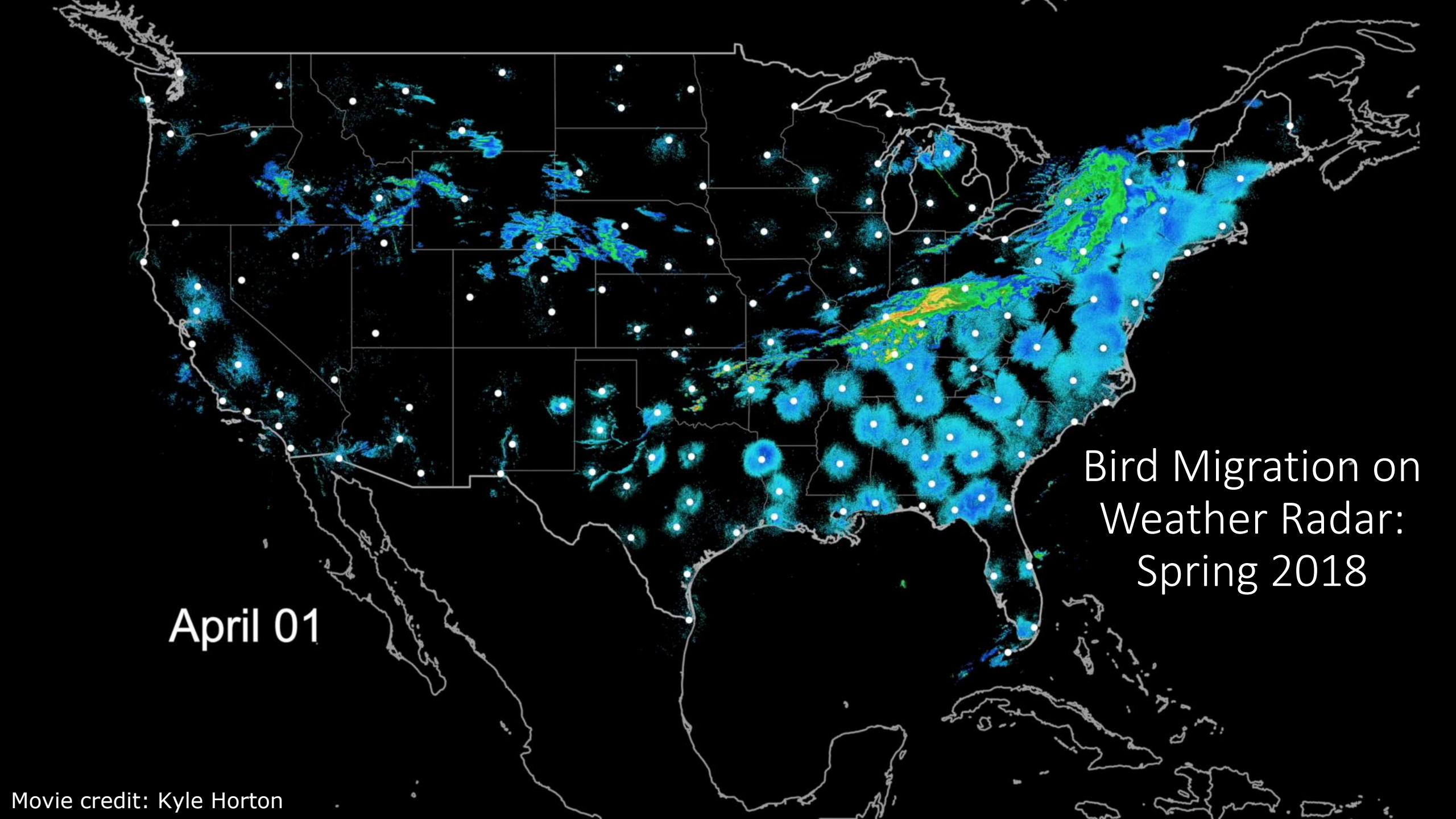


# DARK ECOLOGY

Unraveling Mysteries of Bird Migration using  
Weather Radar and Machine Learning

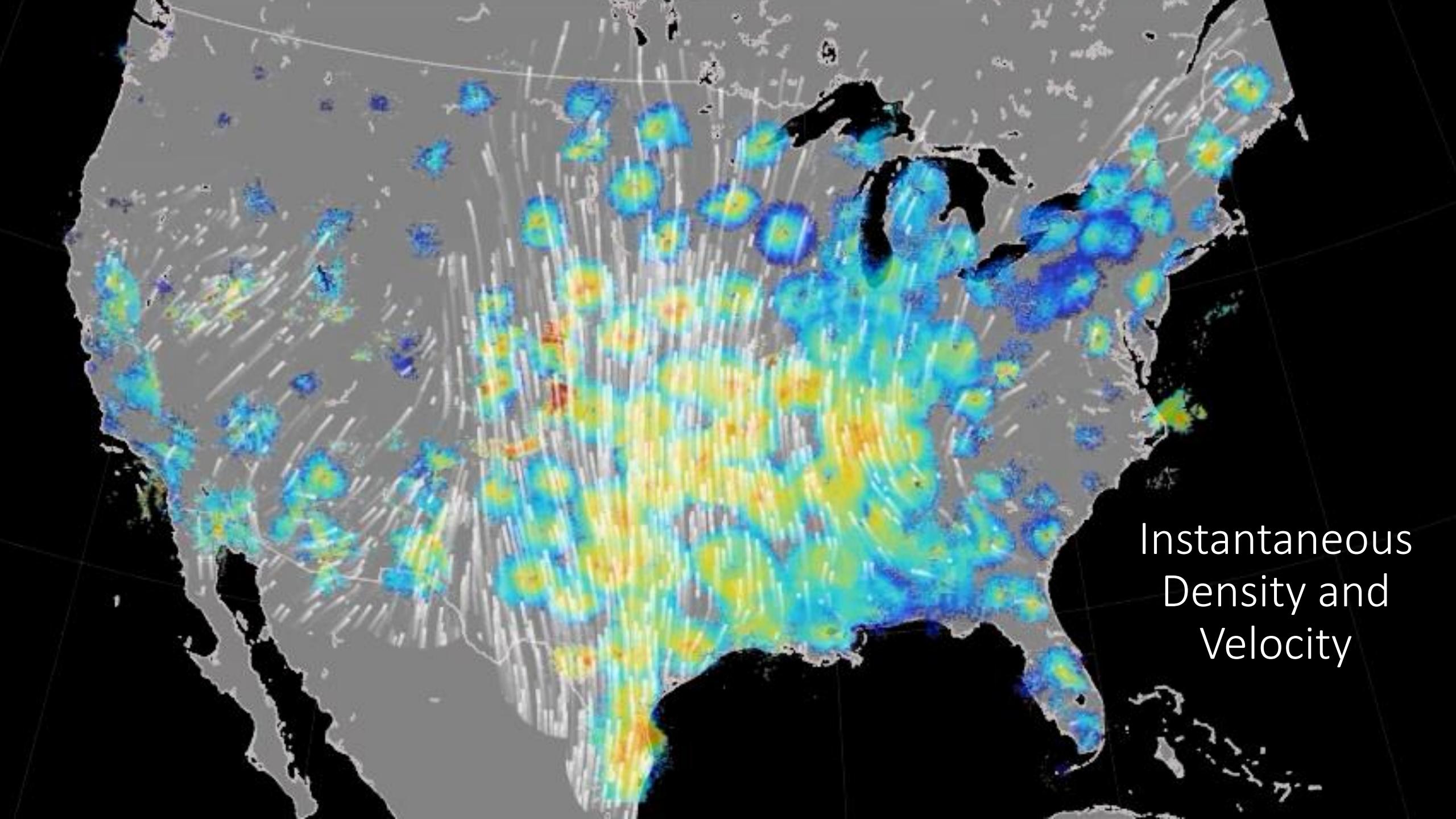
Subhransu Maji

University of Massachusetts, Amherst



April 01

Bird Migration on  
Weather Radar:  
Spring 2018



Instantaneous  
Density and  
Velocity

# Dark Ecology Project

- **Goal:** AI to unlock biological information in 25-year US weather radar archive
  - Basic science
  - Conserve biodiversity, ecosystems
  - Climate change
- **Challenges:** big data, not previously automated

