

# Using Machine Learning to Improve Prediction and Understanding of Convective Hazards

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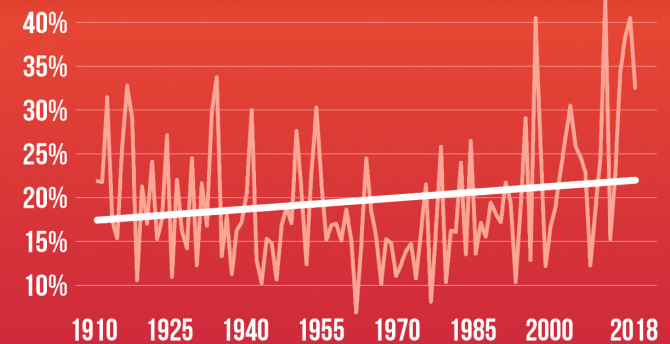
[amcgovern@ou.edu](mailto:amcgovern@ou.edu)

# Use AI/ML to Improve Societal Resilience to Climate Change and Extreme Weather

- Wicked problems:
  - How can humans adapt to a changing climate? Where do we need to build and grow our communities? How do they need to change from current practices?
  - **How can we improve the prediction of new weather extremes?**
  - **How can we improve the adaptation of other species?** Migration patterns, land use changes, etc.
- Proposal: create a joint university, industry, and government *alpha-institute* to bring together researchers in AI/ML and climate and weather

## MORE EXTREME WEATHER

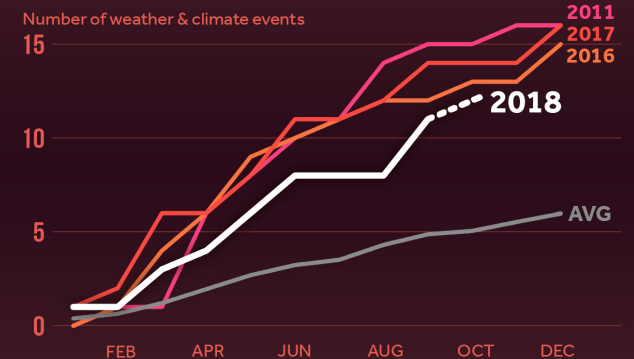
CLIMATE EXTREMES INDEX: TEMPERATURES, PRECIPITATION, TROPICS



Percentage of Continental U.S. much above (or below) normal for six climate indicators.  
Source: NOAA/NCEP Climate Extremes Index. Produced 5/13/2019.

CLIMATE CENTRAL

## BILLION DOLLAR DISASTERS



Cumulative U.S. billion-dollar disaster frequency, 1980-2017 average. Data as of October 9, 2018.  
Source: NOAA/NCEP

CLIMATE CENTRAL



Thank you to  
my students  
(current and  
former)



**Will Booker**  
OU CS MS



**Carmen Chilson**  
OU CS MS, now at Google



**David John Gagne II**  
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**Katherine Avery**  
OU, CS BS



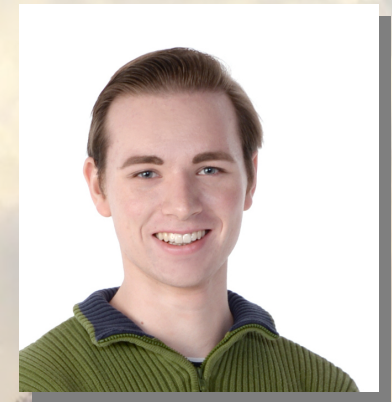
**Amanda Burke**  
OU, SOM MS



**Katy Felkner**  
OU, CS and Letters BS



**David Harrison**  
OU/CIMMS/SPC SOM PhD



**Eli Jergensen**  
OU, Math/Physics BS

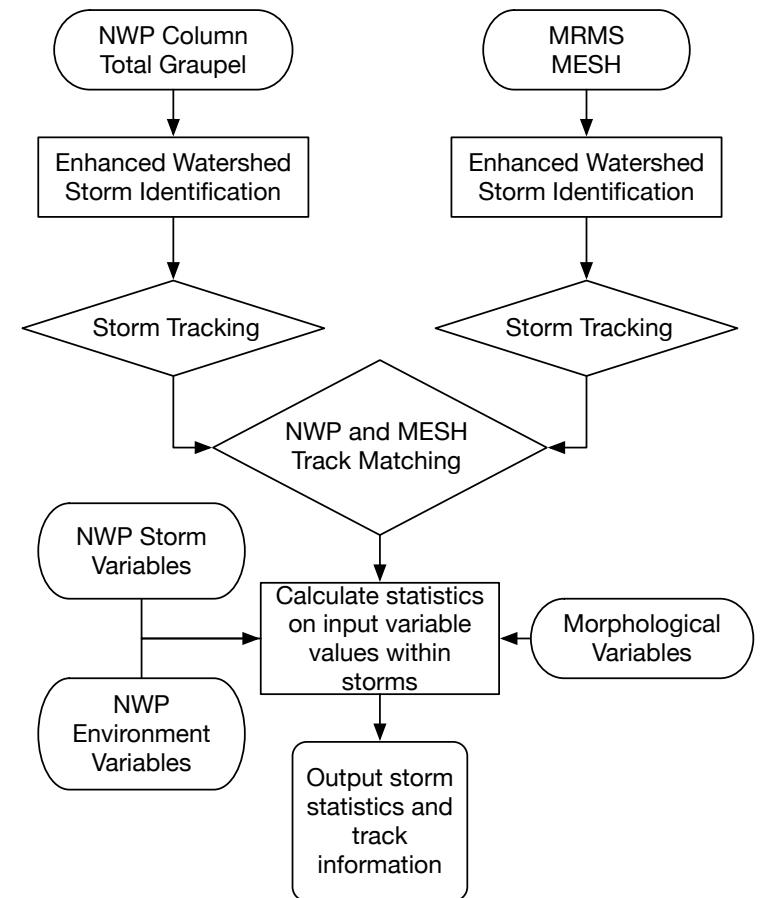
# ML for Weather Outline

- Using ML for severe weather prediction
  - Improving hail forecasting 24-48 hours in advance (traditional ML)
  - Improving nowcasting for tornadoes (deep learning/convolutional neural networks)
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# Storm-Based Hail Forecasting

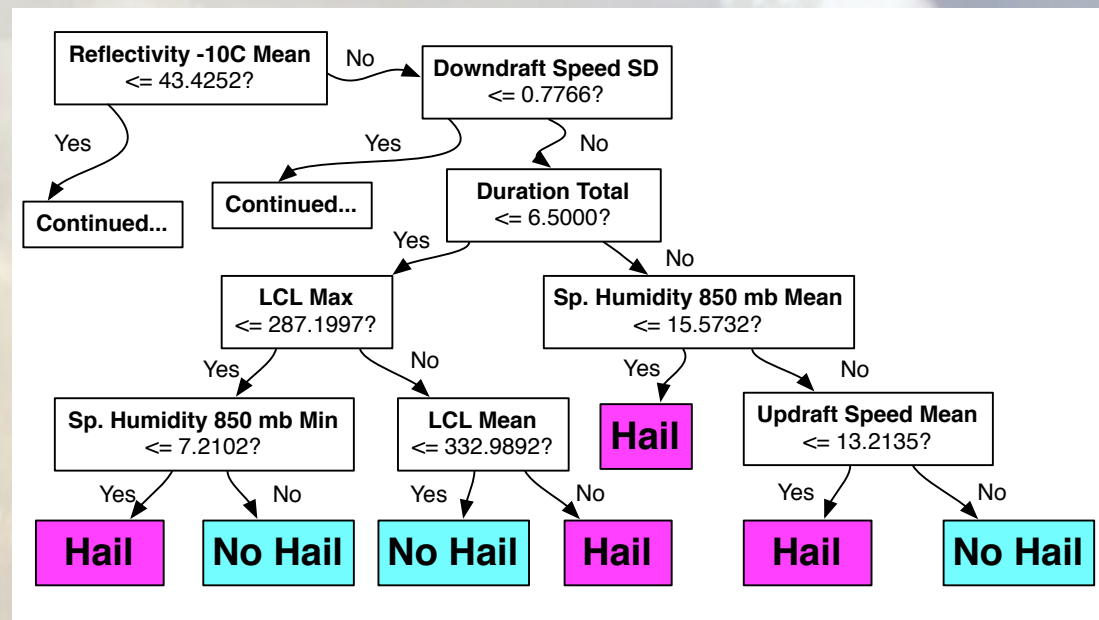
- Overall steps:
  - Create training data from NWP models
  - Train ML models (random forests)
  - Prediction and evaluation
- Implemented and tested in NOAA's Hazardous Weather Testbed
- Details:
  - Gagne et al 2017, WAF
  - Burke et al, in preparation





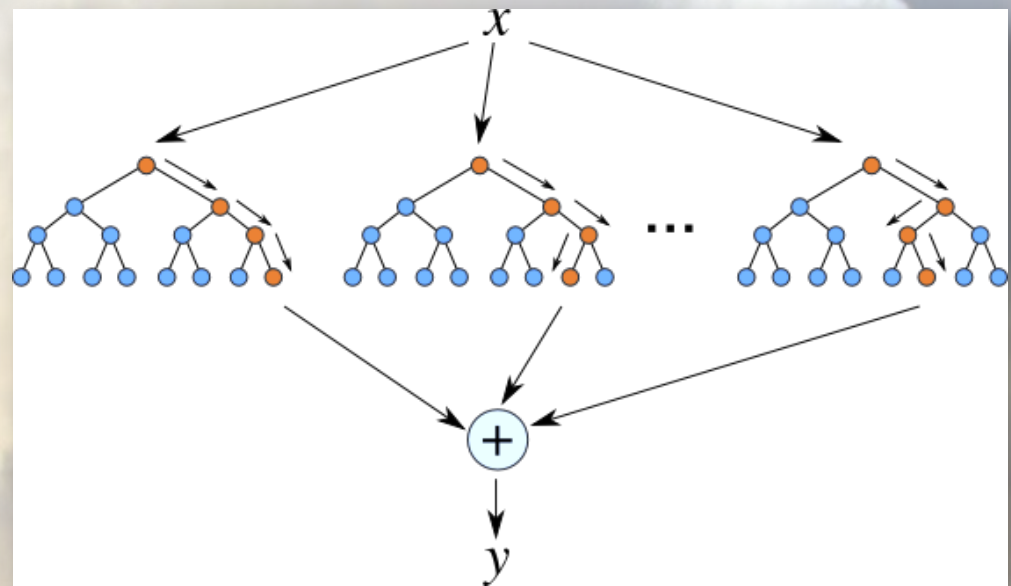
# Decision Trees

- Human-readable ML model
- Can predict:
  - Class labels (hail/no hail)
  - Real-values (hail size, shape parameters)
  - Probabilities
- Demonstrated success in meteorology
  - Selective model



