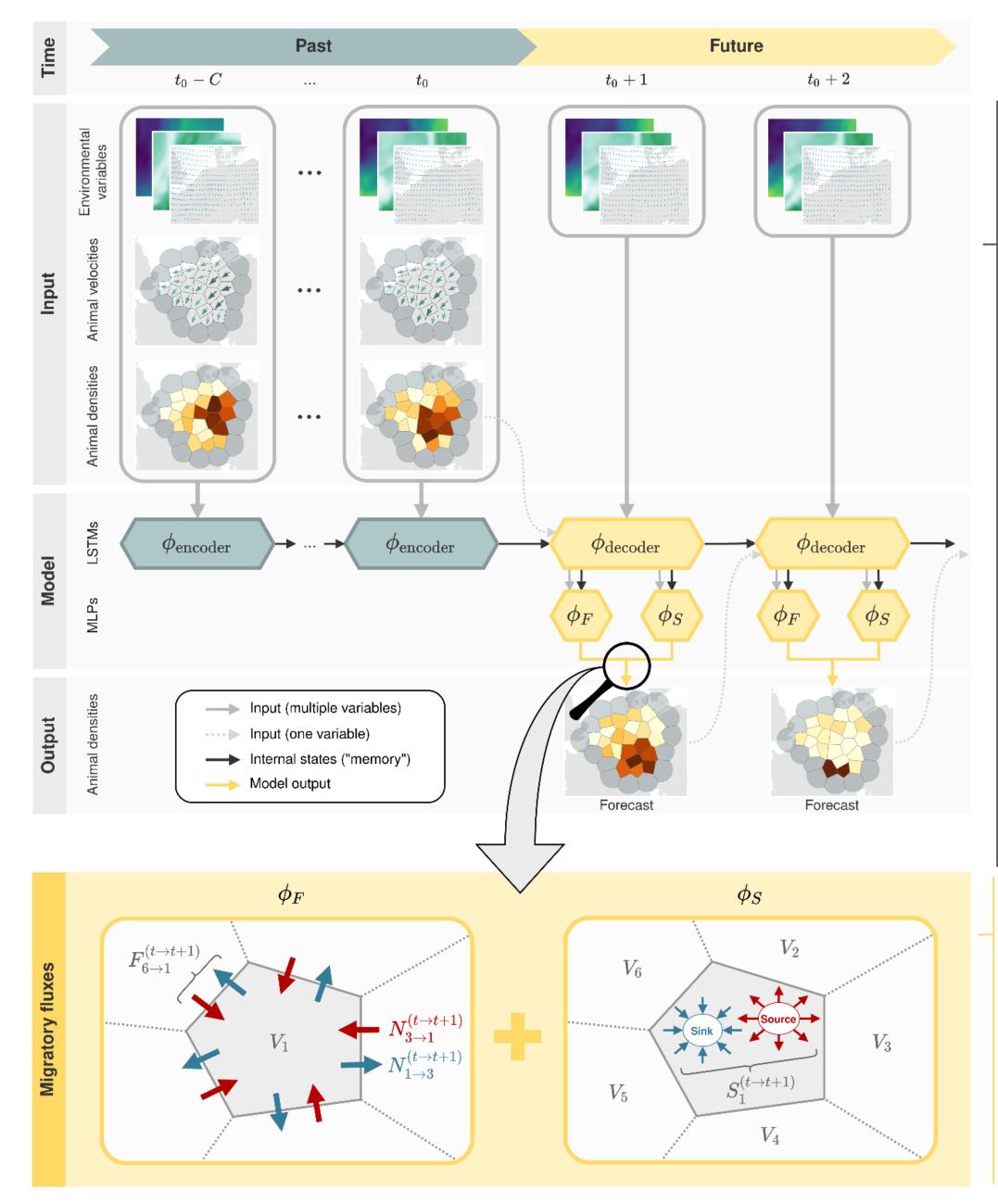
Learn more

Links to the pdf of this poster, full papers and code: https://github.com/emielvanloon/BESmovement2025 extras