UMassAmherst | College of Information & Computer Sciences



The Cornell Lab  
of Ornithology



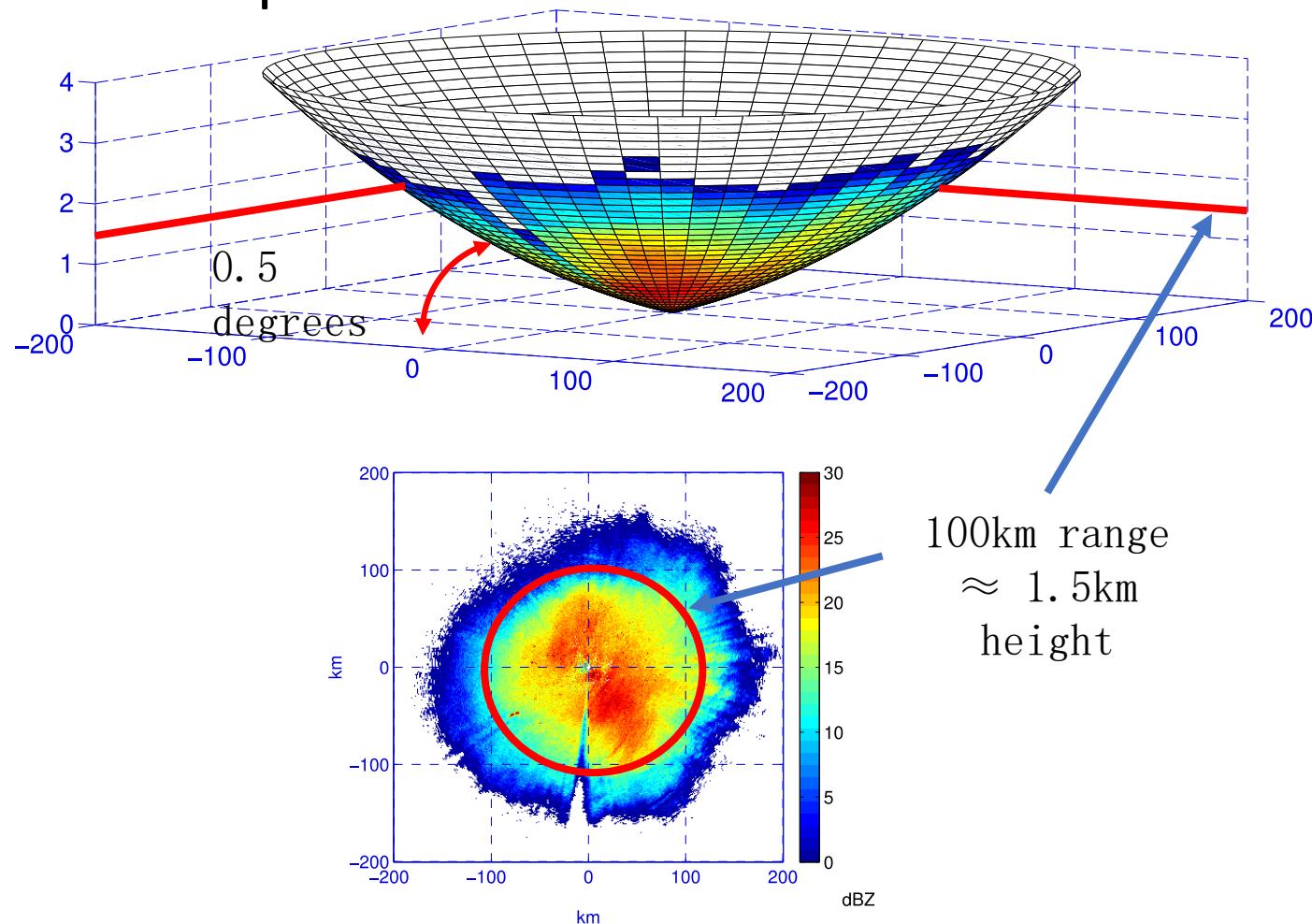
# Radar Background: Reflectivity

- Distance–height relationship

Scan pattern

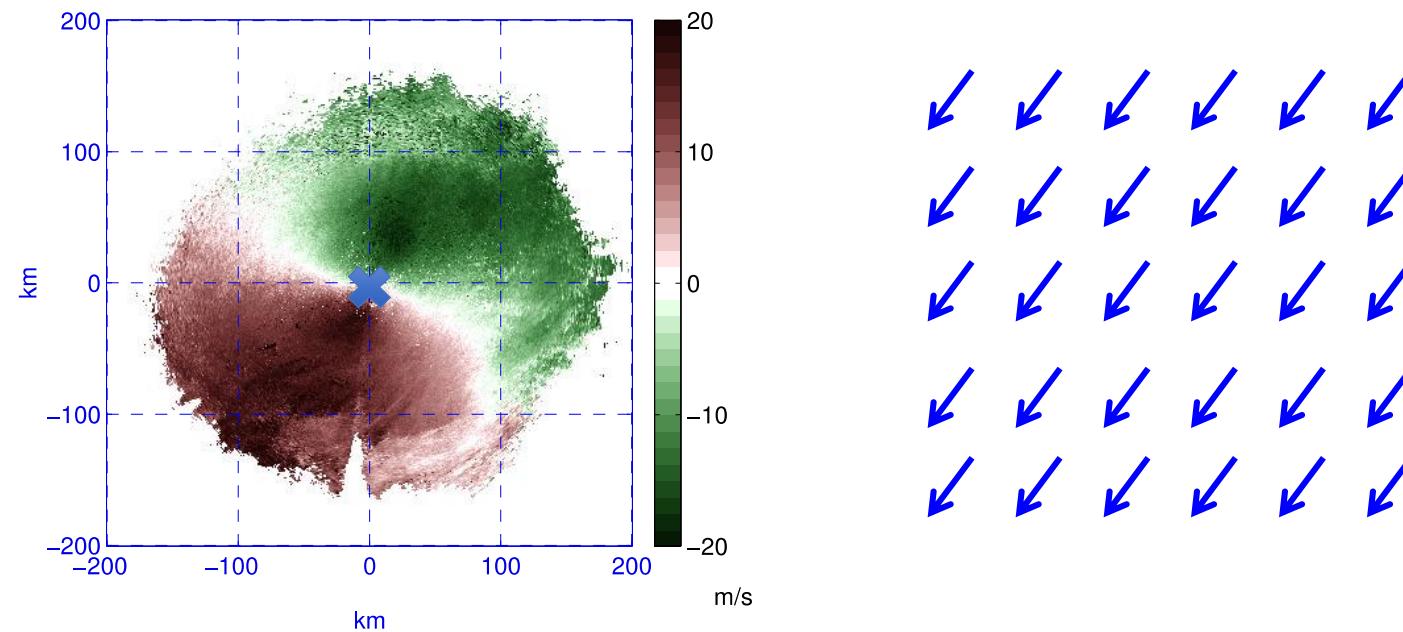


2D image  
(top view)



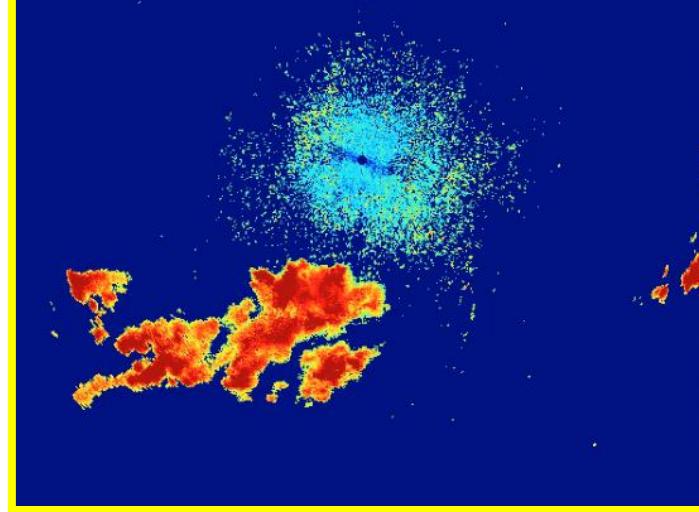
# Radar Background: Radial Velocity

- **Radial velocity**: speed at which targets approach or depart the radar station (Doppler shift)