# Ensembles of Trees

- Random Forests
  - Individual trees trained on bootstrap resampled subsets of data
  - Trees use subsets of attributes at each level
- Each tree votes or averages its prediction



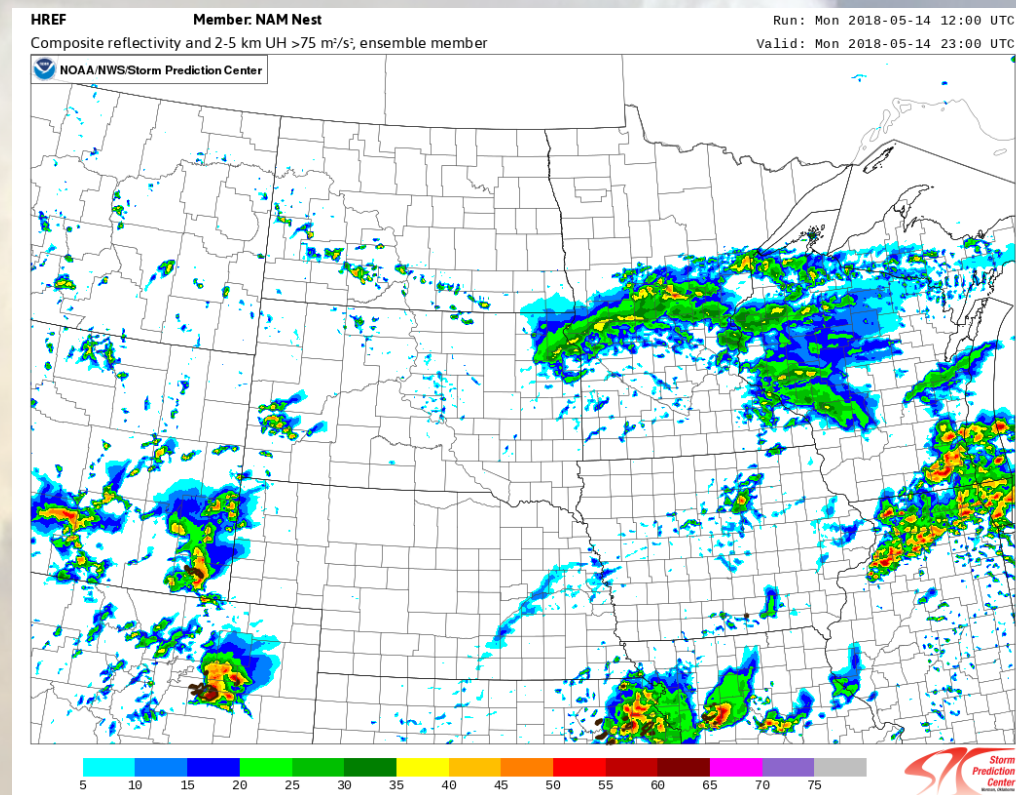
# NWP Convection Allowing Models (CAMs)

- CAMs have high spatial and temporal resolution across CONUS
  - Resolution too low to resolve hazards such as hail
  - ML can predict missing hazards and correct spatial or temporal forecast errors
- Gagne et al 2017
  - CAPS Spring Experiment ensemble
  - NCAR ensemble
- Current work (Burke et al, in preparation)
  - High Resolution Ensemble Forecast version 2 (HREFv2)
    - Operational in Storm Prediction Center (SPC)
  - High Resolution Rapid Refresh Ensemble (HRRRE, summer 2019)



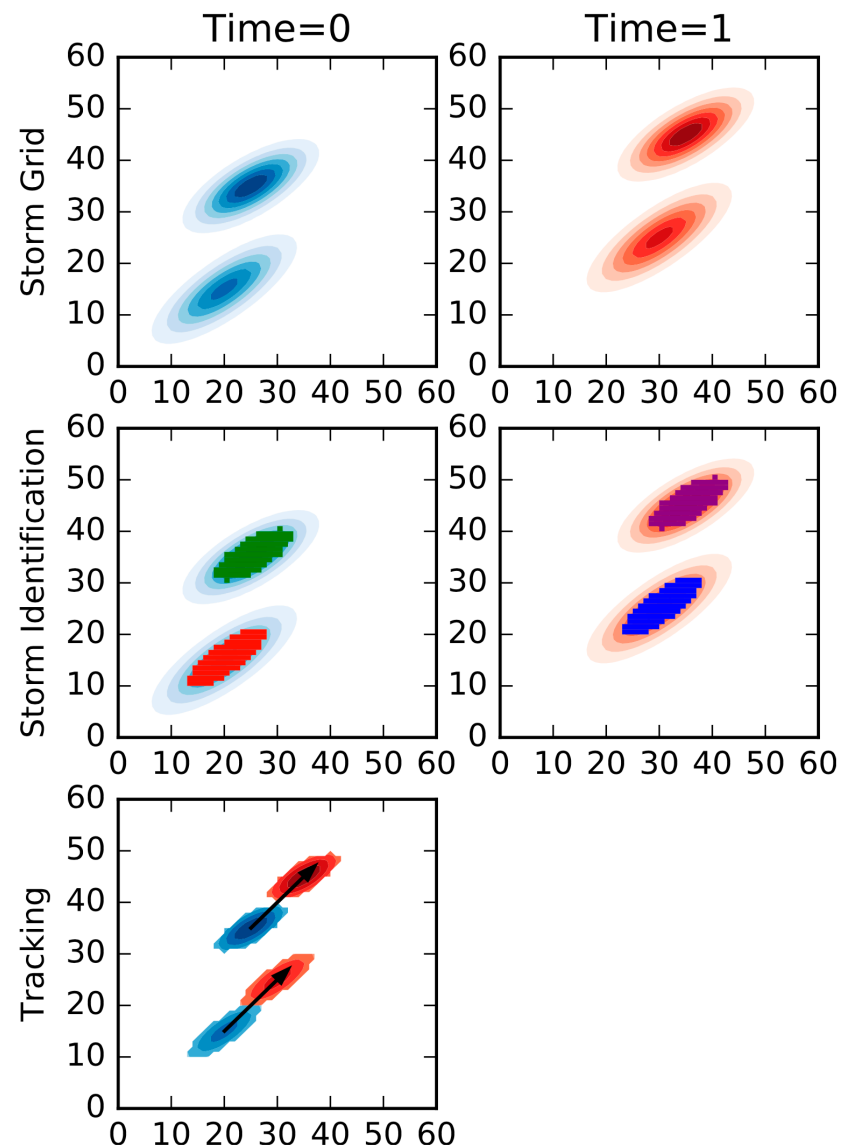
# ML Input

- Extract data for each storm object/track
  - Storm data: updraft/downdraft, reflectivity, precipitation, etc
  - Environment: temperature, CAPE, wind, sounding data, etc
  - Morphological: Area, shape, etc
  - Location: Forecast hour, duration, motion
- Each CAM has slightly different data
  - ML model trained for that CAM



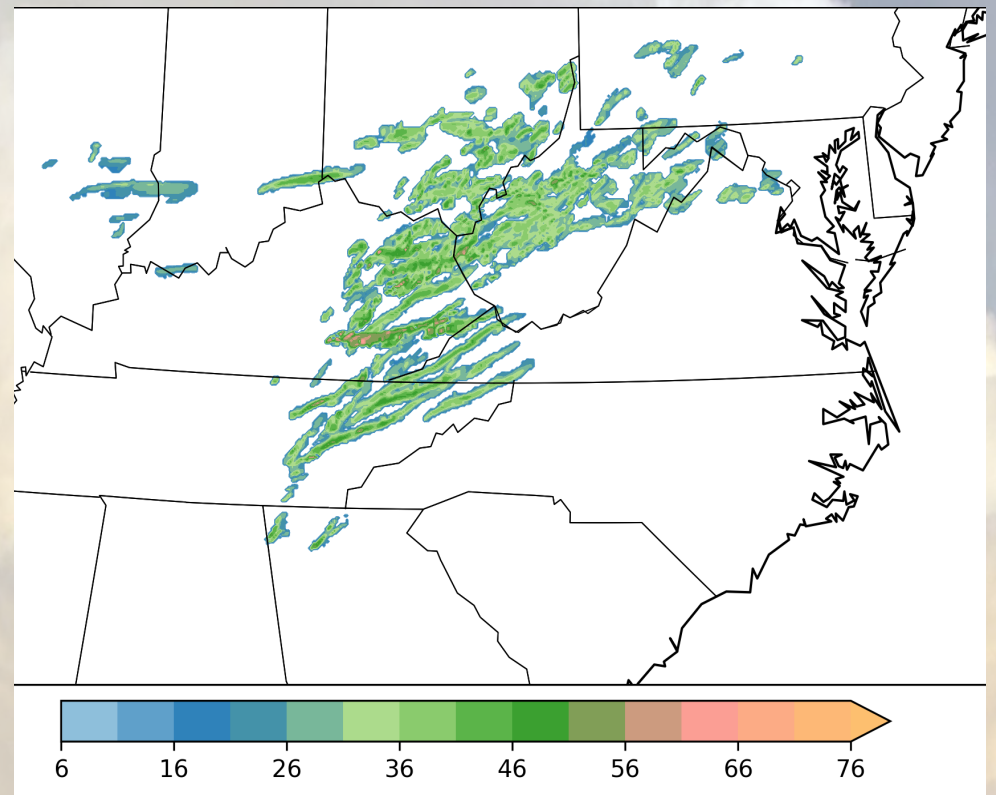
# Identifying and Tracking Hail Objects

- Enhanced watershed algorithm
  - Turning pixels into objects
- HREFv2
  - Max Hourly Updraft (ms-1)  $> 8 \frac{m}{s}$
  - Capture more than just supercells
- Observations
  - Maximum Estimated Size of Hail (MESH)  $> 19\text{mm}$  (3/4 in)