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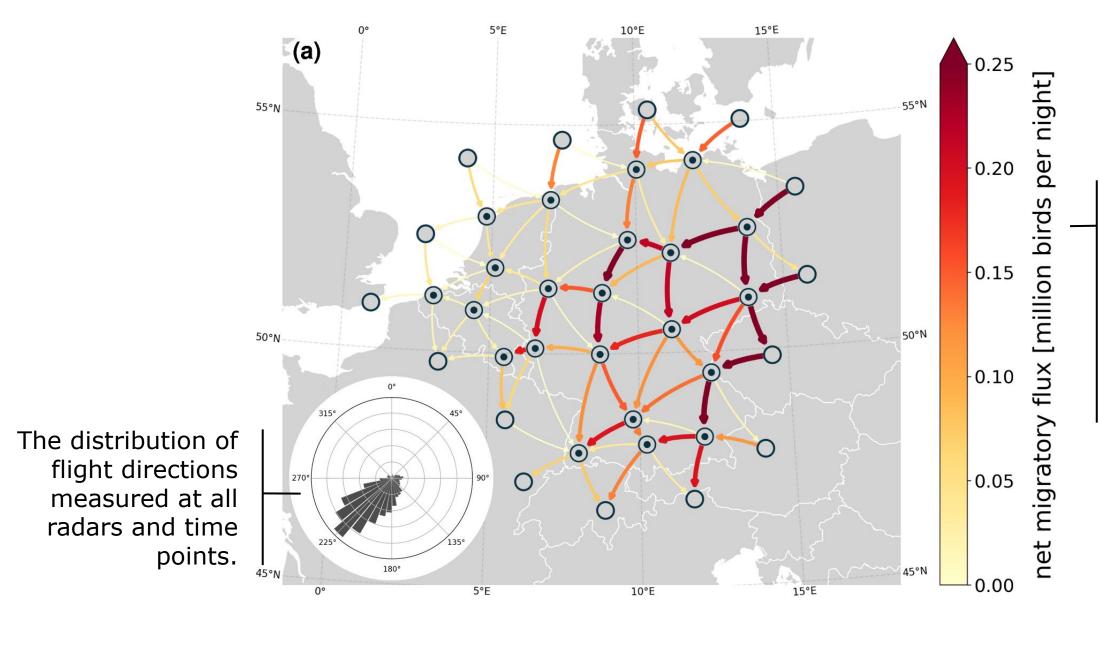
Results 1: Basic Model & First Application



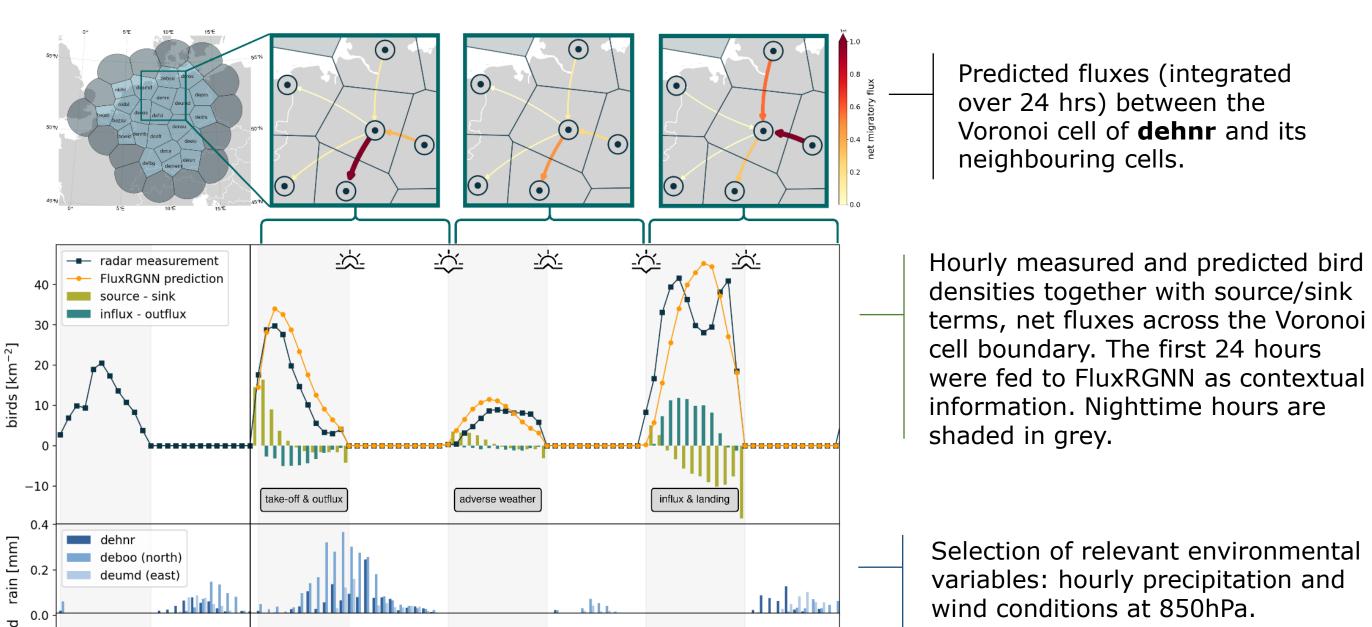
FluxRGNN: Migratory movements are modelled on the Voronoi tessellation of radar locations. Past environmental conditions, vertically integrated bird densities and velocities at each radar are fed to a long short-term memory neural network (LSTM) to extract relevant information.

