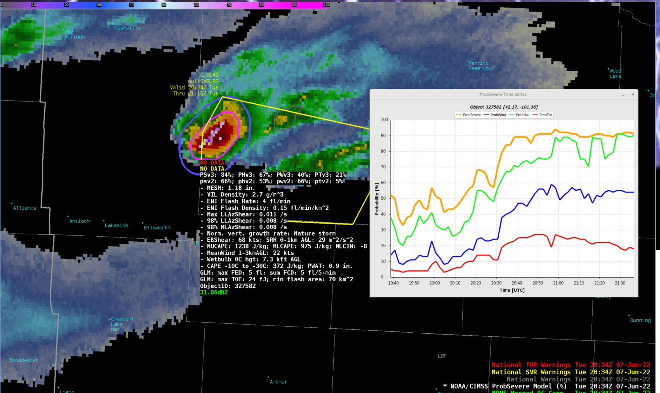
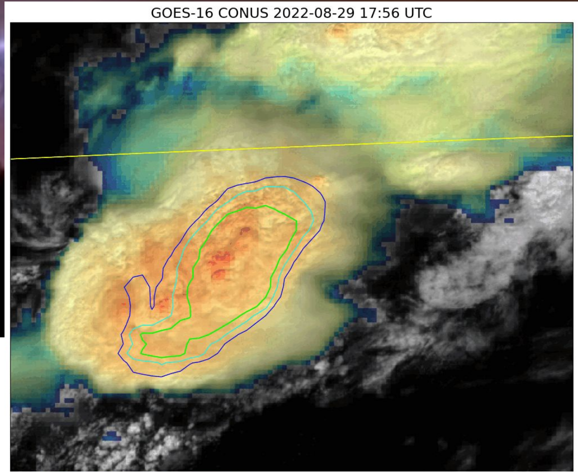
Using AI to predict convective hazards

AMS Committee on Satellite Meteorology, Oceanography, and Climatology (SatMOC) short course

John Cintineo (NOAA/NSSL), Scott Lindstrom (CIMSS)

27 June 2024





Outline

- Overview of ProbSevere
- ENSO and convection
- ProbSevere v3 models
- ProbSevere IntenseStormNet (satellite only)
- ProbSevere LightningCast (satellite only)
  - Deep-learning notebook introduction
- Summary

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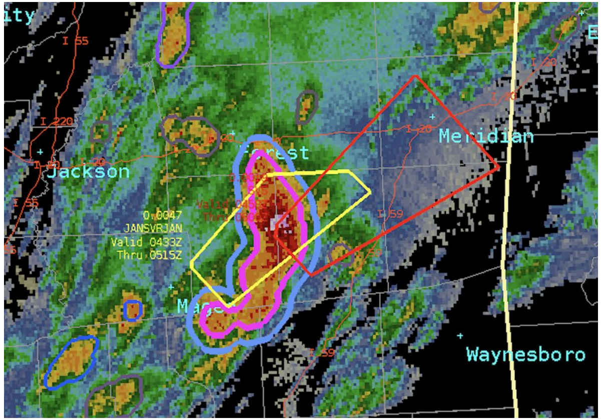
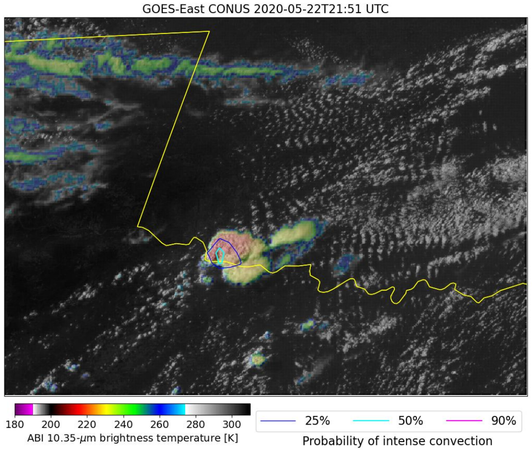
Overview of ProbSevere