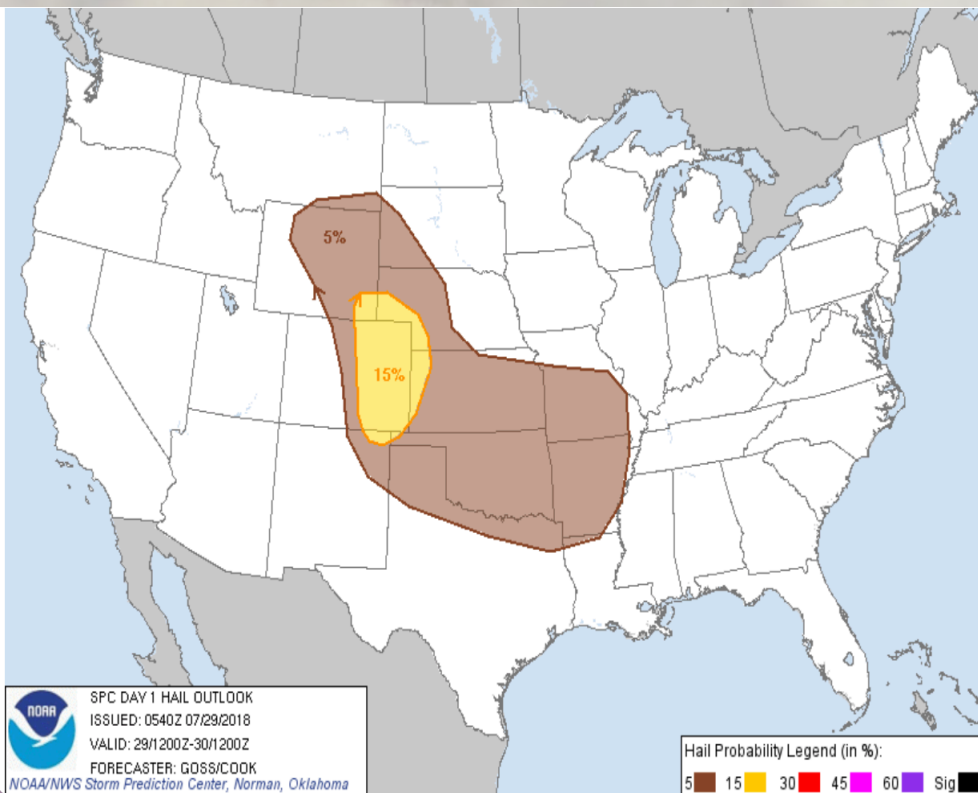
# ML Hail prediction

- Two step prediction
  - Hail or no hail?
- If hail:
  - Predict shape and scale parameters of gamma distribution
- Estimate ensemble neighborhood probabilities
  - Bootstrapping

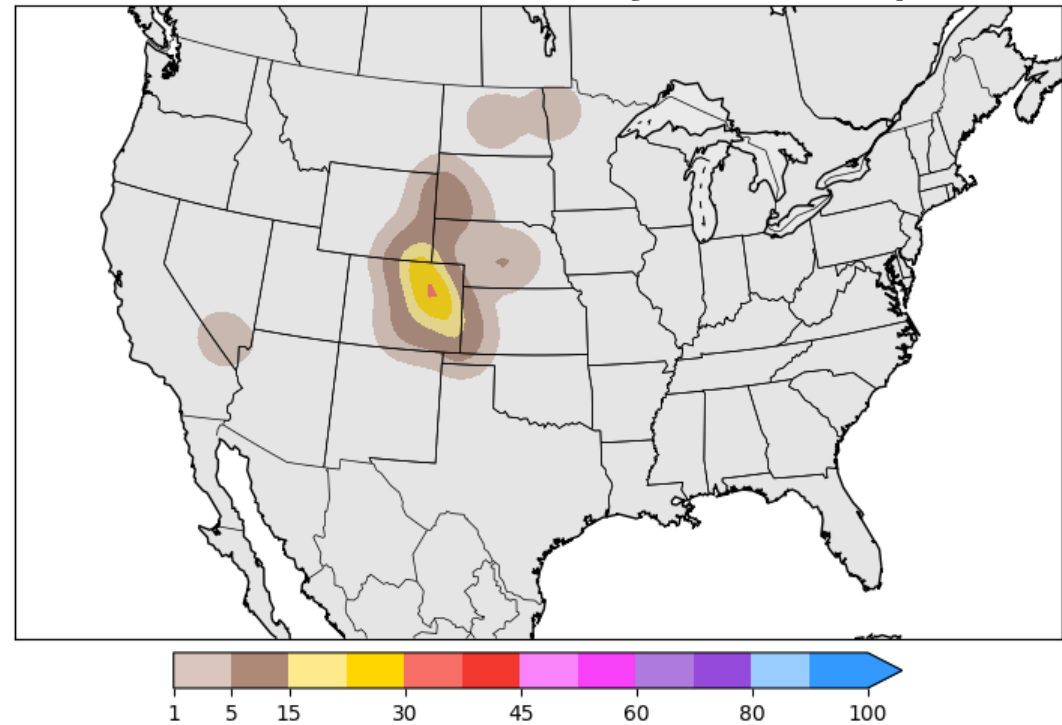




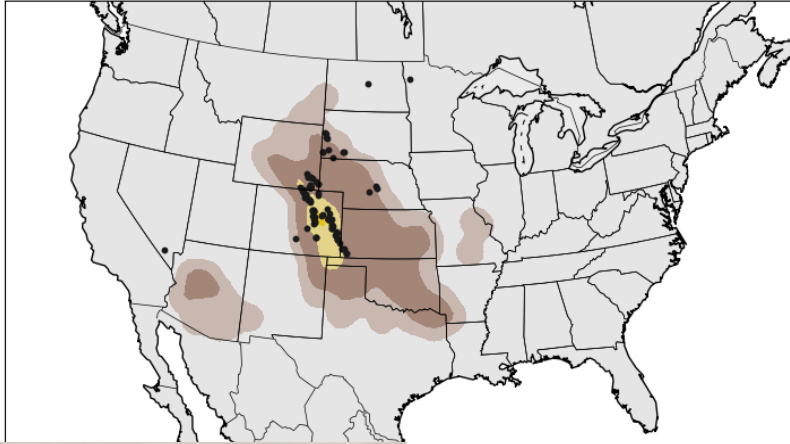
# Case Study: High-End Hail Day



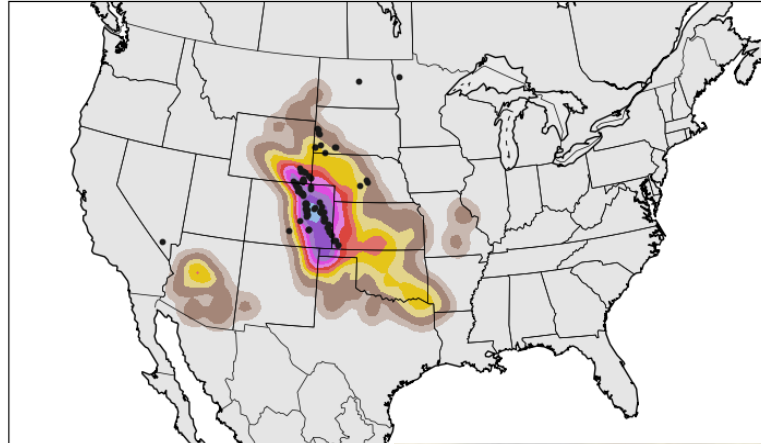
## 180729 >25mm Practically Perfect Output



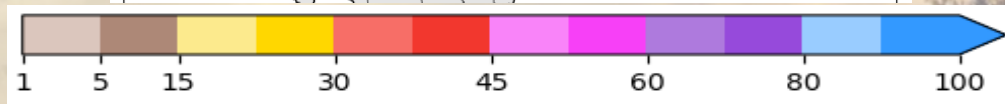
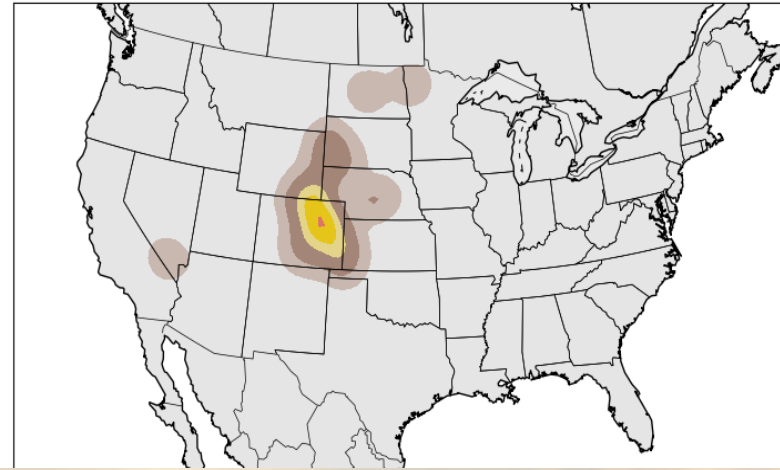
**180729 LSR Calibrated Output  
>25mm NEP**