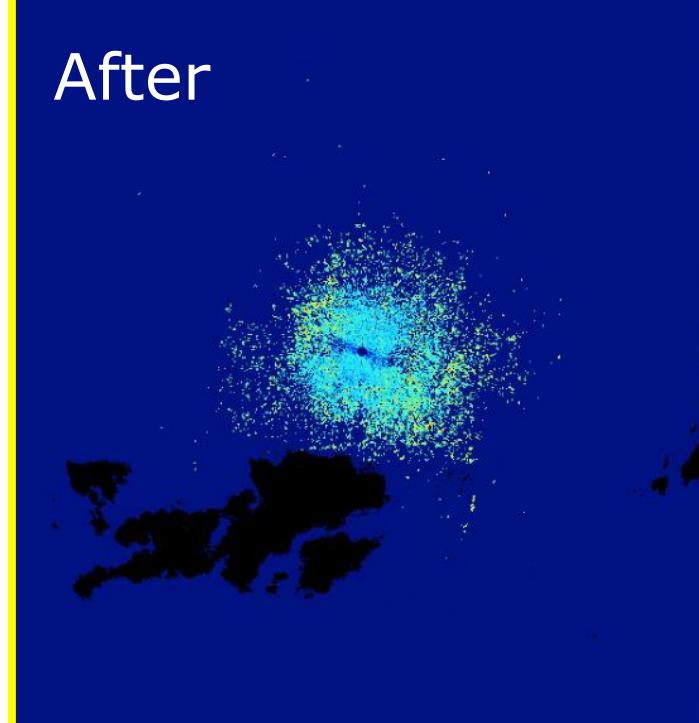


# Removing weather contamination

Before

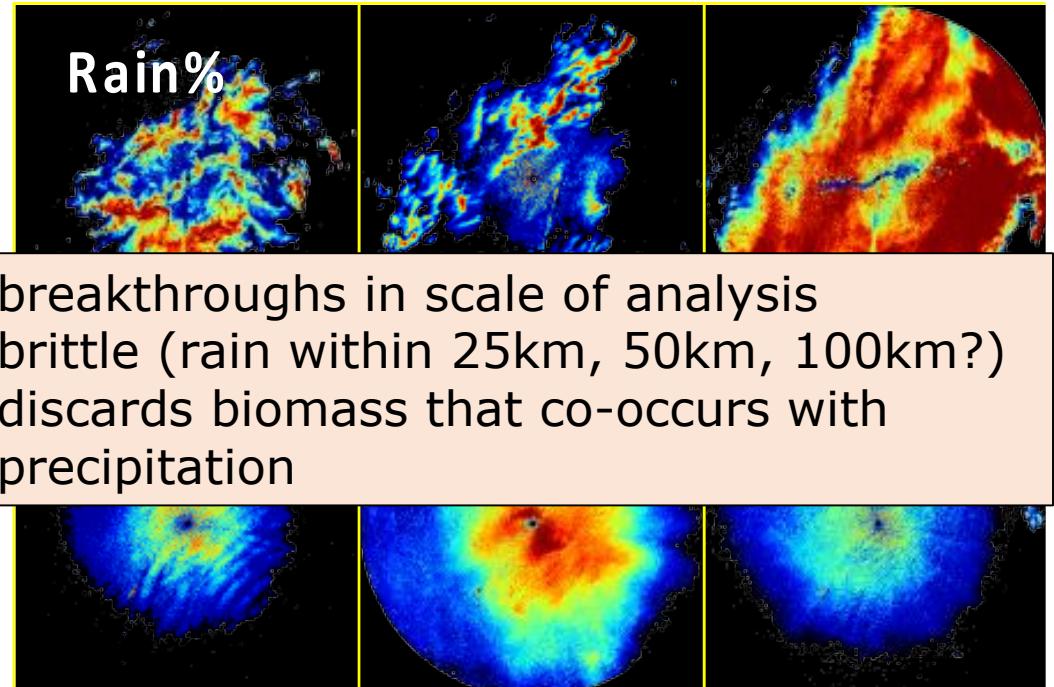


After



# Screening Rain

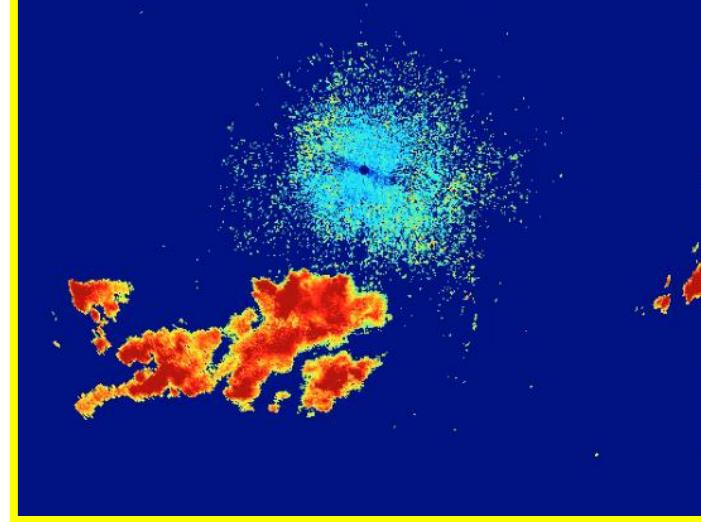
- Manual: most US studies until recently
- “Direct” algorithms for some radar systems
  - Dual-pol: US post 2013
  - European C-band [Dokter et al. 2011]
- ML for *whole-scan classification*
  - Images [Roy-Chowdhury et al. 2016]
  - Vertical profiles [Van-Doren and Horton, 2018]



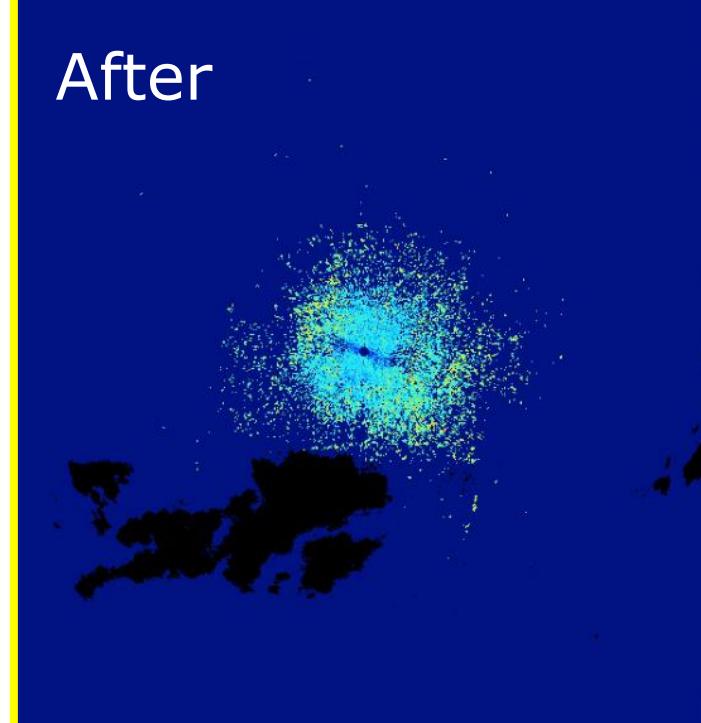
# Rain segmentation

- Flexible to many downstream analyses
- Spatially-explicit
- Retains biomass that co-occurs with precipitation (~19%)

