Severe Hail Forecasting Evaluation: Machine Learning and Severe Weather Proxy Variables

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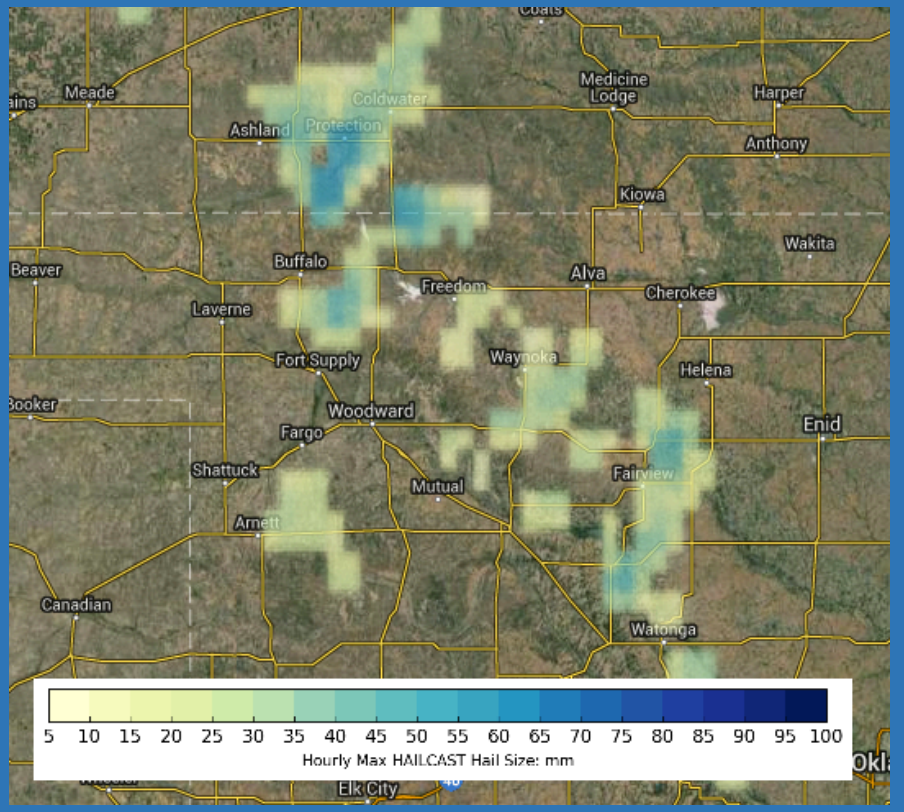
Motivation

Goals

- Estimate hail size distributions with machine learning models using input from CAM ensembles
- Determine value added by ML over hailstorm proxies

Hailstorm Proxies

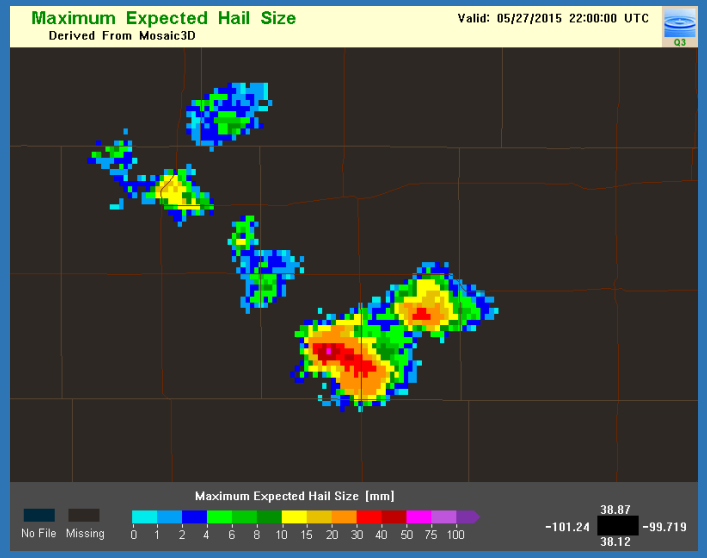
- Updraft Helicity
  - Vertically integrated product of vertical velocity and vorticity
  - Associated with strong, rotating updrafts
- Column Integrated Graupel
  - Total mass of graupel in a vertical column
  - Large hail mass not always associated with large hail diameters
- HAILCAST
  - Hail size estimated from growing simulated hail embryos
  - Triggered when vertical velocity exceeds a threshold



HAILCAST output example.

Ensemble and Observation Data

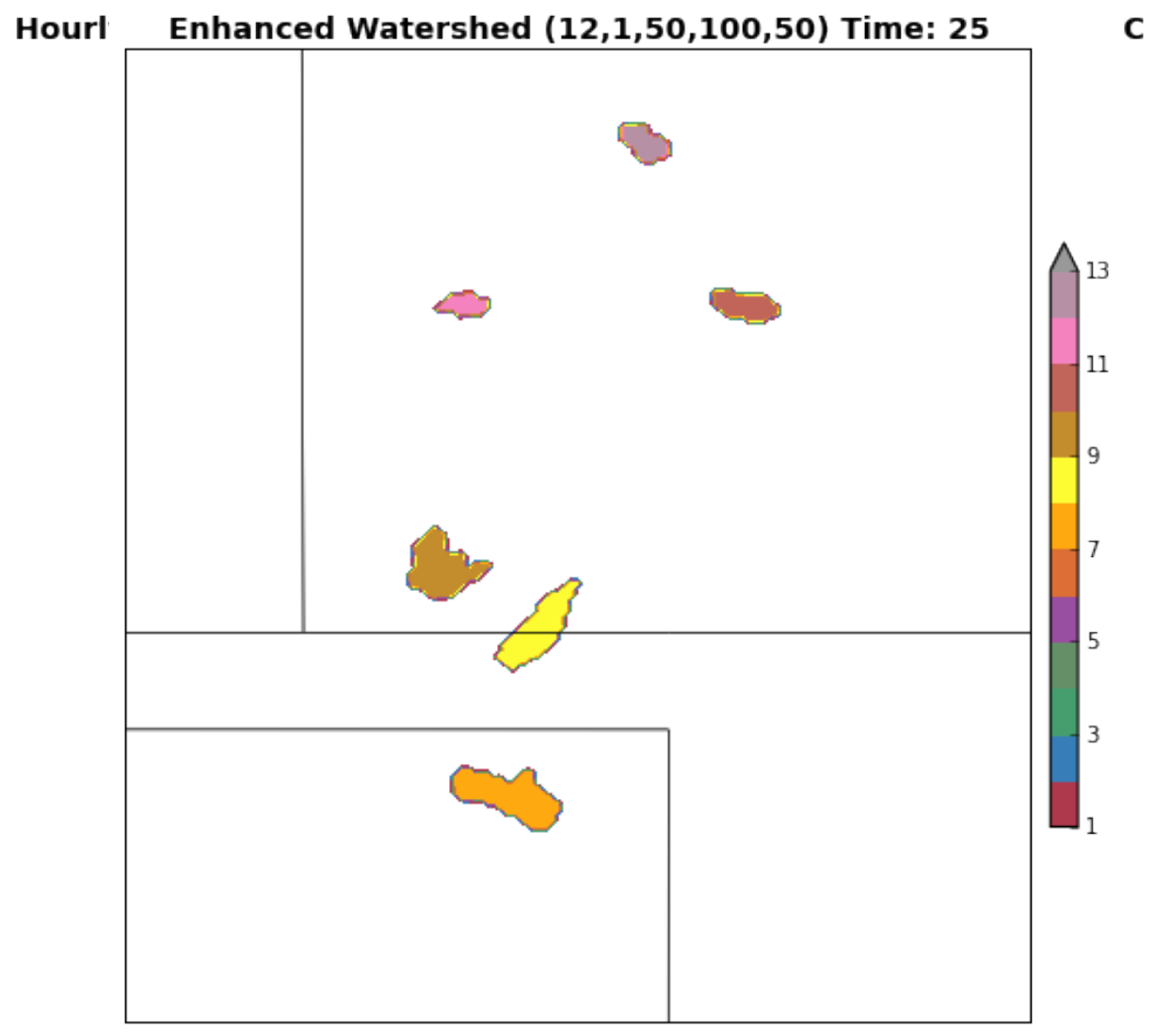
System	CAPS Ensemble
Dynamical Model	WRF-ARW 3.5.1 (2014), 3.6.1 (2015)
Run Period	May-June 2014 and 2015
Grid Spacing	4 km in 2014, 3 km in 2015
Microphysics	Thompson, Morrison, P3, Milbrandt and Yau
PBL	MYJ, MYNN, YSU
Data Assimilation	3DVAR with radar data assimilation