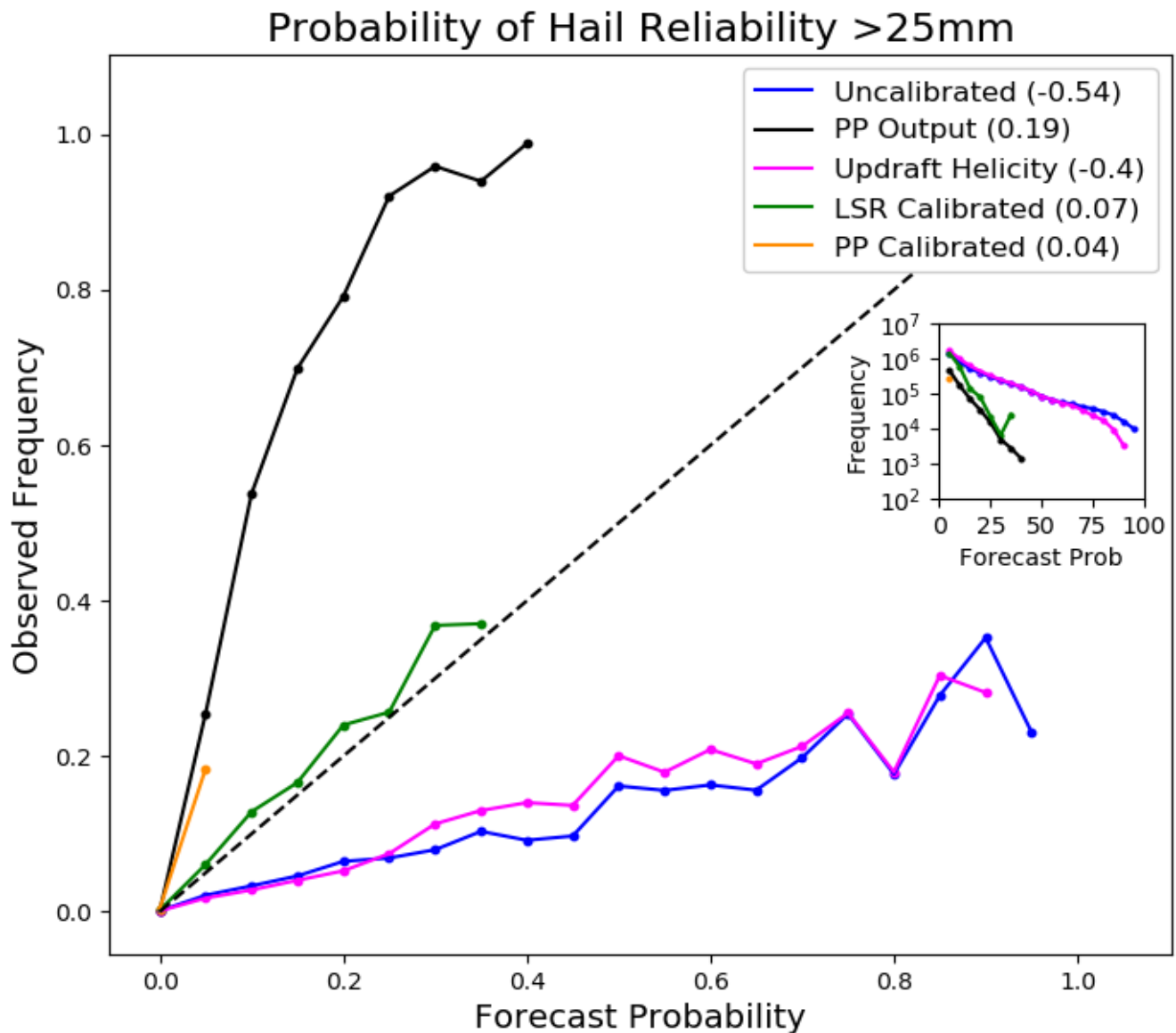
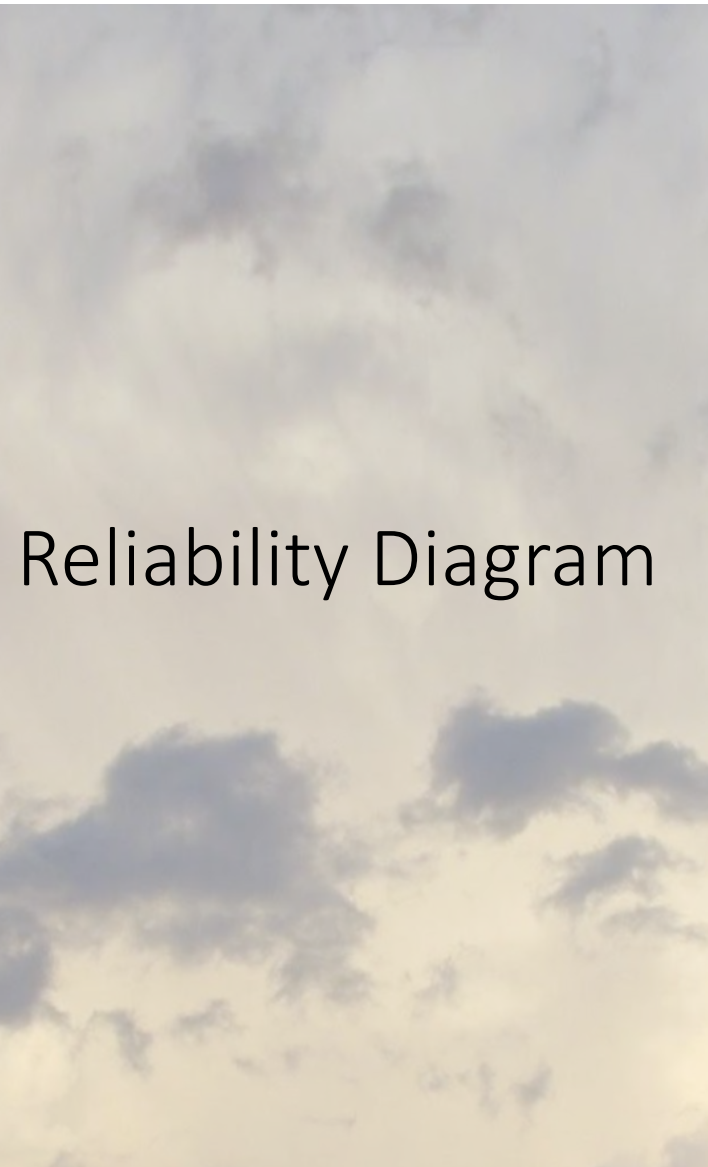


**180729 Uncalibrated Output  
>25mm NEP**



**180729 >25mm Practically Perfect Output**







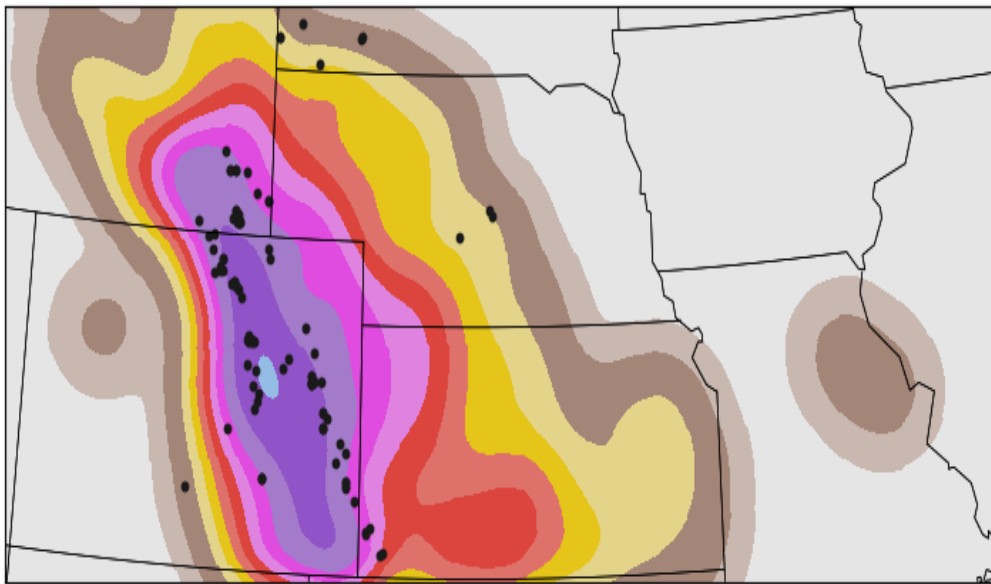
## Regions

- Train regional models by weighting CONUS storms

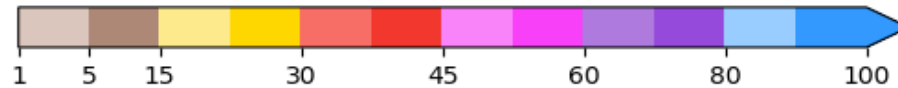
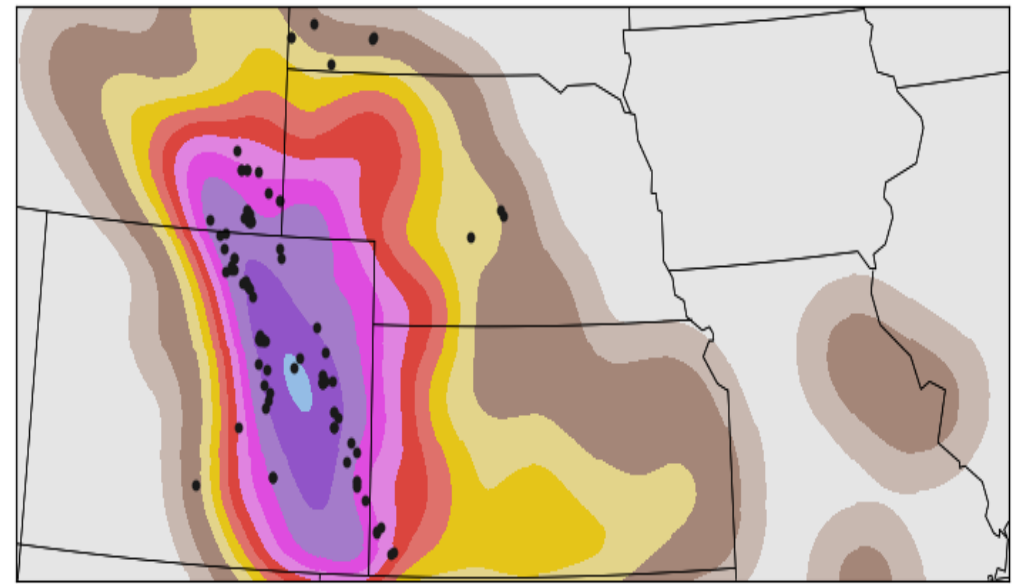


# Case Study: Central Plains Sector

180729 CONUS Trained Output  
>25mm NMEP



180729 Sector Trained Output  
>25mm NMEP

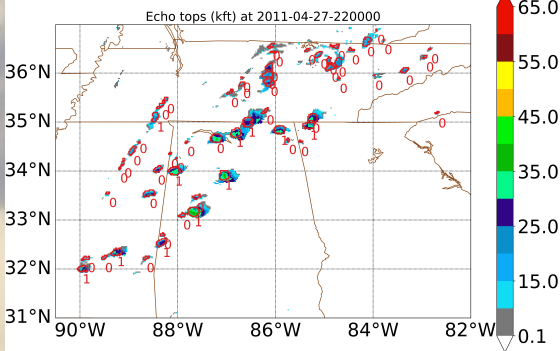
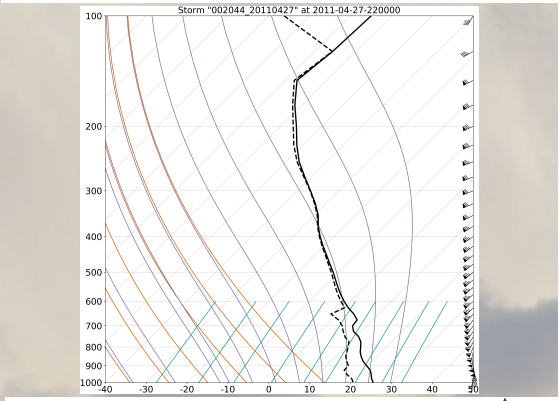
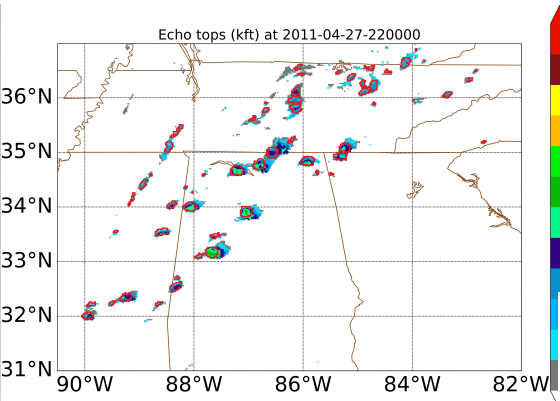


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# Tornado Prediction with Deep Learning



**Multi-radar composites**  
GridRad database  
0.02-degree spacing  
5-minute intervals

**Numerical models**  
Rapid Update Cycle (RUC) for times before May 1 2012  
Rapid Refresh (RAP) for May 1 2012 - present  
13- or 20-km spacing  
1-hour intervals

**Tornado reports**  
*Storm Events* database

**Identify and track storms**  
Local maxima in 40-dBZ echo top  
Echo top must be  $\geq 4$  km ASL  
Maxima must be separated by 0.1 deg N (~11 km)

**Create storm-centered soundings**  
Nearest-neighbour interp from the most recent RUC/RAP analysis and nearest grid cell.