Before

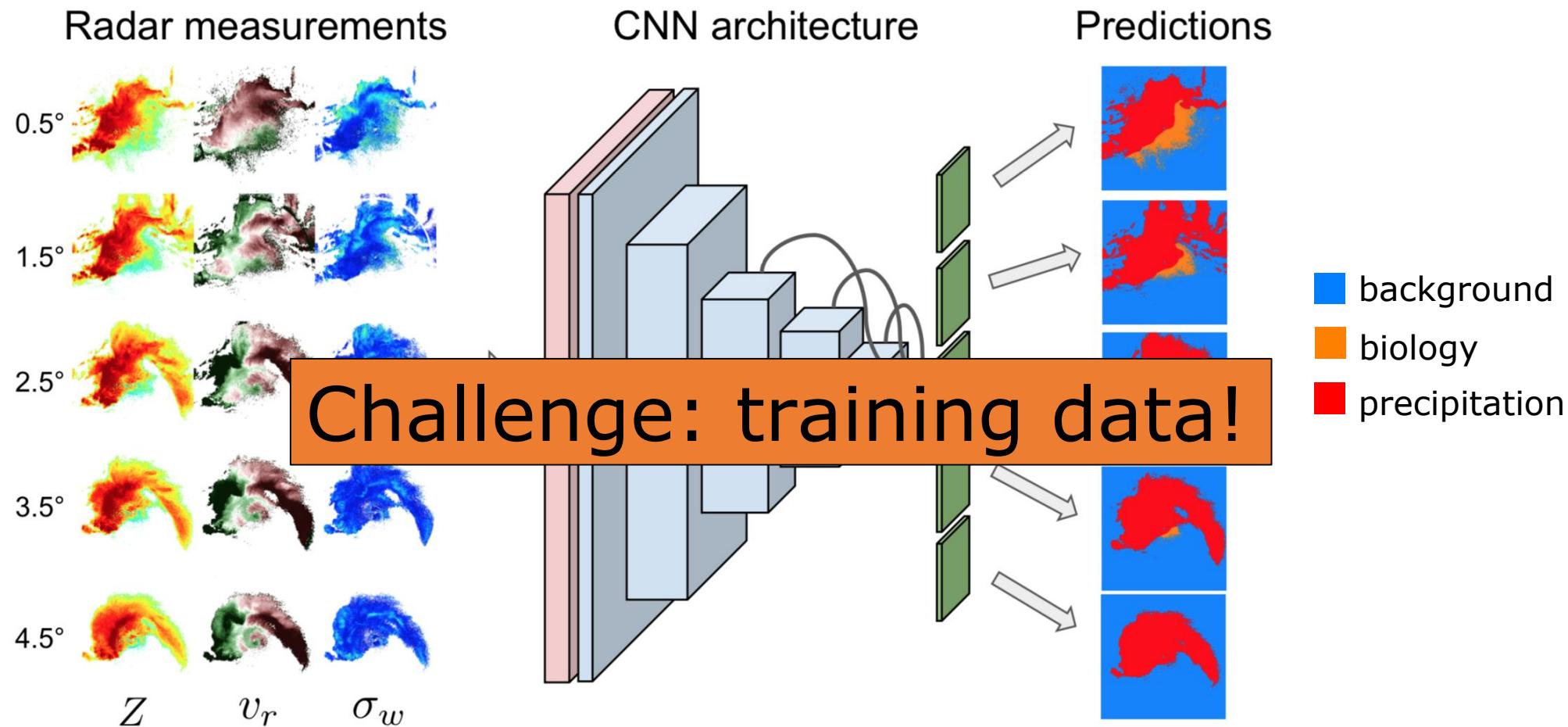


After





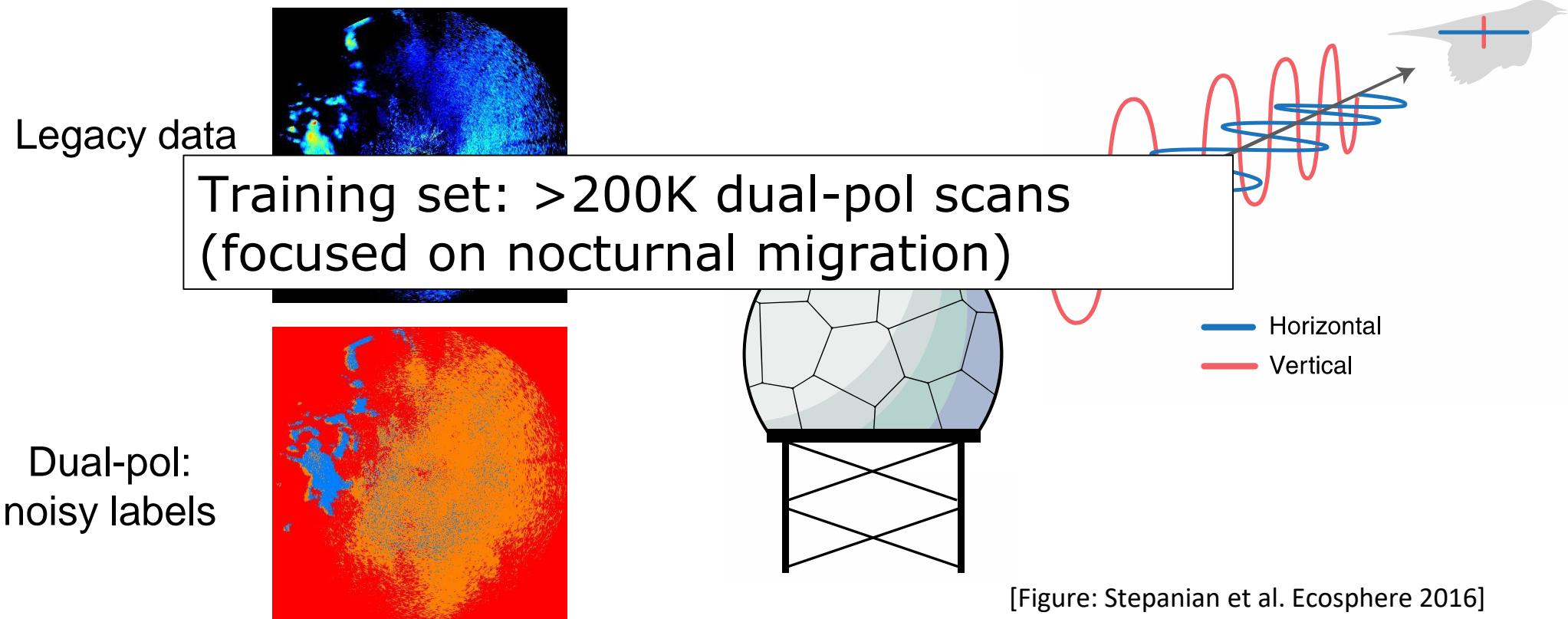
# MistNet – CNN for Weather Radar



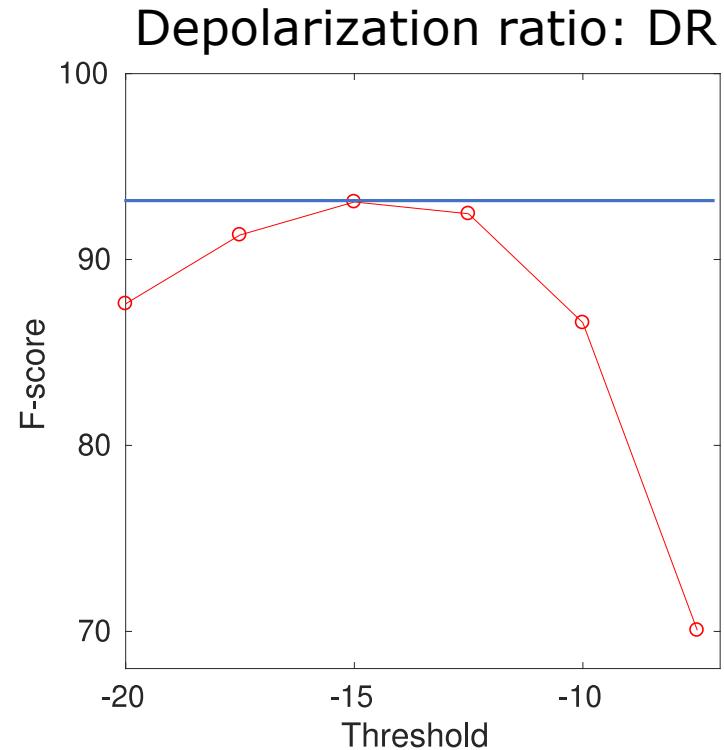
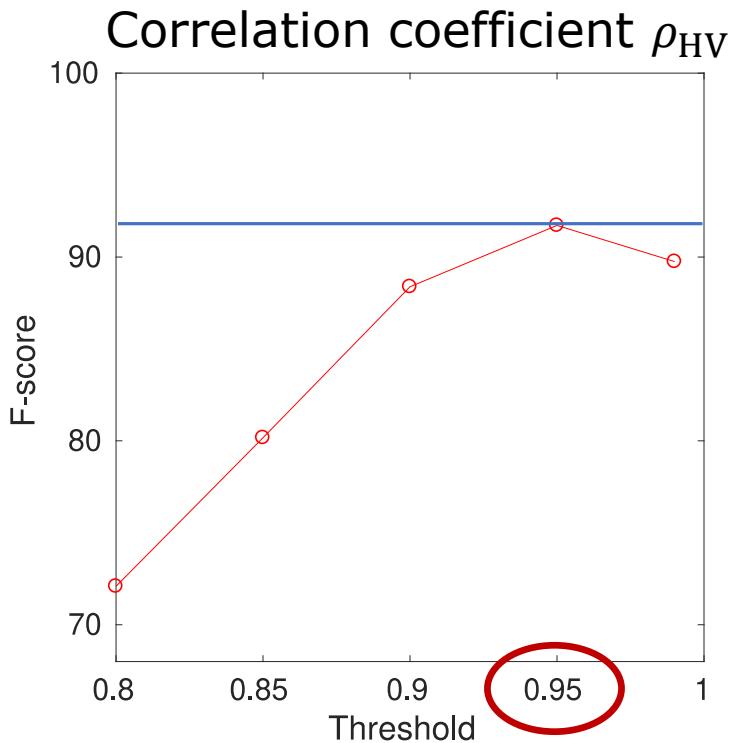
**MistNet: Measuring historical bird migration in the US using archived weather radar data and convolutional neural networks**, Tsung-Yu Lin et al., Methods in Ecology and Evolution, August 2019

# Weak Supervision

**2013 Dual polarization upgrade:** abundant noisy labels



# Quality of Dual-Pol Thresholding Rules

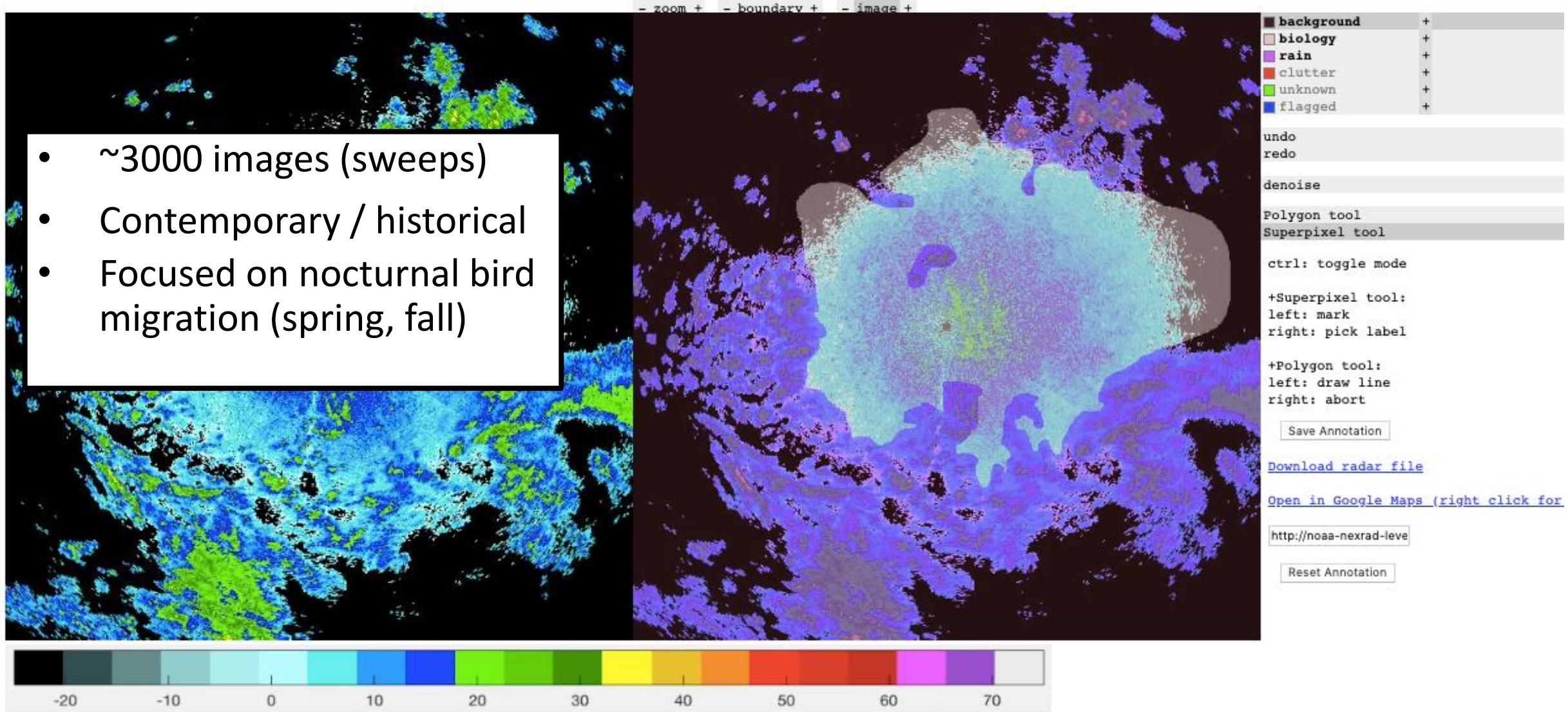


$$DR = 10 \log_{10} \left( \frac{Z_{DR} + 1 - 2Z_{DR}^{1/2} \rho_{HV}}{Z_{DR} + 1 + 2Z_{DR}^{1/2} \rho_{HV}} \right)$$

[Kilambi et al., 2018]

# Evaluation: Human Labels

[Prev](#) [Index](#) [Next](#) ID = 30; KBGM; 2012-04-15 03:10:21; elevation = 0.48