Observation Data

- NOAA NSSL Multi-Radar Multi-Sensor (MRMS)
- 1 km radar mosaic over US
- Maximum Expected Size of Hail (MESH)
- Used as observations for machine learning models

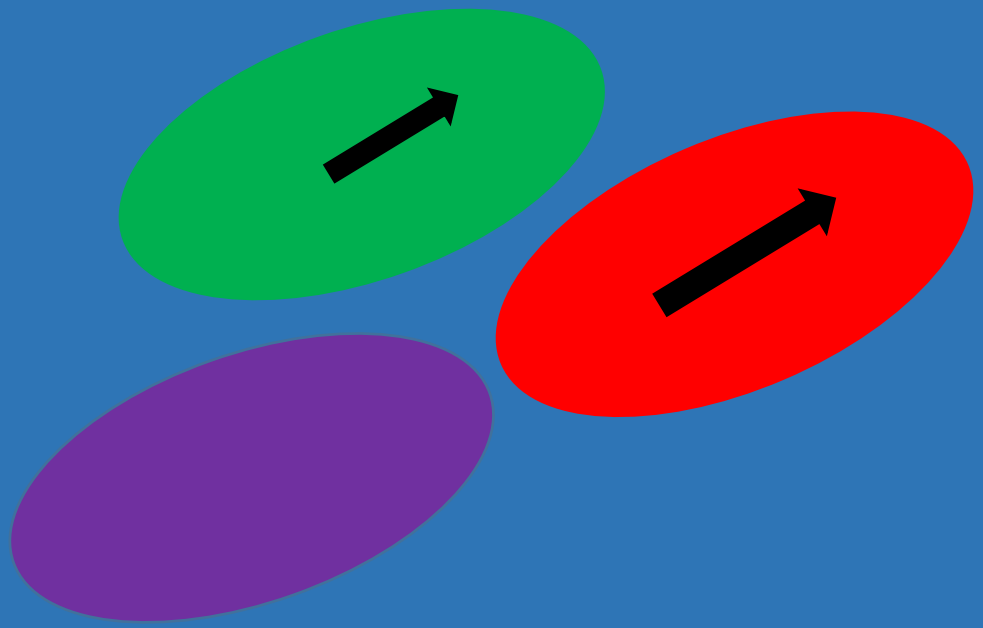
Potential Hailstorm Identification



- Hailstorm Proxy: Hourly Max Column Integrated Graupel
- Enhanced watershed (Lakshmanan et al. 2009) used to identify storm "objects"
- Objects must have area within specified range