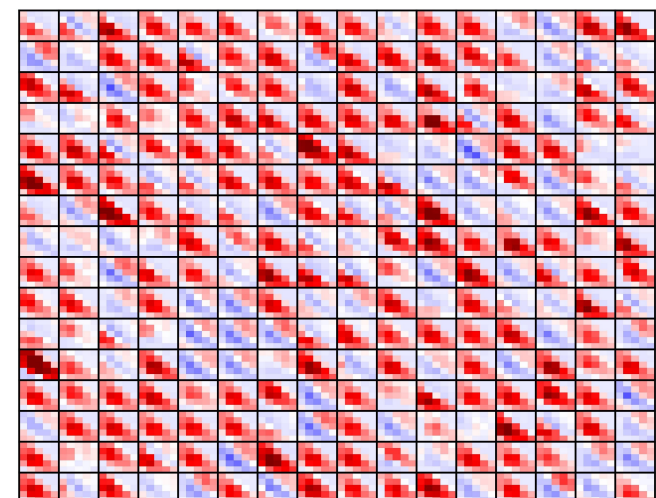
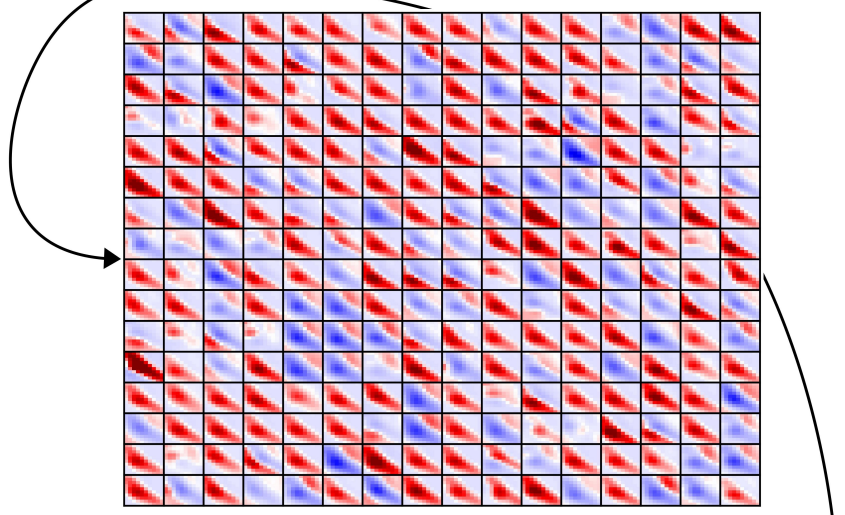
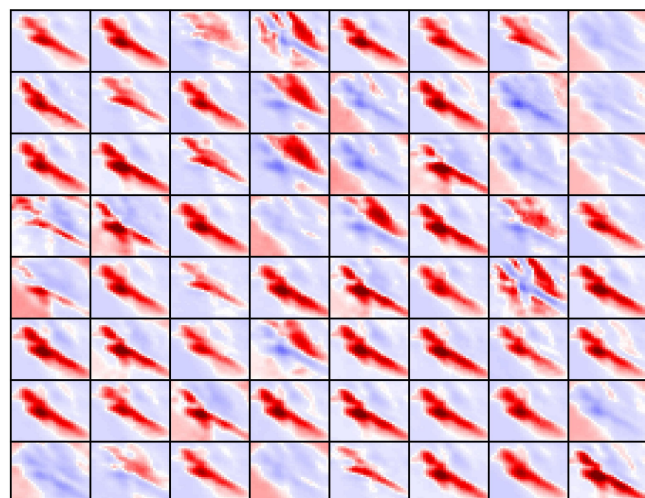
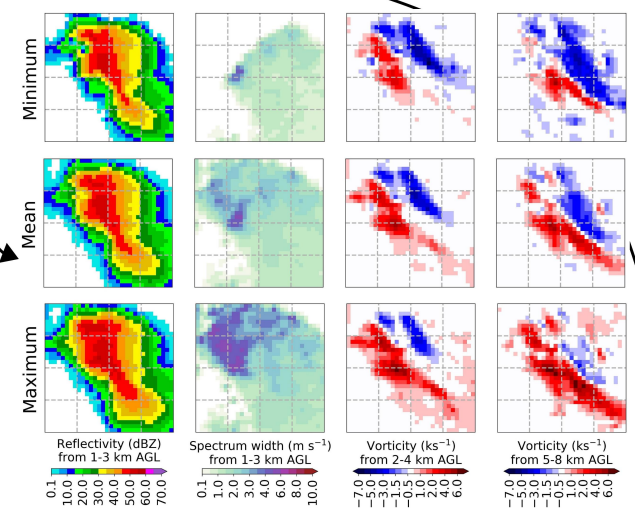
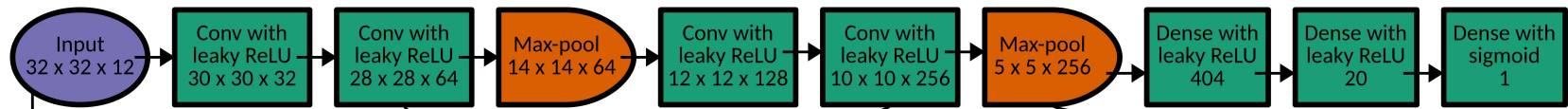
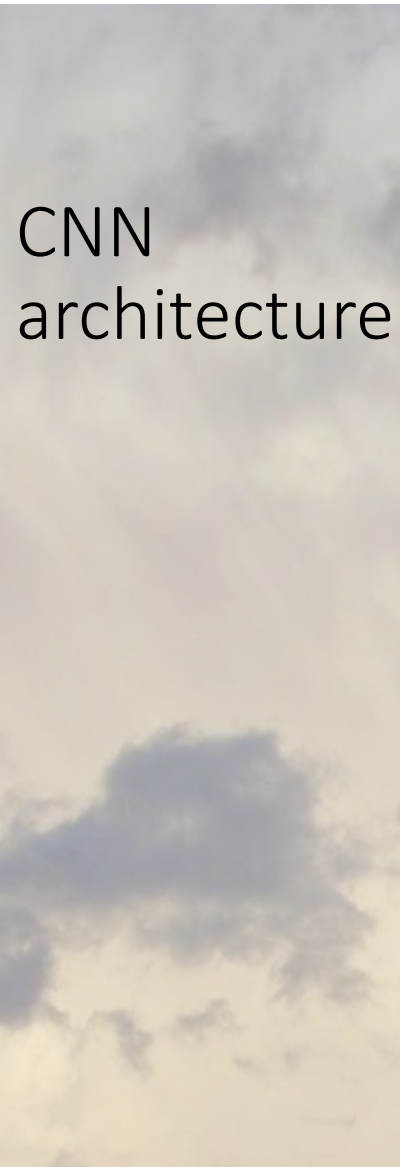
**Link each tornado to nearest storm cell**  
(as long as distance  $< 10$  km)

**Create storm-centered radar images**  
Grid rotated so that storm motion is always in +x-direction ("new east").

**Label each storm object**  
"Storm object" = one cell at one time step.  
Label = 1 if tornadic within the next hour, 0 if not.

**Development data**  
Predictors = storm-centered radar image and sounding  
Verification = tornado label  
Training data: 2011-2014  
Testing data: 2015-2016