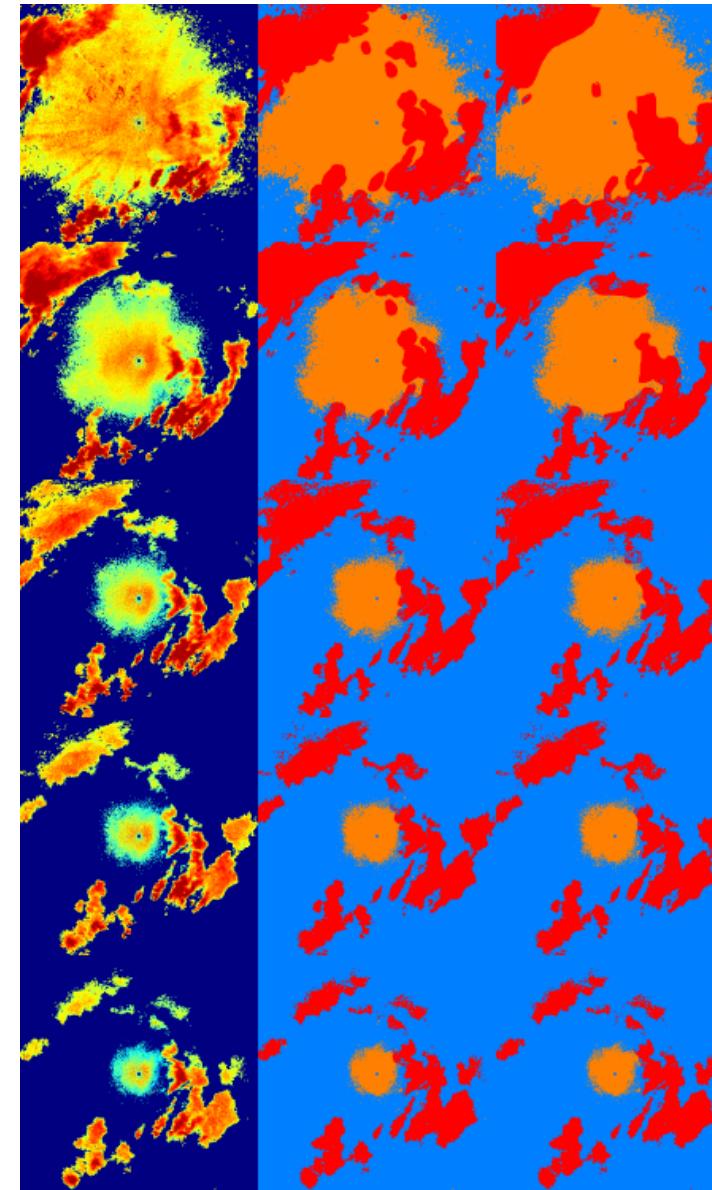


Range 150 km

Input

MistNet

Human

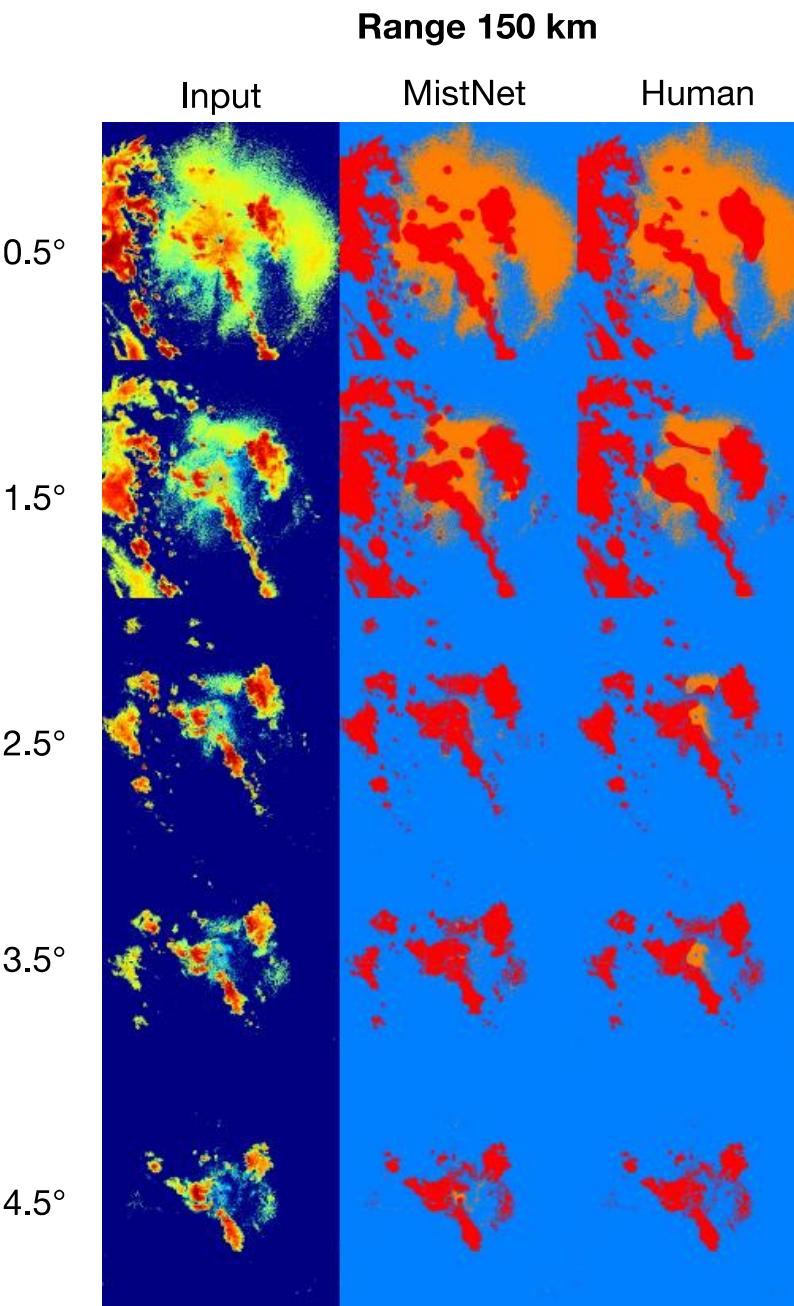


# Qualitative Results

Mobile, AL, Sep 1 2007, 3:10 UTC

# Qualitative Results

Binghamton, NY, Oct 1, 2014, 2:18 UTC



# Quantitative Results

Method	Precision	Recall	F-score
$\rho_{HV} > 0.95$	90.1	93.4	91.7
$DR < -15$	89.0	96.6	93.1
MISTNET	99.1	96.7	97.9

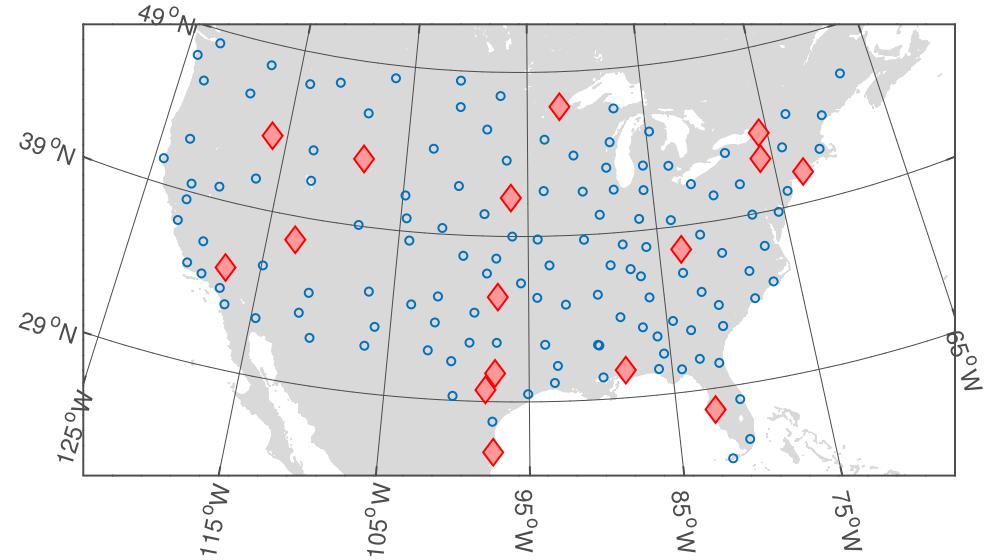
Contemporary (2017)

Historical  
(2 stations 1995–2017)

Precision      Recall  
98.7            95.9

98.7% of what we  
keep is biology

Preserve 95.9%  
of biomass

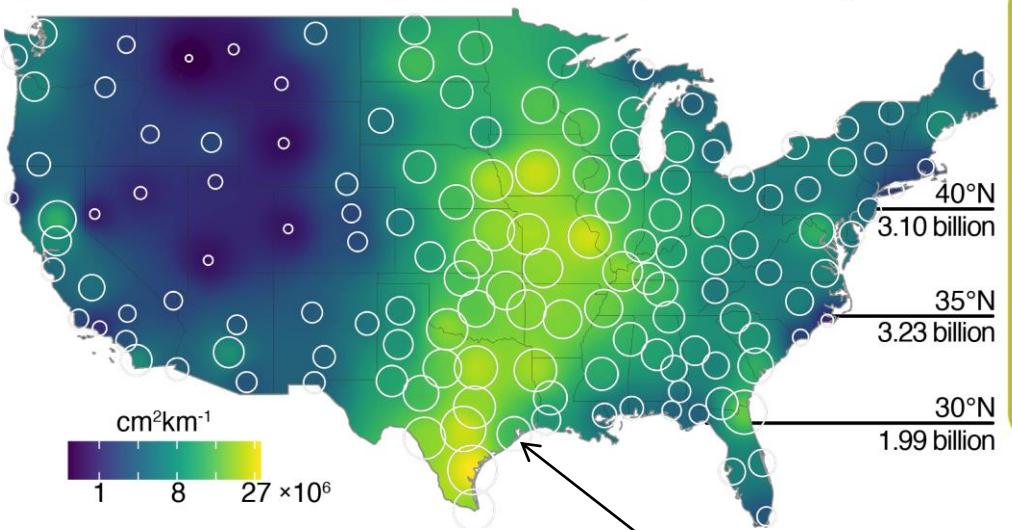


# Case Studies

13 million scans, 1.2 years compute time



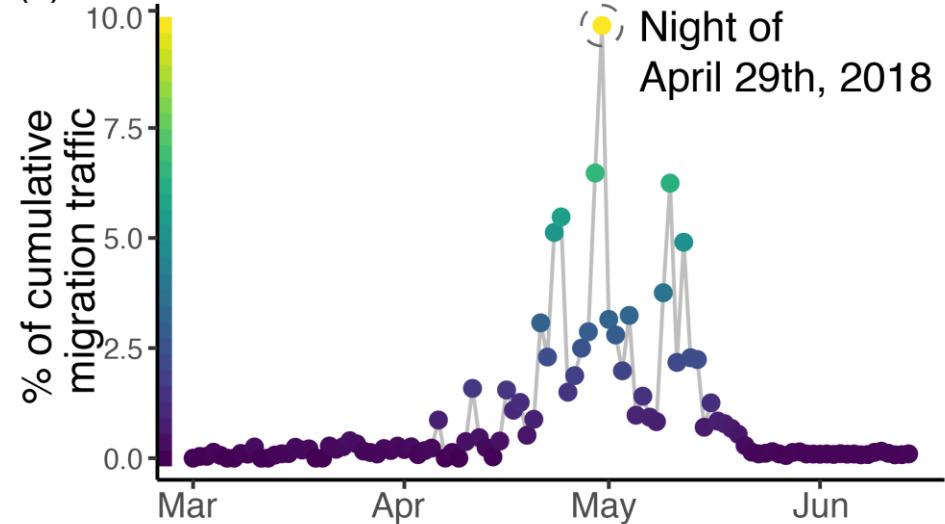
(a) U.S. cumulative migration traffic (1999-2018)