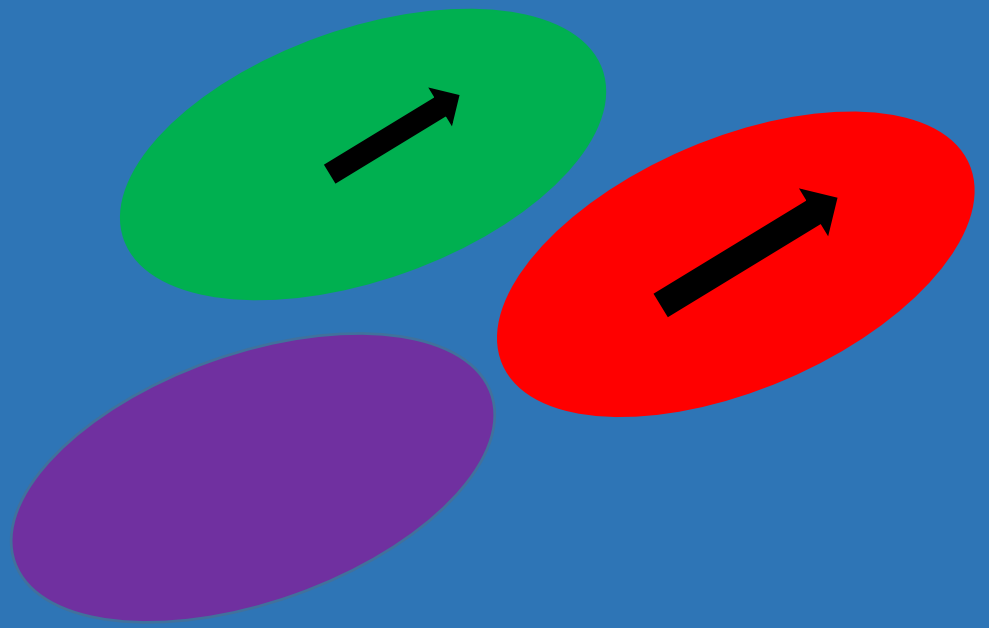
Hailstorm Tracking

Estimate Storm Motion



Use cross-correlation filter to find direction of motion

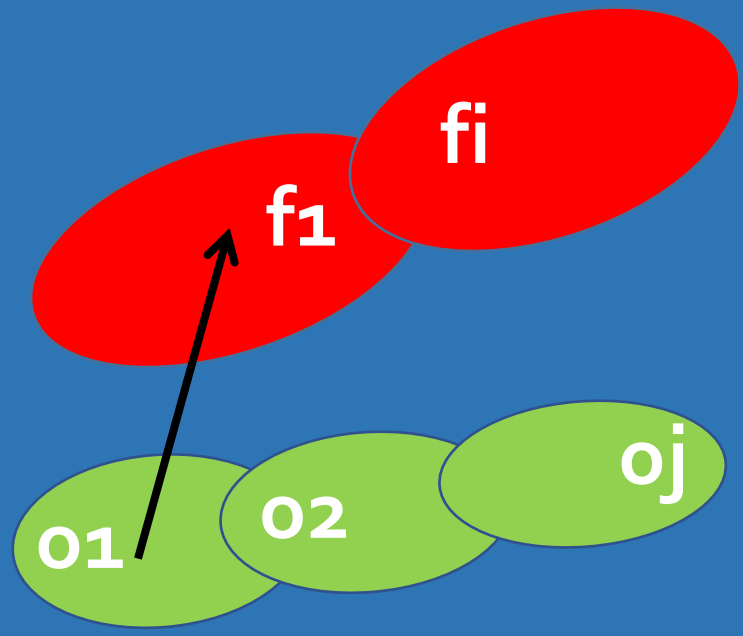
Translate Objects and Match



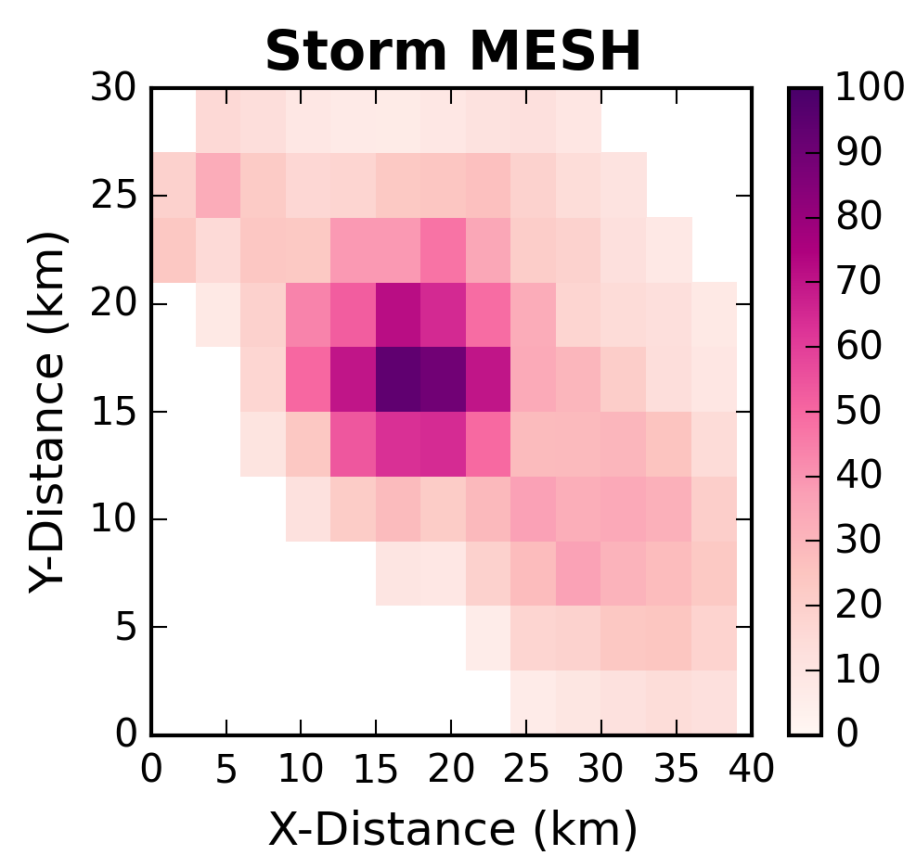
Calculate translated centroid distances and optimally match nearest pairs

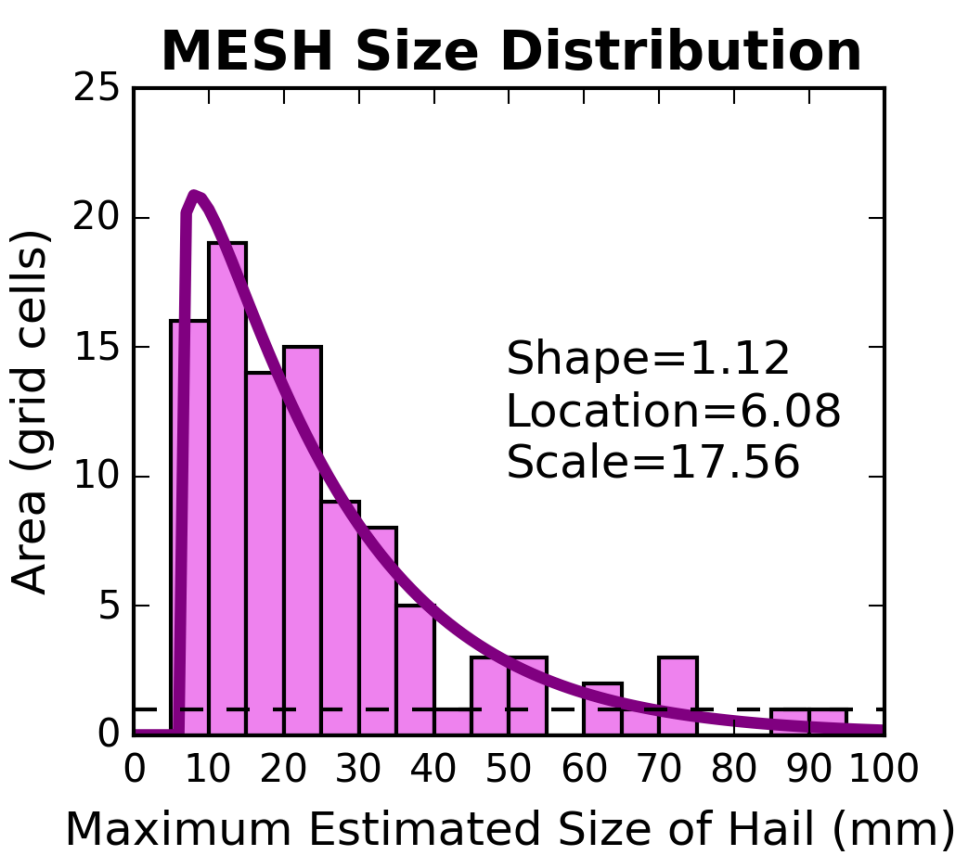
Hailstorm Matching

- Forecast and observed storm tracks are matched
- Weighted average of space, time and track properties
  - 50%: Start centroid Euclidean distance
  - 30%: Start time absolute difference
  - 10%: Duration absolute difference
  - 10%: Mean area absolute difference
- Distance and time differences are tightly constrained
- Duration and area are loosely constrained