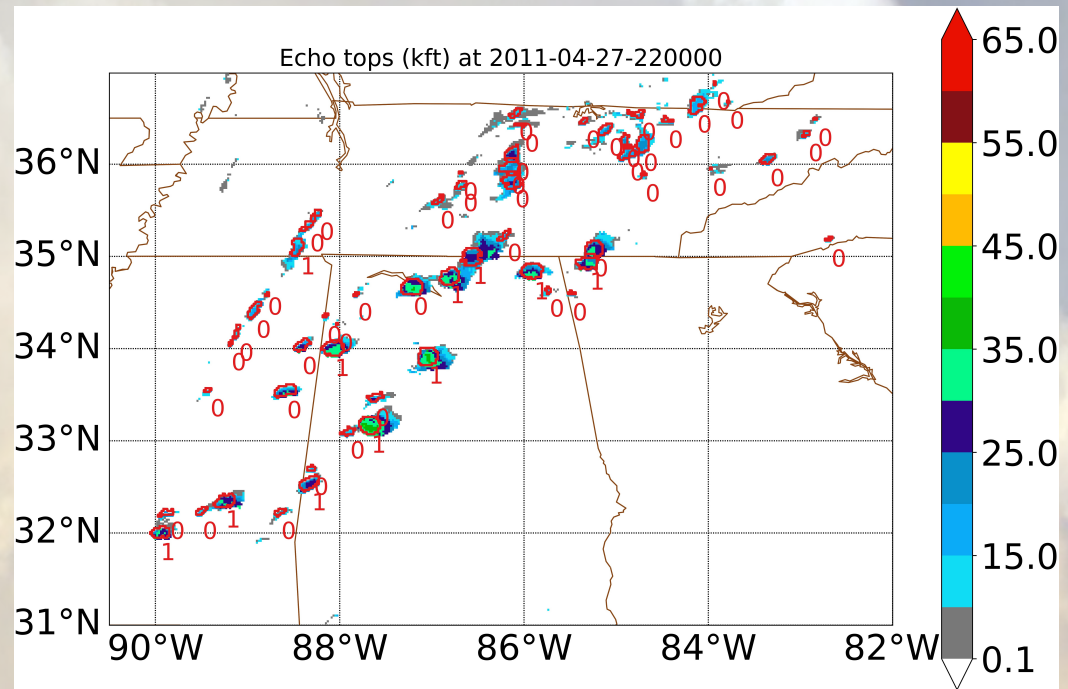
# CNN architecture





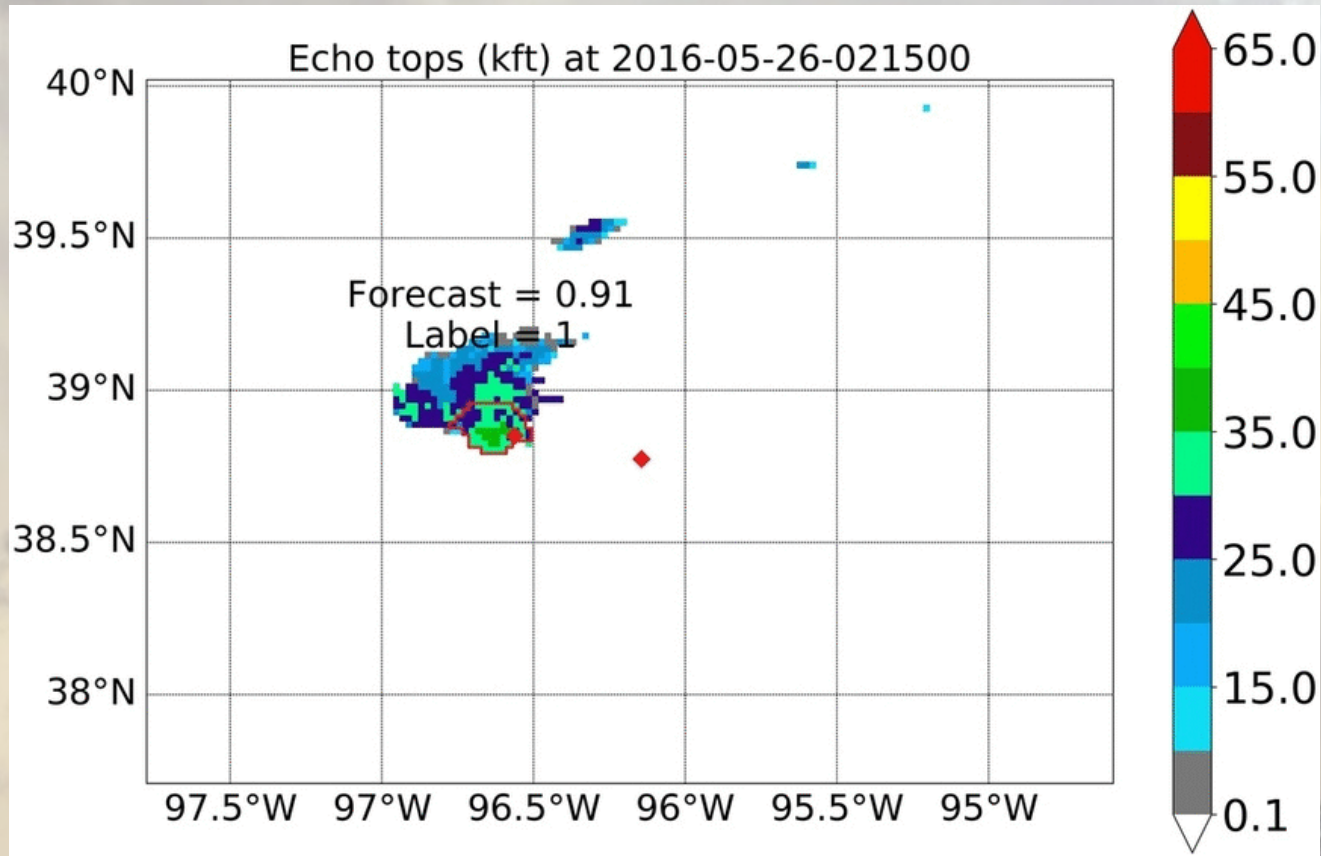
# Tornado Experimental Data

- 1 storm object = 1 storm cell at one time step
- Training set: 2011-14
  - Tornadic objects: 8385
  - Non-tornadic (no tornado in the next hour): 447,922
  - Downsample non-tornadic to 50/50
- Testing set: 2015-16
  - Tornadic: 1420
  - Non-tornadic: 39,639

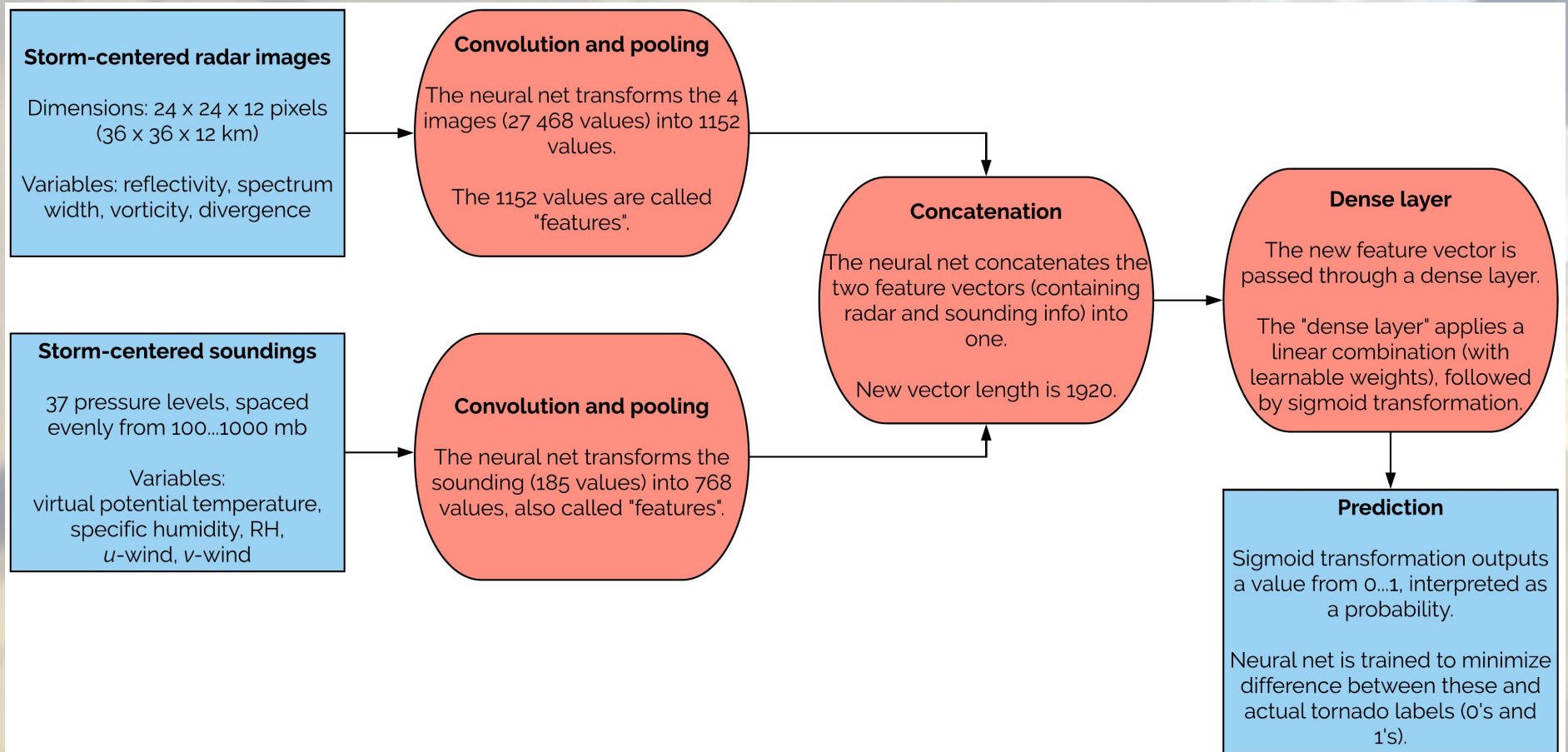




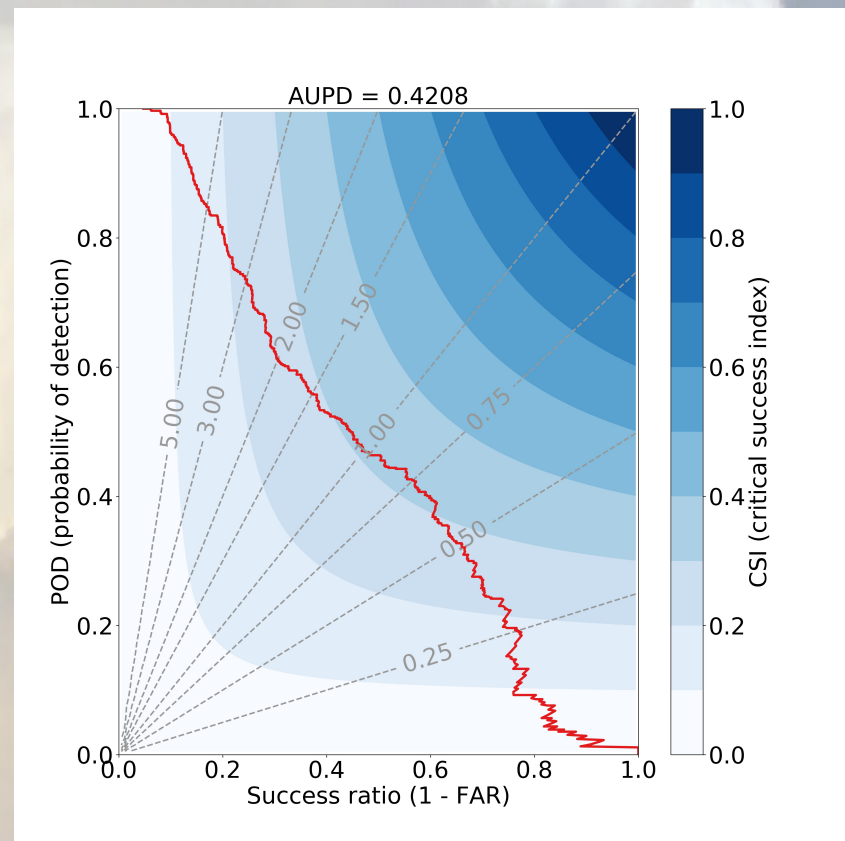
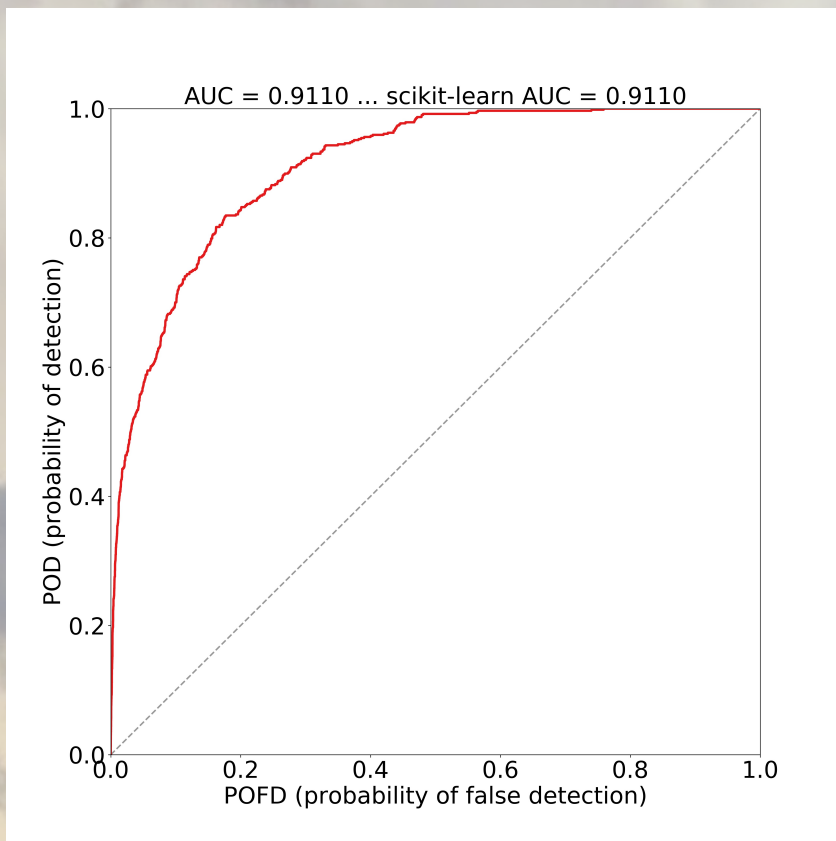
# Tornado Labels