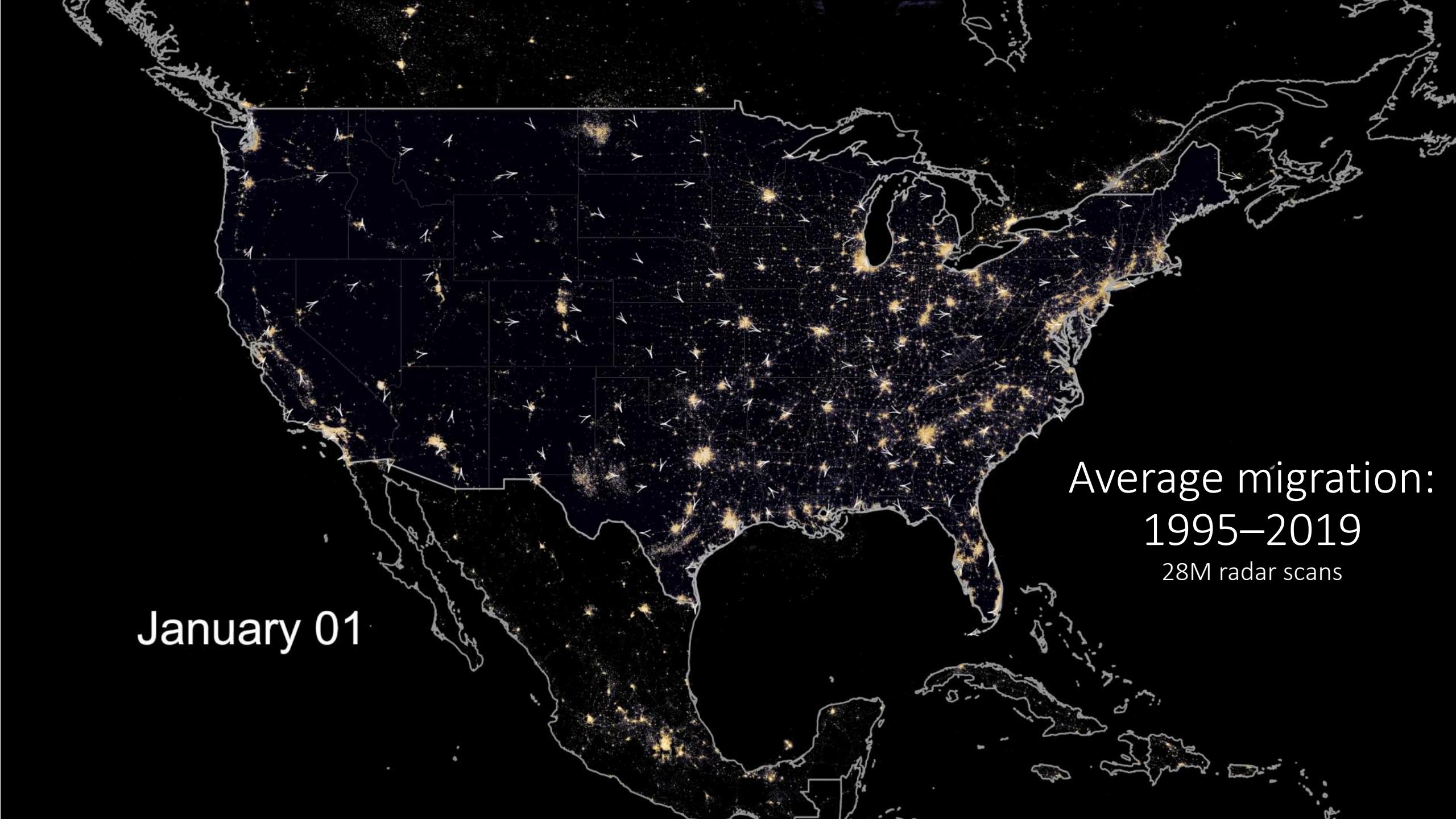
Spatial mapping

Houston

(c) Houston 2018



Nightly variation



January 01

Average migration:  
1995–2019  
28M radar scans

# MistNet: Outlook

- Code available: <https://github.com/darkecology/wsrlib>
- Coming soon: R, Python, versions
- European version (w/ Bart Hoekstra @ Univ. Amsterdam)
- Dataset: vertical profiles of biomass for entire US radar archive (>200 million scans; >90% complete)
- Spatially-explicit analyses

# Detecting and Tracking Swallow Roosts

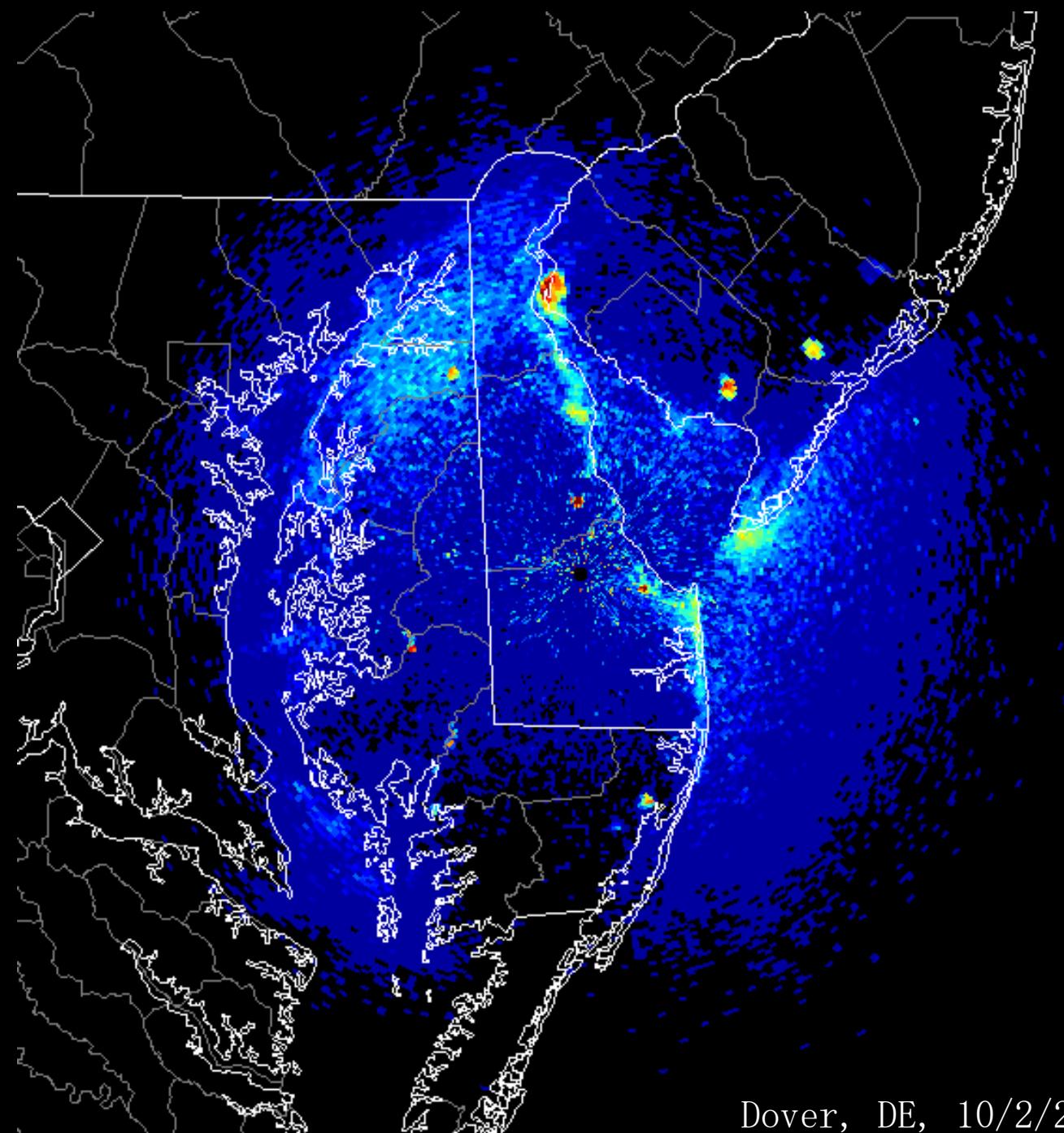
Migration behavior of a single species



[Cheng et al., 20XX]