Gamma Hail Size Distribution

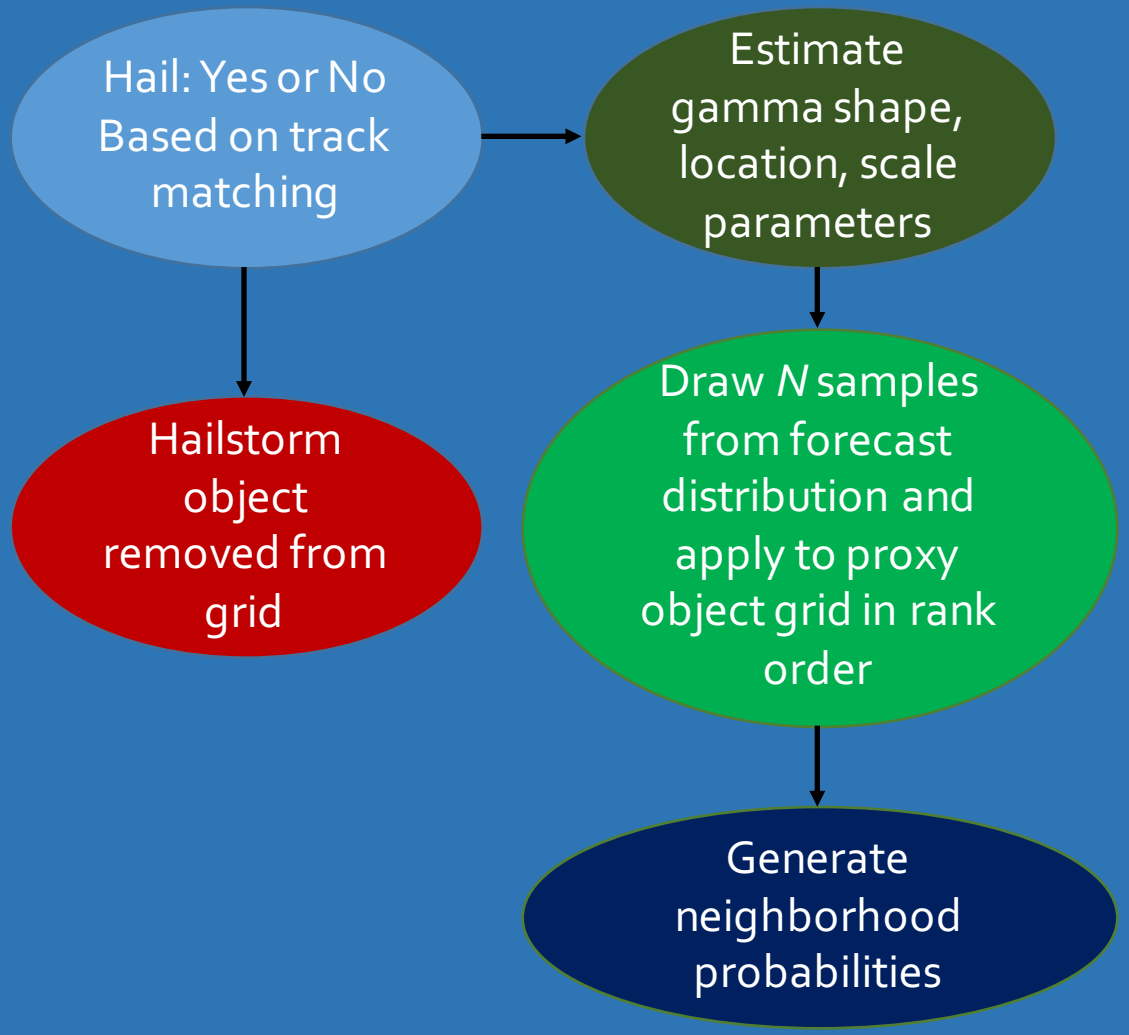




Wide range of hail sizes within MESH object
Large hail occurs within small area

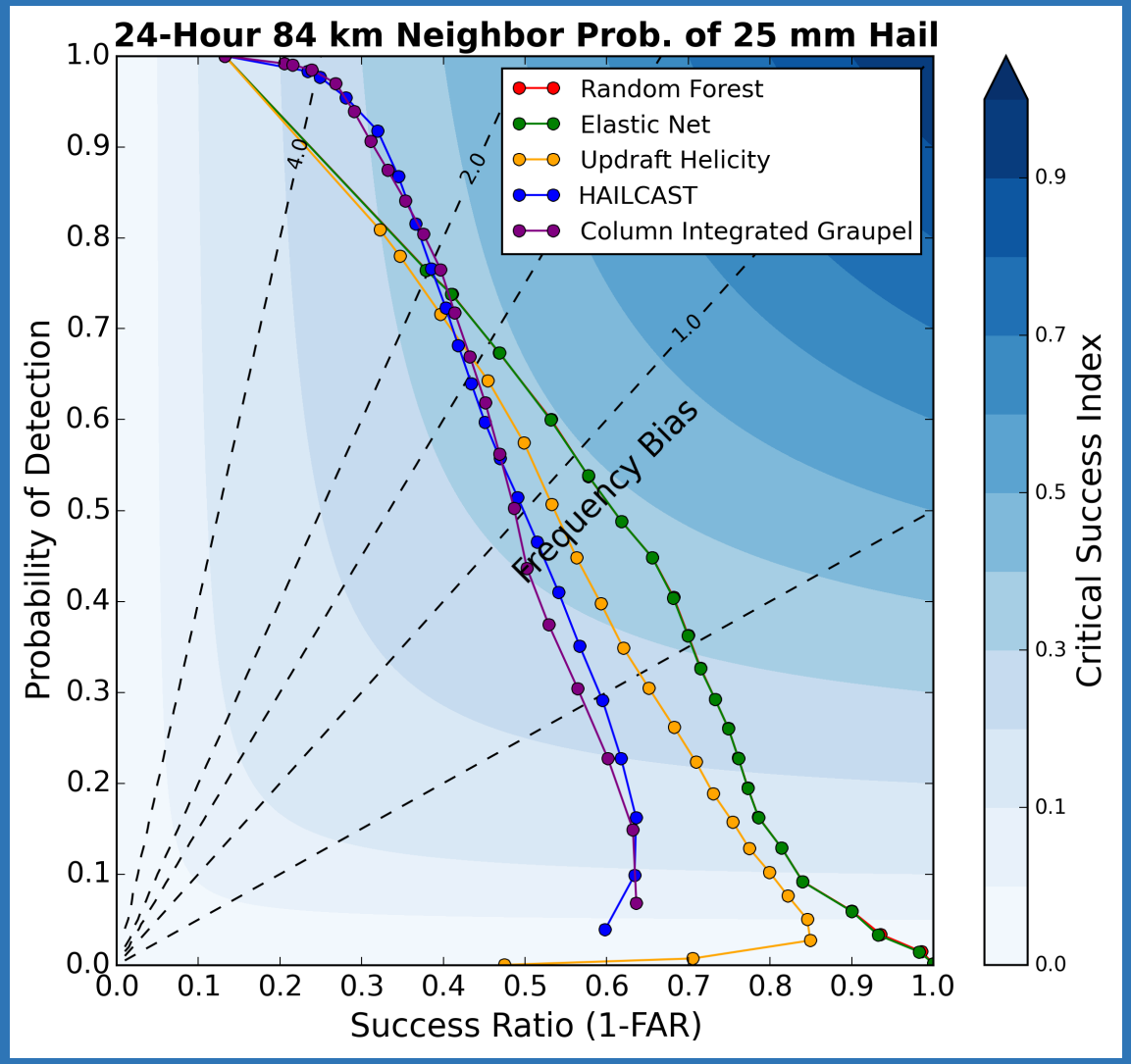
Distribution of MESH pixels
Fit gamma PDF to MESH values
Compress distribution information into 3 values