A second LSTM combines this information with environmental forecasts and previous model outputs. Finally, two multi-layer perceptrons predict bird movement fluxes between adjacent Voronoi cells and local source/sink terms.

The predicted terms are combined into bird density forecasts according to a mechanistic description of population-level movements.



Average nightly migratory fluxes predicted by FluxRGNN using radar measurements of nocturnal bird migration in autumn 2017.



Lippert et al. 2022

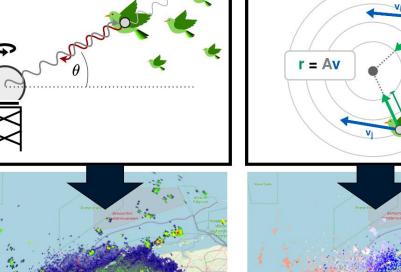
Motivation

Accurate and detailed spatio-temporal bird migration predictions are required for effective bird conservation and human-bird conflict mitigation.

Weather radars generate promising data, yet turning these into accurate predictions remains a challenge, a.o. due to the complexity of individual behaviors and the sparsity of the radar network.

Migratory movement by birds can be measured through weather radar

| reflectivity | animal density | Doppler shift | radial velocity |



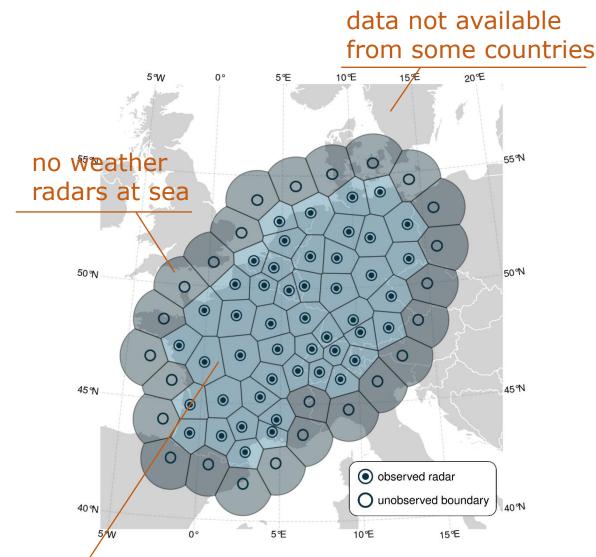
radar reflectivity
bird densities appear
in green,; pink pixels
indicate extremely
high reflectivity from
wind turbines and
boats.

Force of the state of the state

Doppler shift estimates the ground speed in the direction of the radar beam - movements towards in blue and movements away in red.

Radars form a continental-scale network, which is unfortunately not perfect; some issues:

data not available



radar observations are not space-covering (only a small circle within each Voronoy polygon)

Results 2: Refinements & New Application

FluxRGNN+ allows for higher resolution forecasts on any desired tessellation (involving a regularization parameter λ) and includes an alternative flux parameterization to integrate available velocity measurements. It thereby ensures meaningful estimates of implicitly learned take-off and landing processes.