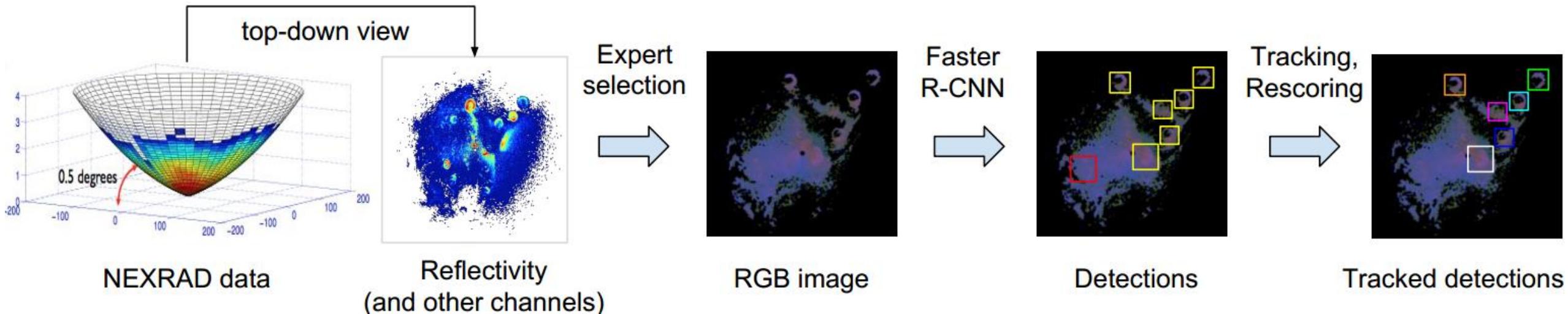


# Communal Roosts



Dover, DE, 10/2/2010@6:52AM

# Approach: Detect and Track



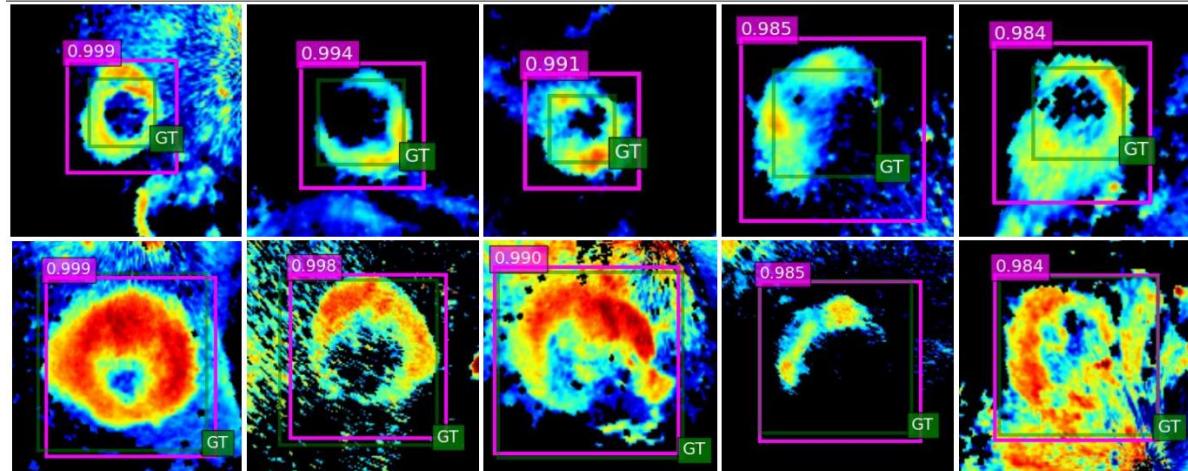
## ➤ Faster R-CNN for radar image

- ImageNet pre-training is useful
- Deeper networks are better

Model	w/ ImageNet pretraining	w/o ImageNet pretraining
VGG-M	<b>41.0</b>	34.8
Shallow VGG-M	37.7	33.1

# Challenge: Variable annotation styles

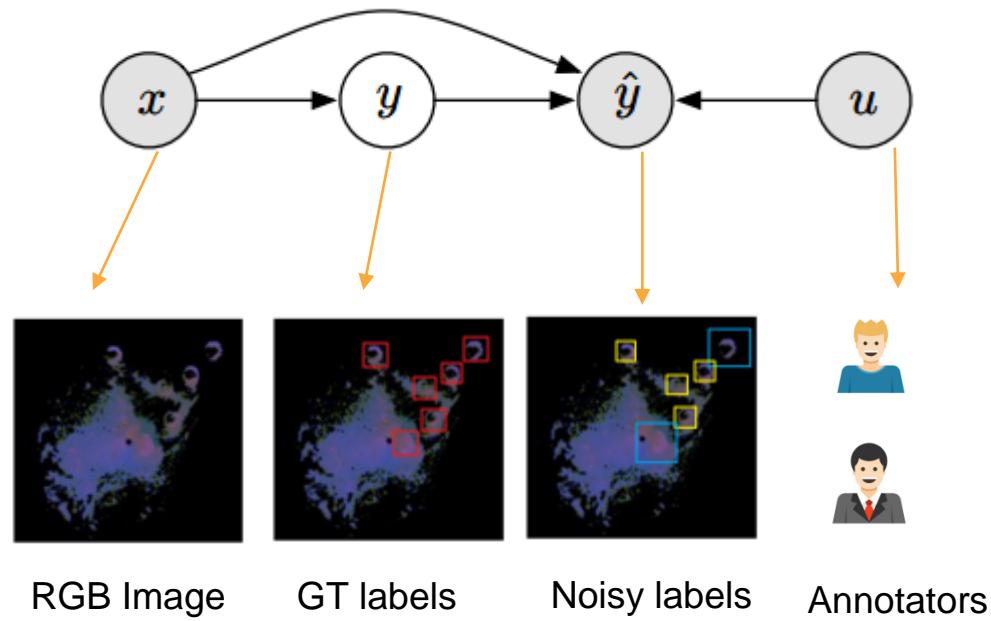
Station	Size of trainset	Faster RCNN (mAP)
KDOX	902	9.1



Noisy roost annotations lead to inaccurate evaluation

- **Challenge: Roost labels are abundant (more than 60K) but very noisy:** Considerable labeling variability, *much of which is specific to individual users.* → Inaccurate evaluation and potentially hurt training.

# An EM approach for learning with noisy annotations

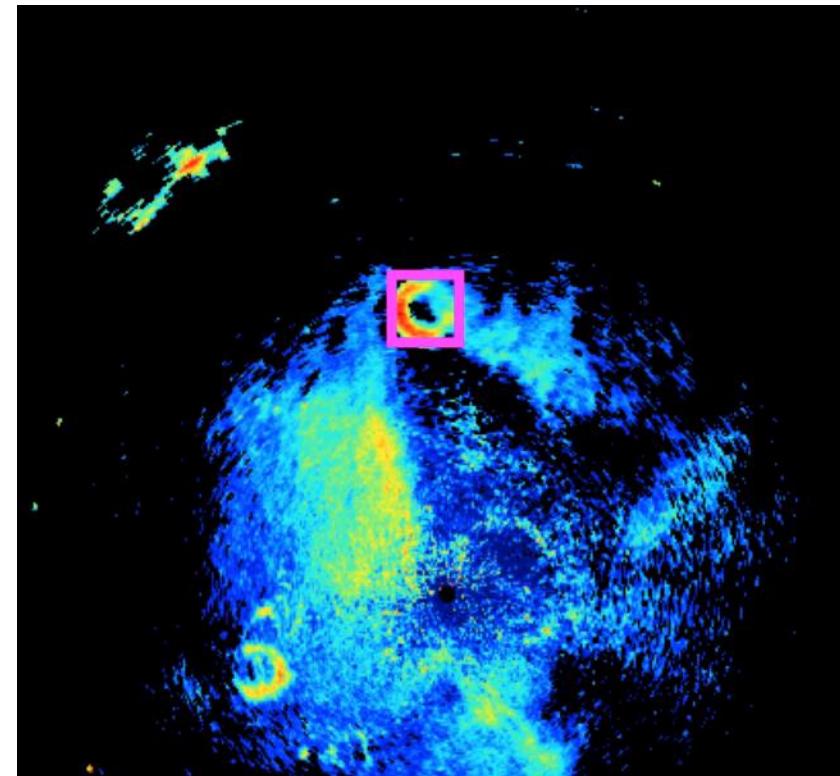
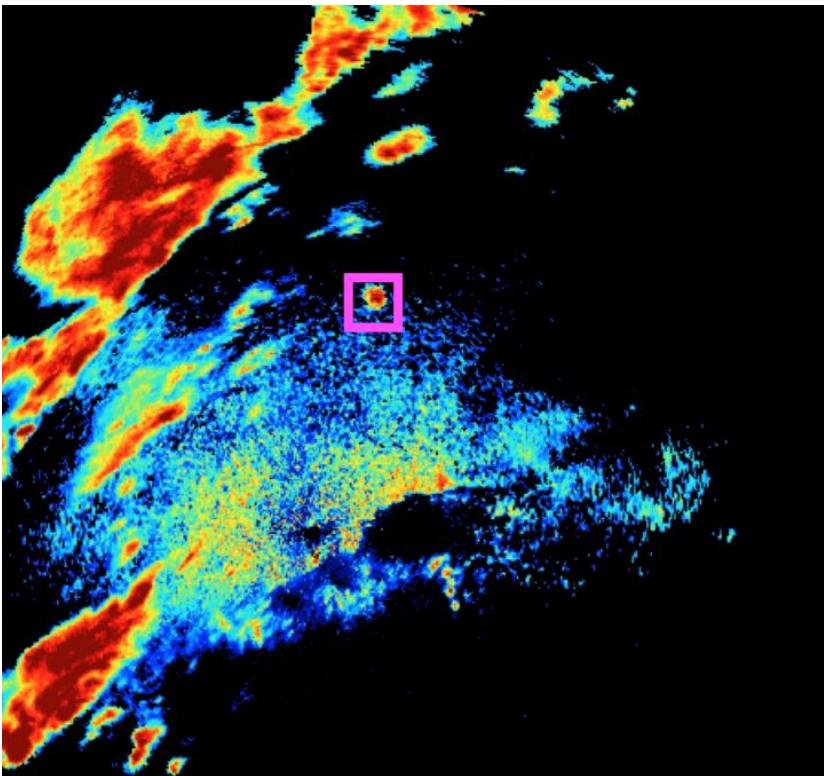


$p_\theta(y|x)$  is the *detection model*.