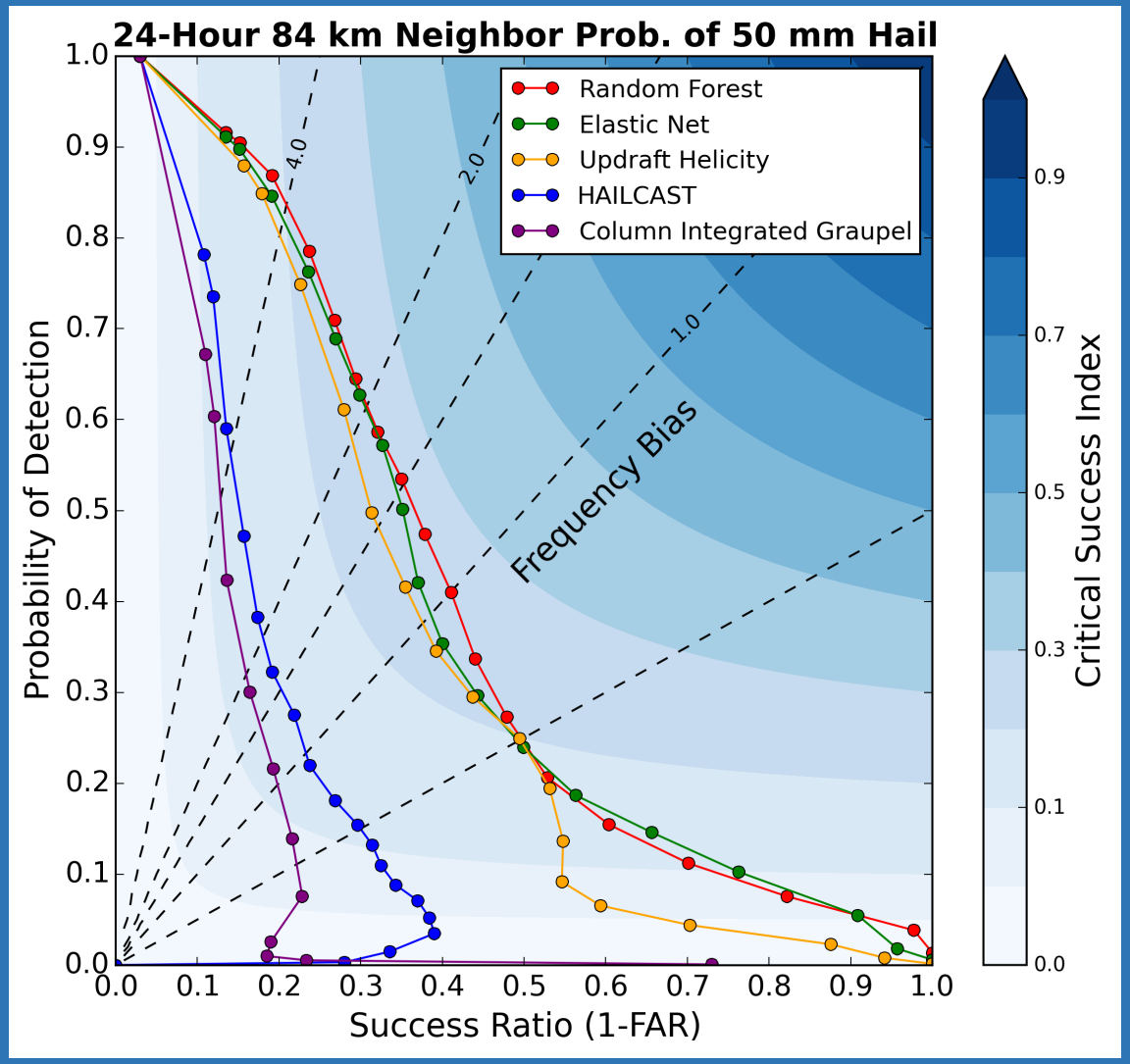
Machine Learning Procedure



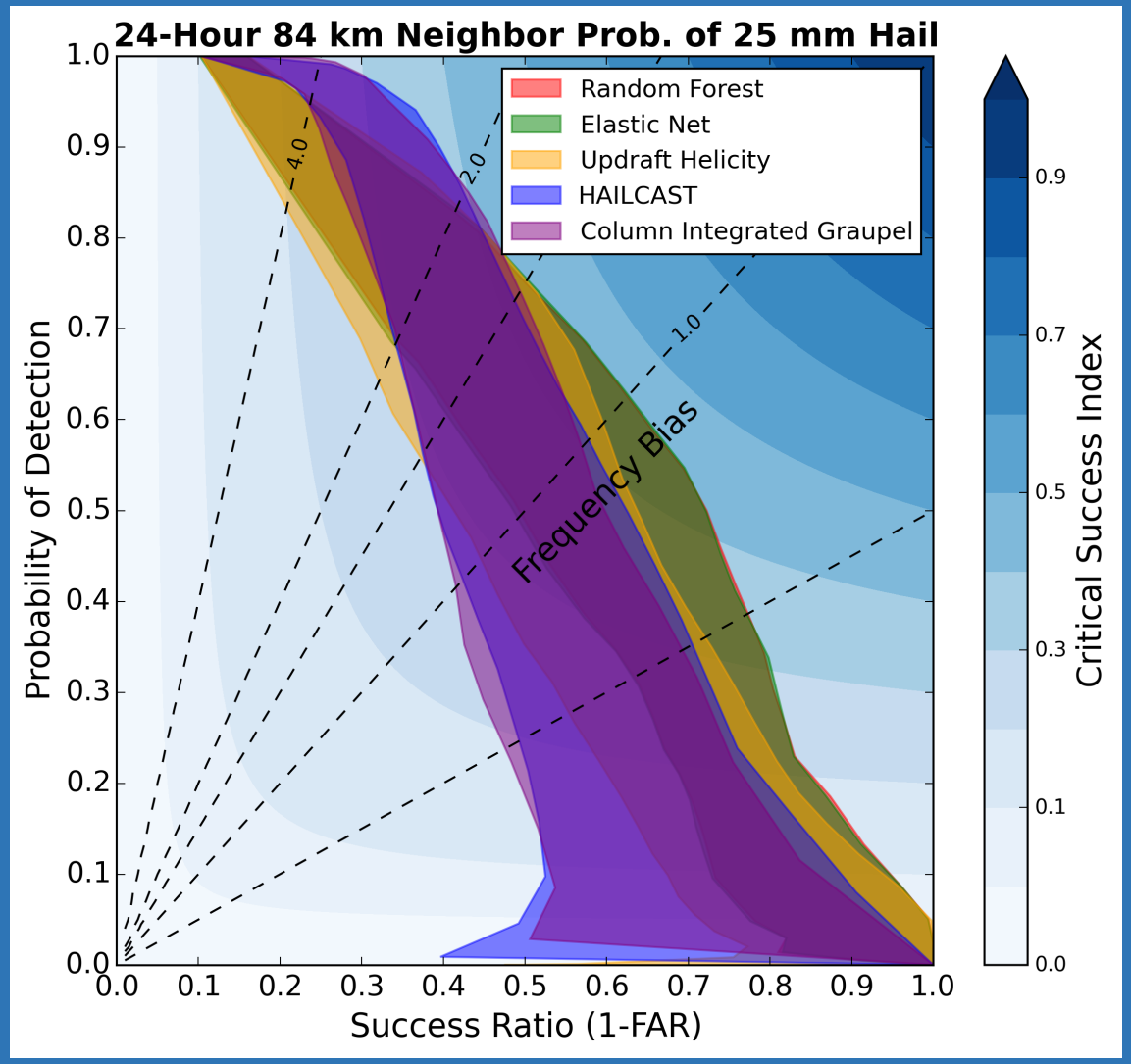
- Machine Learning: scikit-learn
  - Open source Python library
  - Contains parallelization options
- Models
  - Random Forest
  - Elastic Net
- How to increase training set size?
  - Train one model for full domain
  - Group similar ensemble members into same training set
- Neighborhood Ensemble Probability
  - Spatial smoothing and amplification
  - Applied to ML and storm proxies