To evaluate the model, we used the NEXRAD radar network for the USA (Crum & Alberty, 1993; Ansari et al., 2018). Atmospheric variables were extracted from the ERA5 reanalysis dataset (Hersbach et al., 2020), habitat types and other landscape characteristics were extracted the NLCD landcover data (Yang et al., 2018). The autumn migration season (1 Aug. to 15 Nov.) was considered. Years 2013 to 2018 for model training, 2019 for hyperparameter tuning and model selection, and 2020-2021 for final model evaluation.

Encoding: $f_{R\to C}$ maps sparse radar measurements to model entities (hexagonal cells).

Forecast is generated based on within-cell source/sink terms Si and cell-to-cell fluxes $F_{j\rightarrow i}$.

Black circles indicate measurement areas around radars, the movements are modeled on a hexagonal tessellation.

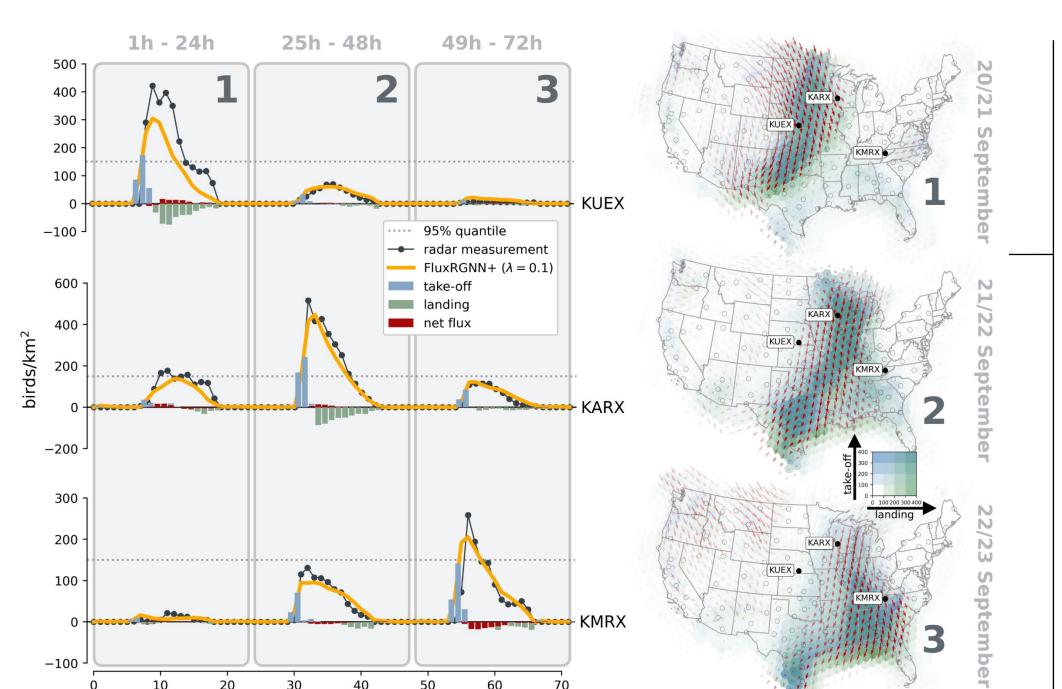
cells C

o radars R

radar-to-cell cell-to-cell cell-to-radar

 $\lambda = 0.1$ $\lambda = 0.01$ FluxRGNN+ 0.100 historical average measured ≥ 0.075 0.050 0.025 - $\lambda = 0$ $\lambda = 0.01$ $\lambda = 0.1$ 50 25 50 25 75 25 50 speed [km/h] speed [km/h] speed [km/h] ----- $\lambda = 0.01$ $\lambda = 0.1$

Averaged errors for training and test radars are comparable; lowest errors with λ of 0.1. Histograms of predicted and measured quantities for test radars; best agreement with λ of 0.1.



forecasting horizon [h]

Example forecast of three consecutive high intensity migration nights (nrs 1-3) in September 2021 trained with $\lambda = 0.1$ on years 2013-2020.

Decoding:

 $f_{C \rightarrow R}$ maps

predictions

measurement

cell-level

back to

space.

Evaluation of

speeds and

trained with

directions,

validation.

predicted flight

varying λ , using

10 fold cross-

The three time series match the radars marked in the maps on the right. To distinguish between take-off and landing, we separate hours with positive and negative source/sink term and aggregate them respectively.

Red arrows on the maps indicate average velocities in areas with substantial migration.

Lippert et al. 2024