$p_\beta(\hat{y} \mid x, y, u)$  is the *forward user model*

$p_{\theta,\beta}(y \mid x, \hat{y}, u)$  is the *reverse user model*. → variational reverse user model  $q_\phi(y \mid x, \hat{y}, u)$

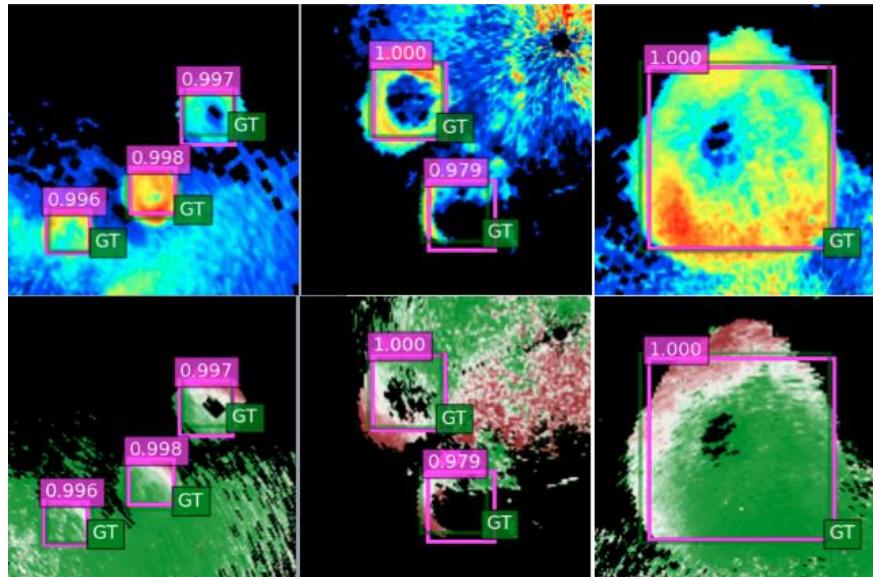
## Example Detections and Tracks



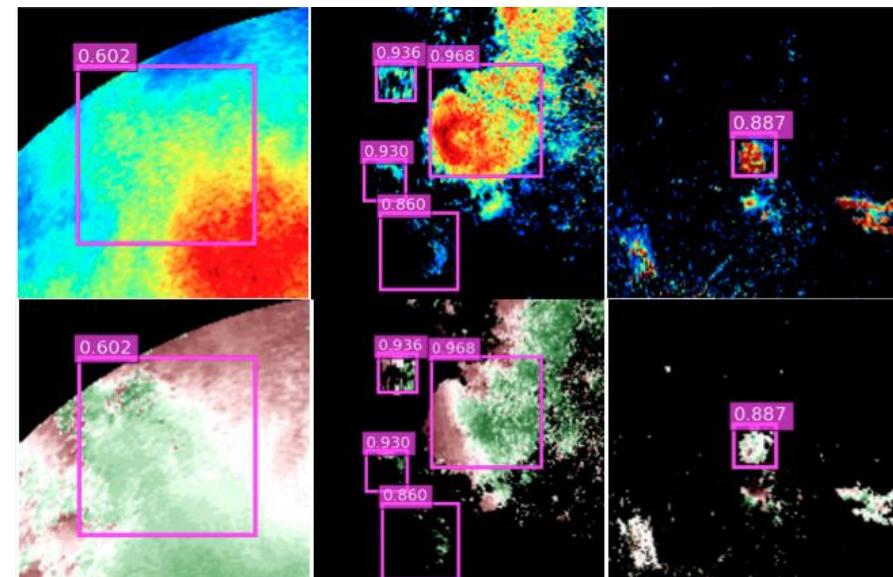
# Error Analysis



Post processing	Swallow roost	Precipitation	Wind mills	Other roost	Misc. clutter	Unknown
Before	454	109	47	38	22	8
After	449	5	0	38	21	8

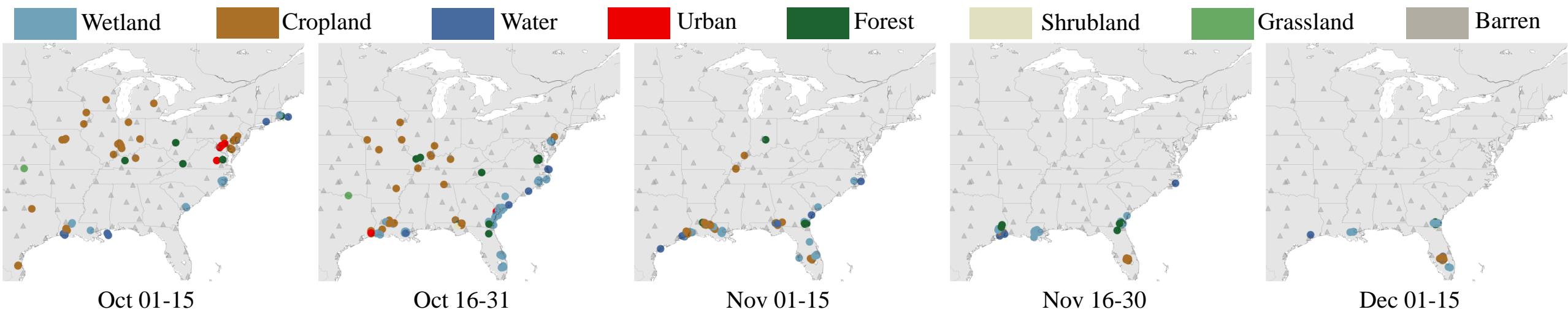


correctly detected roosts



rain, roosts of other species,  
windmills

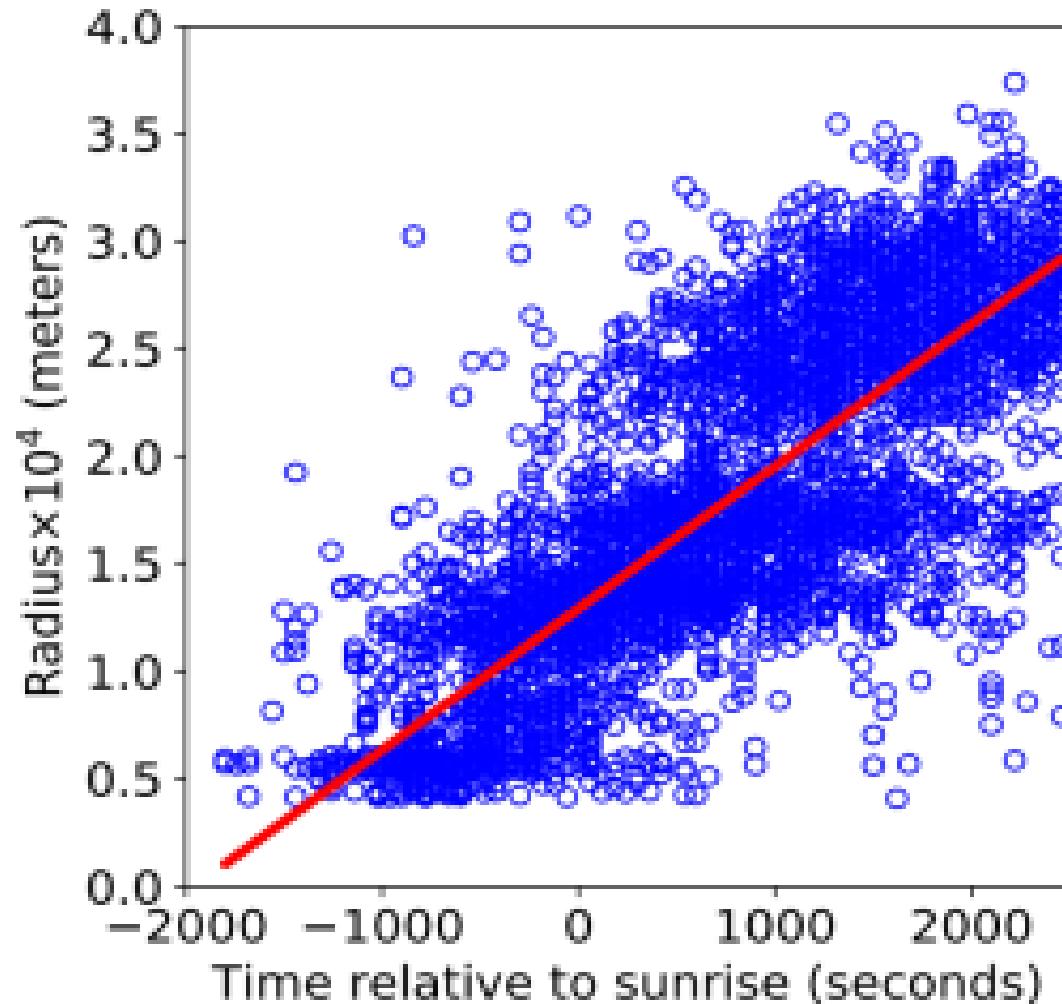
# Where do the swallow roost?



**Habitat:** natural wetlands (e.g., cattails and phragmites) or agricultural

Widespread statistics of roost locations and habitat usage throughout a migratory season has not previously been

# Roost emergence dynamics



Estimated airspeed velocity of tree swallows is 6.61 m/s (unladen)

# DARK ECOLOGY



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