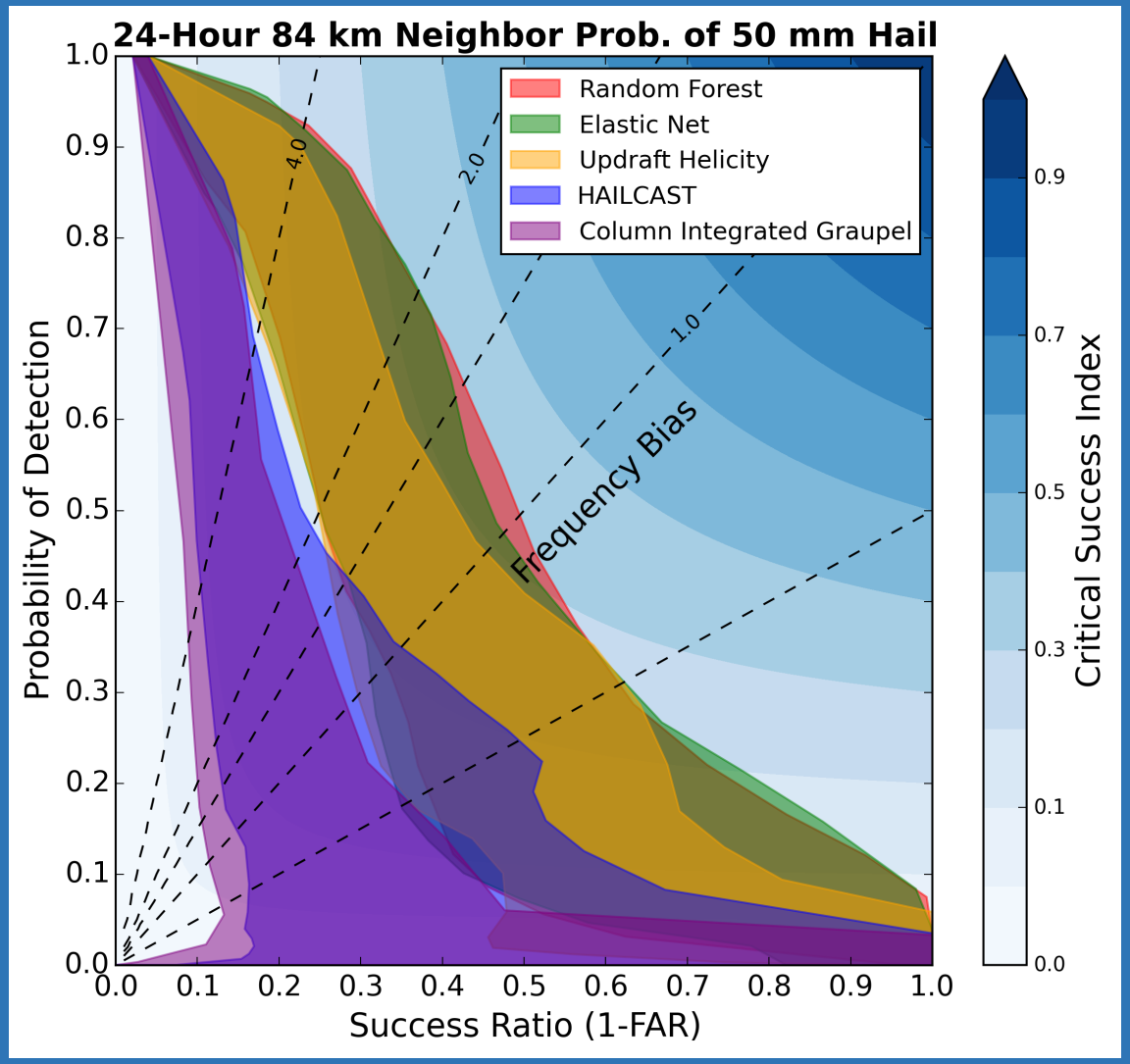
Neighborhood Probability Performance



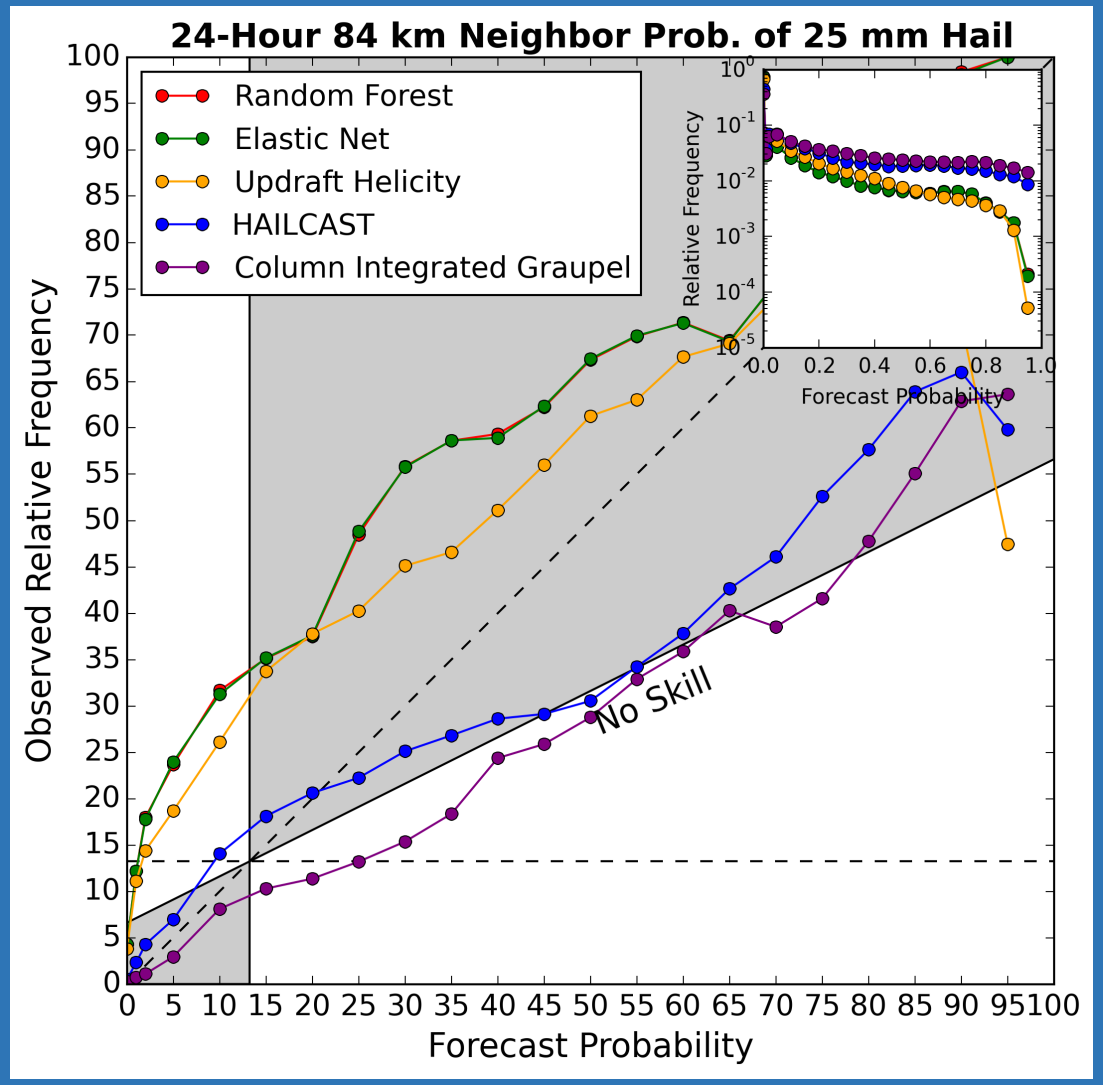


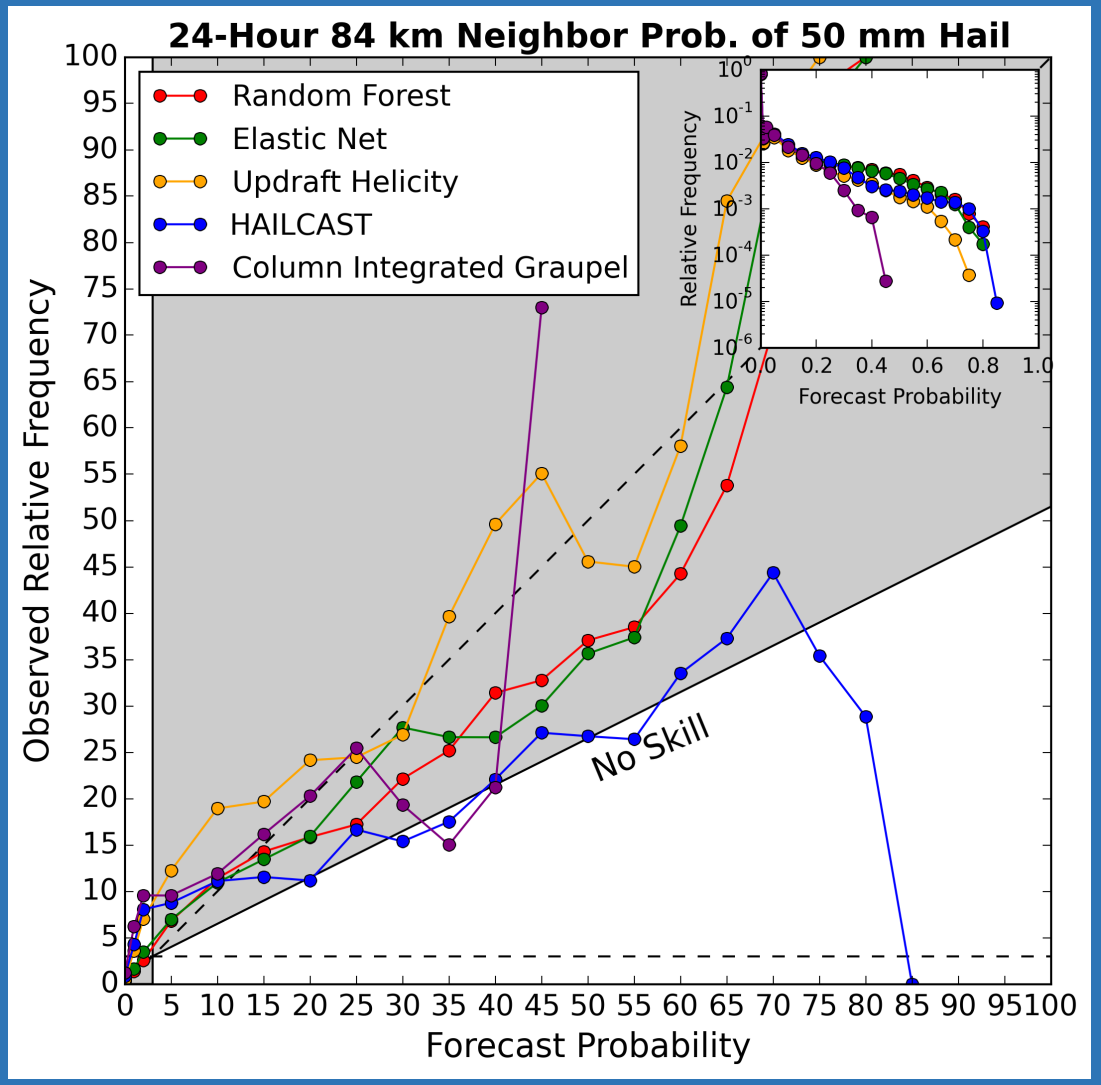
Neighborhood Probability Performance



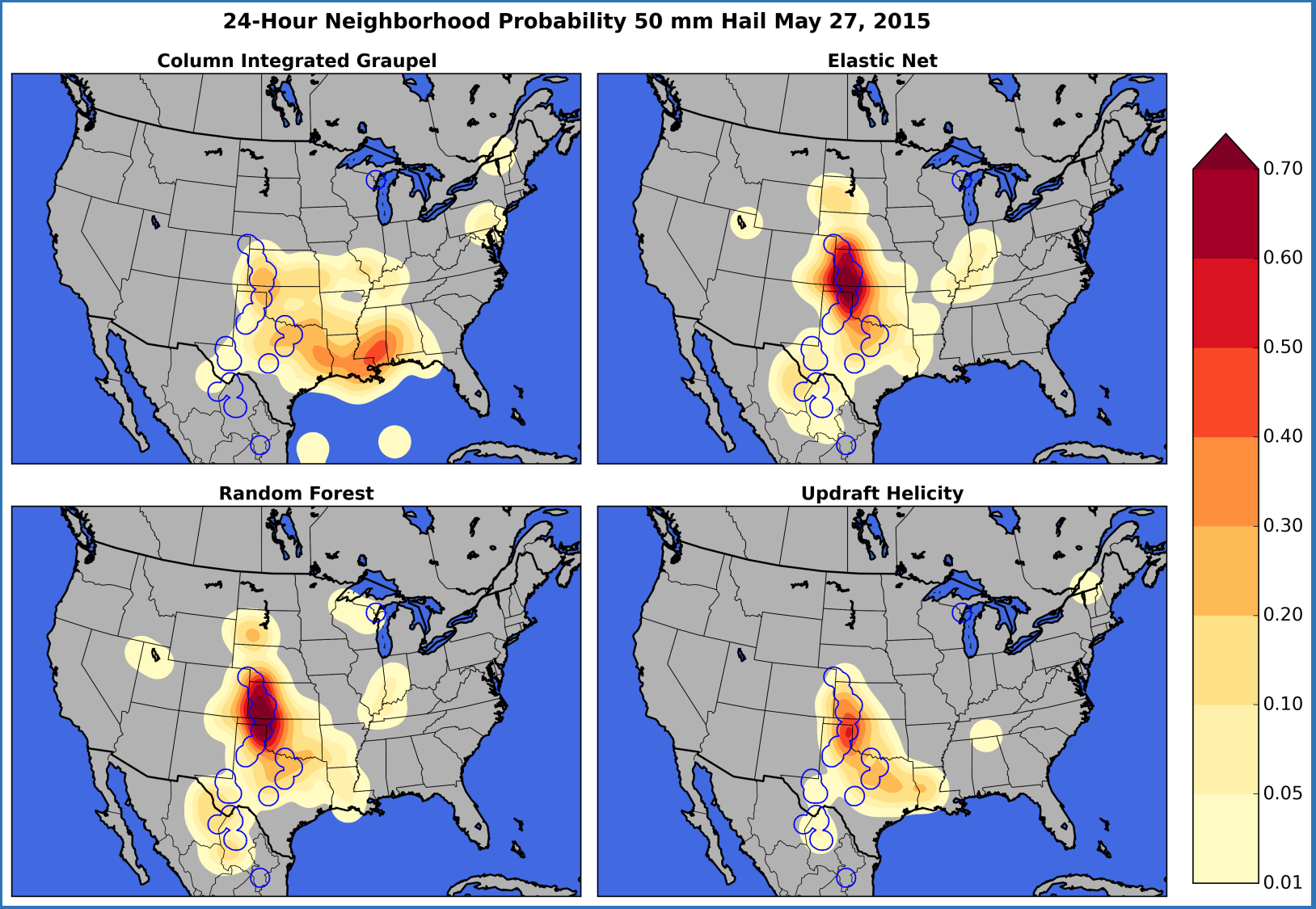


Neighborhood Probability Performance



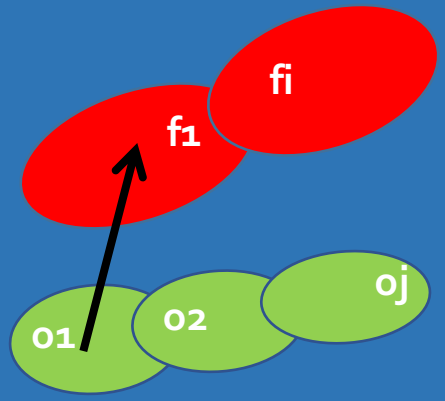


Case Study: May 27, 2015