# Convolutional Net Architecture



# ROC and Performance





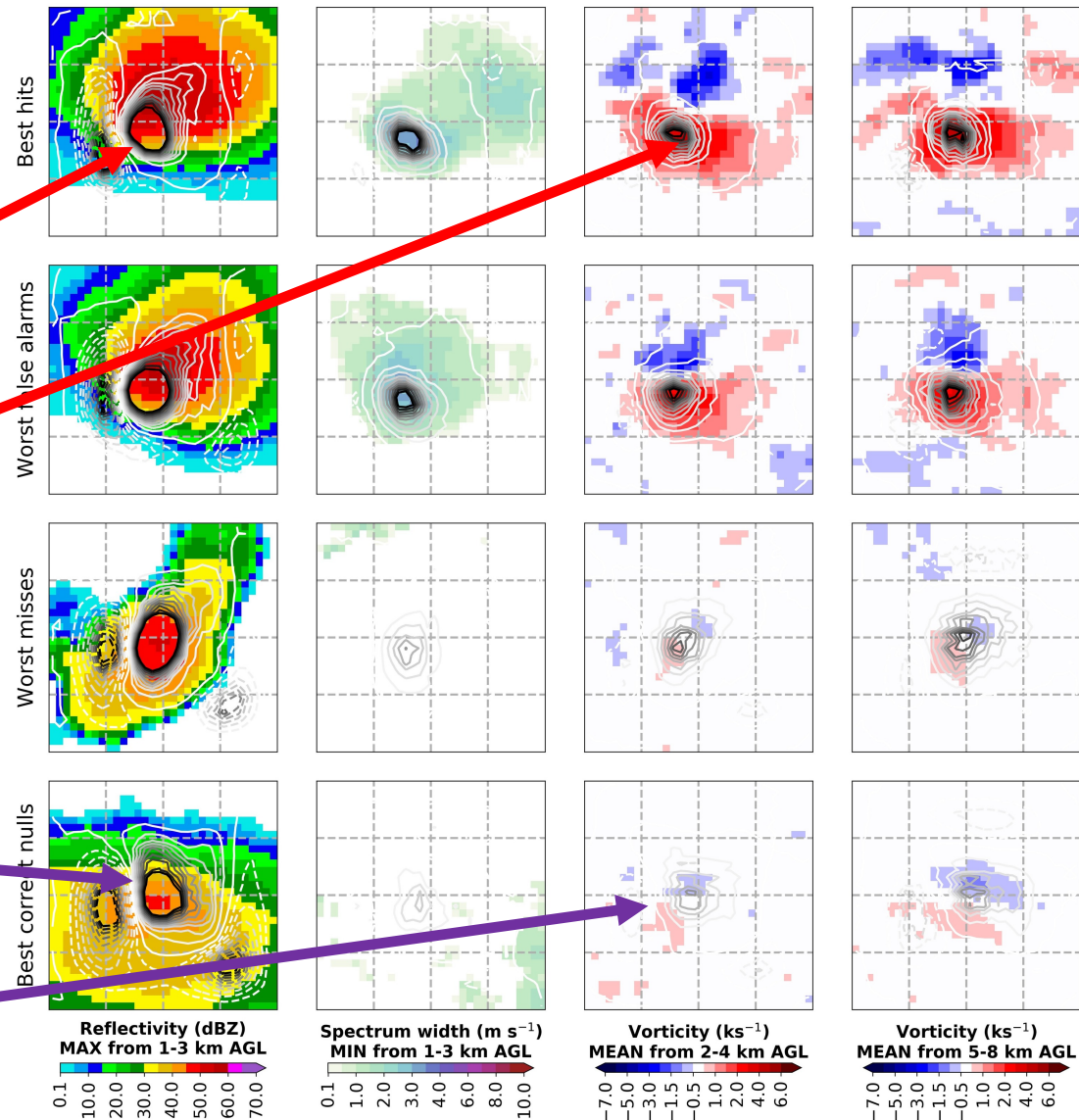
# What the model is learning: Saliency

Strong reflectivity core with hints of a hook

Region of vorticity near "hook"

Disorganized storm with weak reflectivity

No strong vorticity



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# Why Study Bird Roosts?

- Purple Martins and Swallows roost in large colonies visible on the radar
- Important for ecological conservation (Shiple et al. 2017)
- Reasons to study birds roosts and migration (Bauer et al. 2017)
  - Wind turbine collision
  - Habitat deterioration
  - Pest control
  - Crop damage
  - Dispersal of pathogens



Tree Swallow by Prem Balson



Purple Martin by Greg Homel, Natural Elements Productions



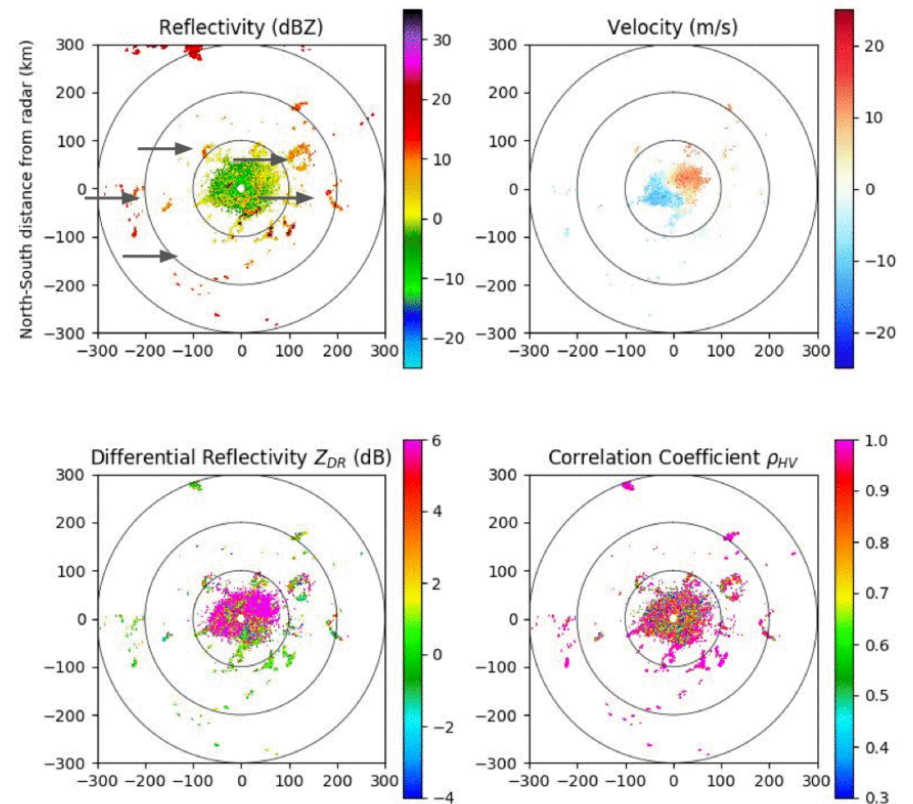
<https://shewicklundphotographs.com/2014/07/20/hundreds-of-purple-martins/>



# NEXRAD RADAR DATA

- Data:
  - Level 2 NEXRAD data
  - 0.5° scan
- Roosts most visible at sunrise
- Products used (when available):
  - Reflectivity
  - Velocity
  - Correlation Coefficient (dual-pol)
  - Differential Reflectivity (dual-pol)