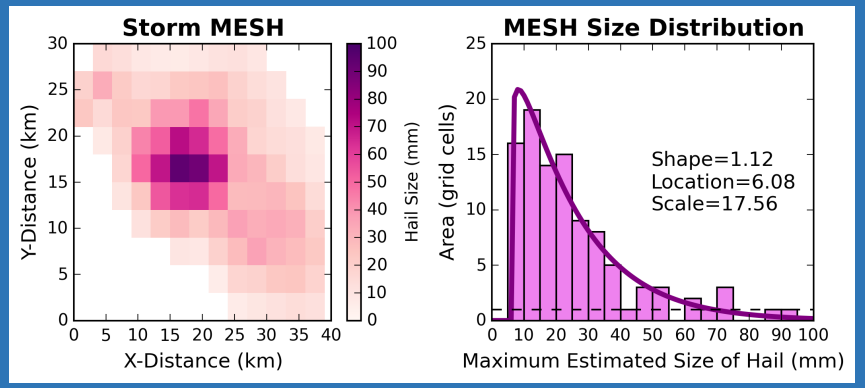


- Observed 50 mm or larger hail within 84 km is shown with the blue contours
- Column-integrated graupel probabilities highest in areas with non-hail-producing storms
- ML models match highest probabilities with largest hail
- Updraft helicity has smallest false alarm area

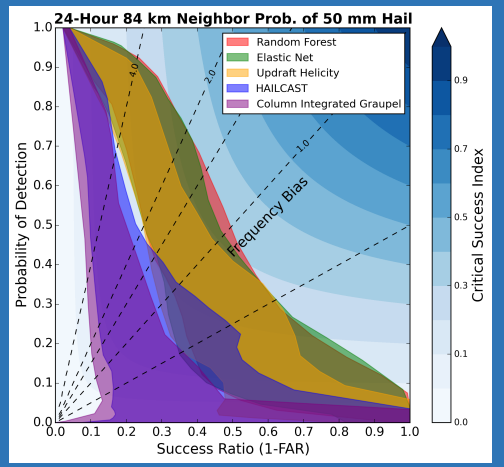
Summary



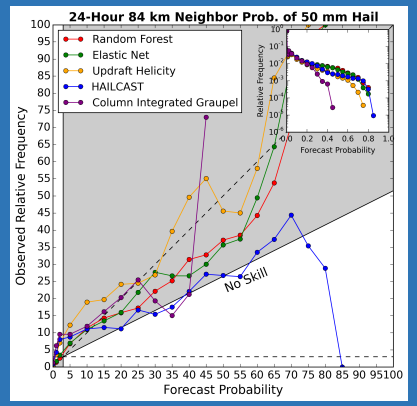
Forecast and observed hail storms are tracked and matched



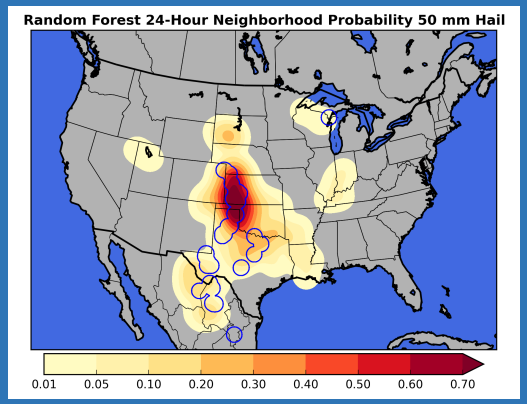
Machine learning predicts hail size distribution parameters



ML methods outperform HAILCAST but not updraft helicity



ML methods are more reliable



ML methods can discriminate very large hail regions

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