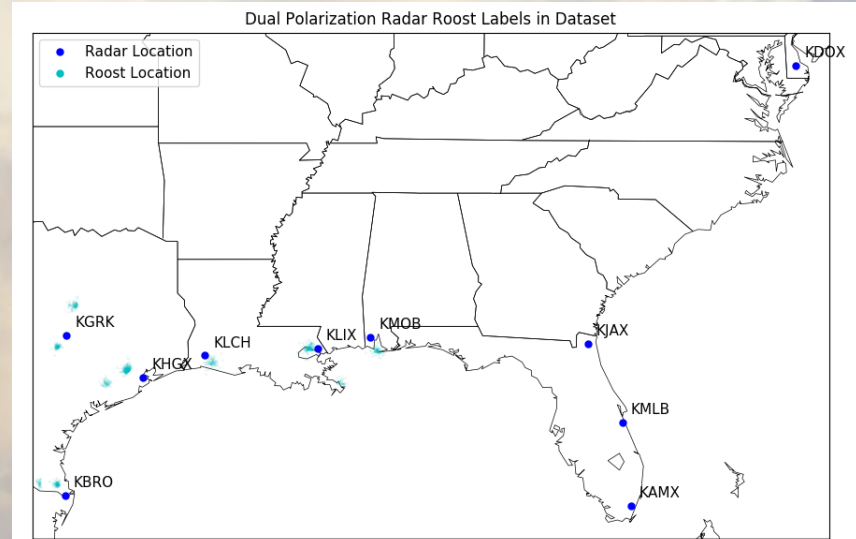
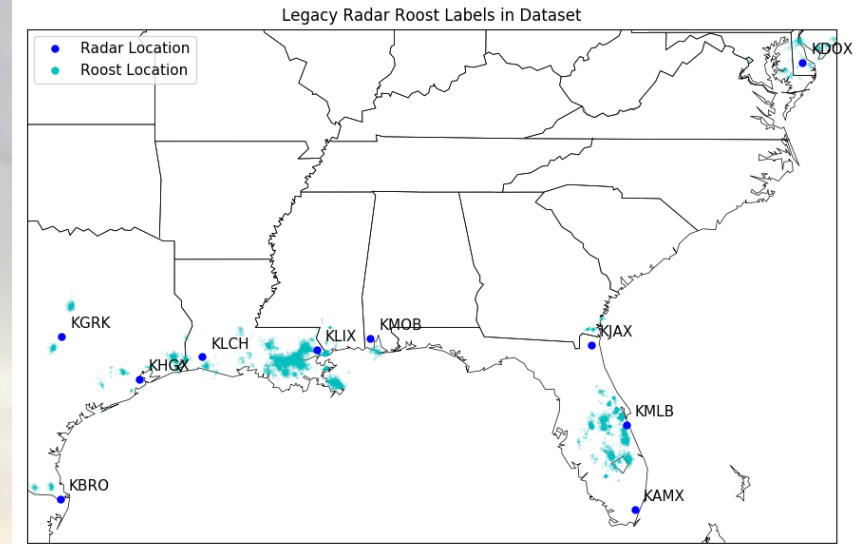
## Roost at sunrise



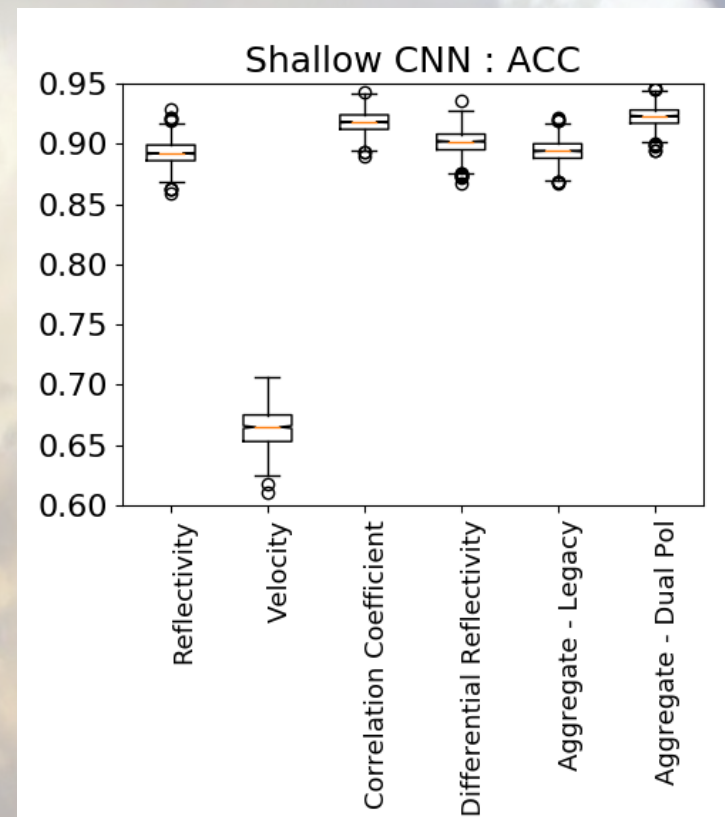
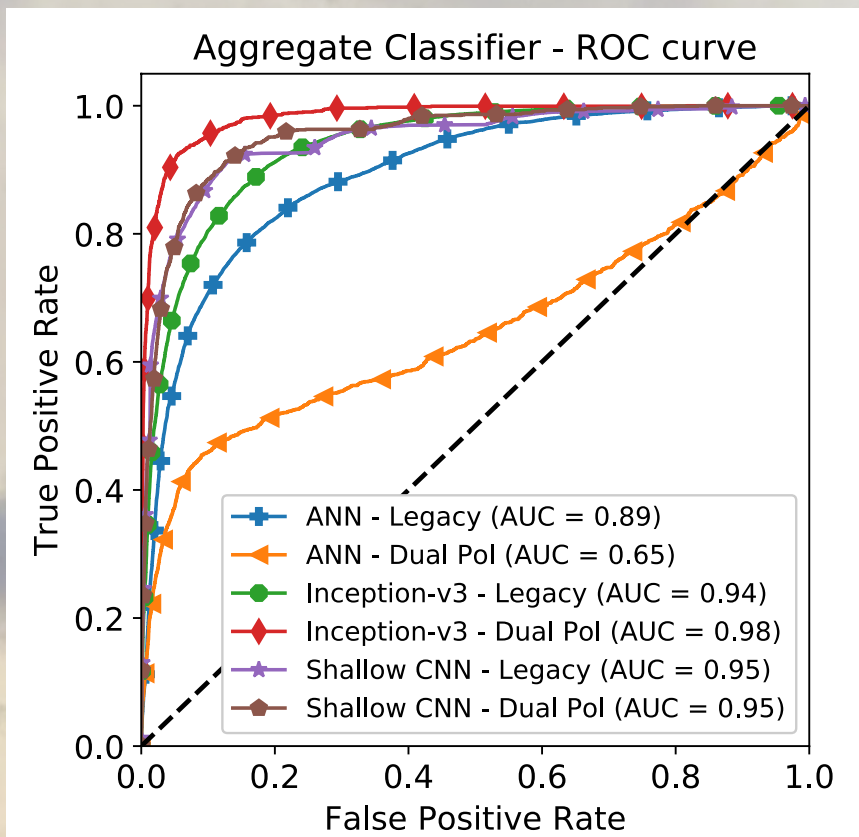
# Dataset

- Labels: Roost and No Roost
- Two sets of radar data: legacy and dual-pol
- 10 different radars: KAMX, KBRO, KDOX, KGRK, KJAX, KHGX, KLCH, KLIX, KMLB, and KMOB
- Hand-labeled data from OU and UMass Amherst

	Roost	No Roost
Legacy	11,112	19,939
Dual-pol	1,346	10,806



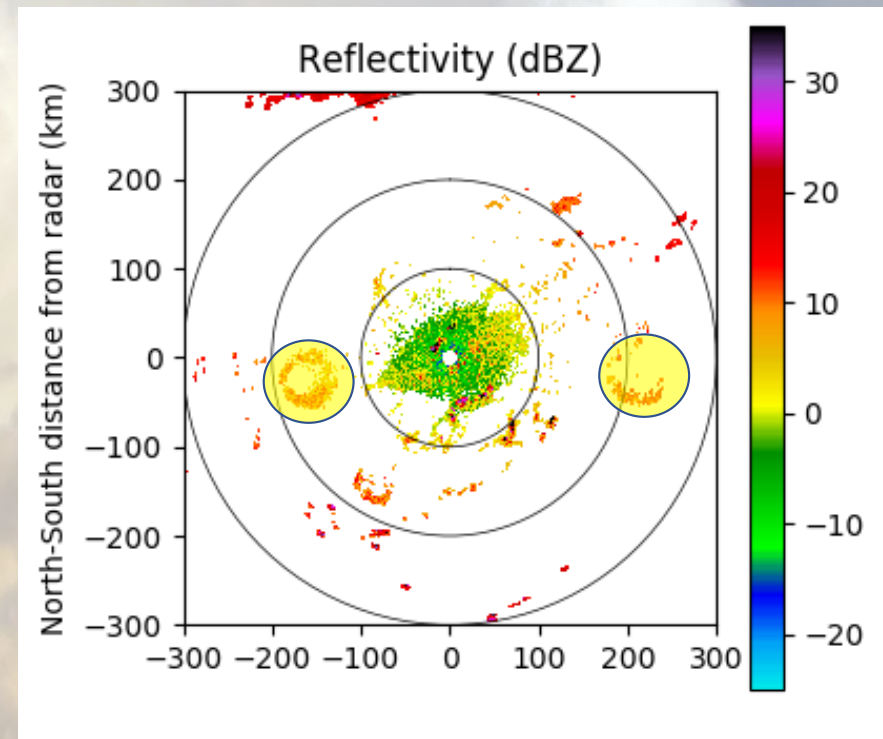
# Results





# Current and Future work on Roosts

- Identify locations of bird roosts
- Track changes in behavior over time
- Mitigate risk



# Acknowledgments

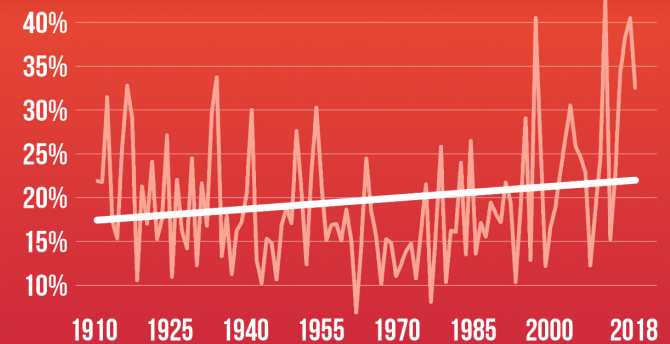
- Some of the computing for this project was performed at the OU Supercomputing Center for Education & Research (OSCER) at the University of Oklahoma (OU).
- This material is based upon work supported by the National Science Foundation under Grant Numbers EF-1340921, DGE-1545261, AGS-1802627 and NOAA JTTI Grant No. NA16OAR4590239 and NA18OAR4590371.
- Funding was provided by NOAA/Office of Oceanic and Atmospheric Research under NOAA-University of Oklahoma Cooperative Agreement #NA16OAR4320115, U.S. Department of Commerce.
- **I've got an open PhD position right now!**

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- Contact me: Amy McGovern  
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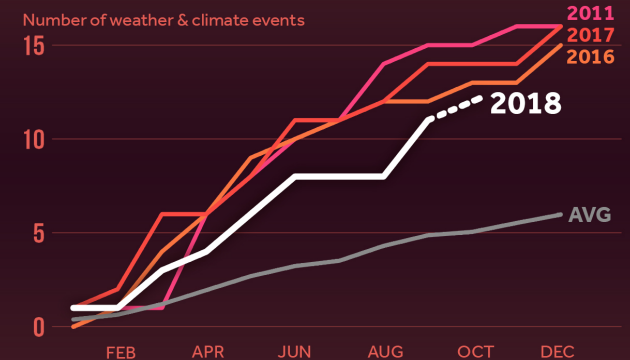
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