1. ProbSevere v3



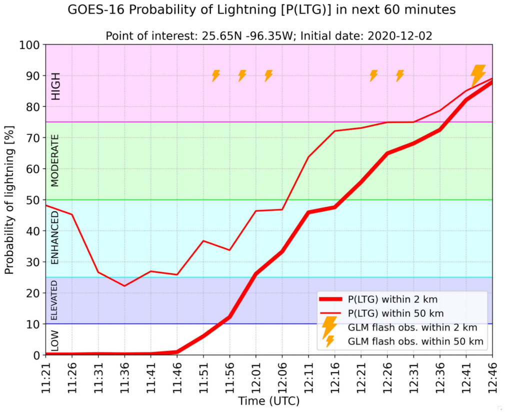
ML models for nowcasting large hail, wind gusts, and tornadoes

2. IntenseStormNet



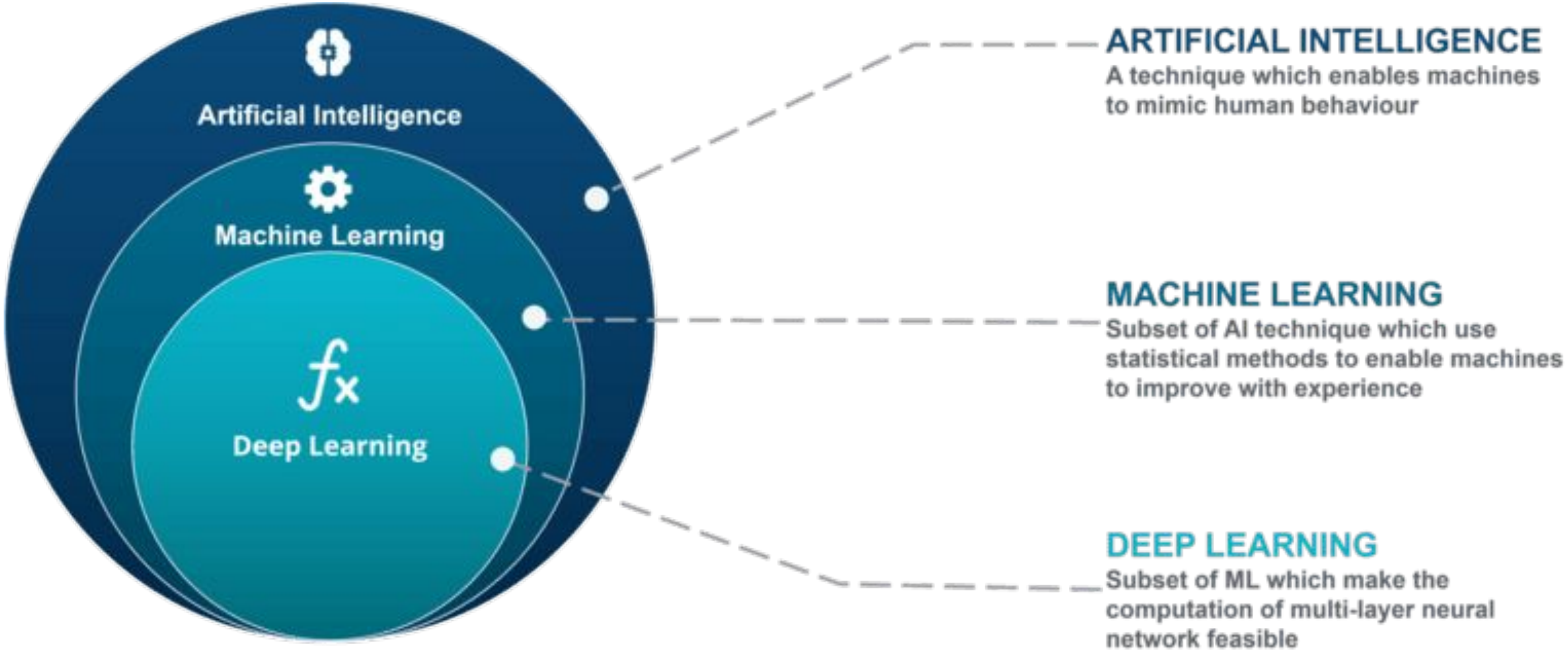
Deep-learning model using only satellite images to detect “intense” parts of storms

2. LightningCast



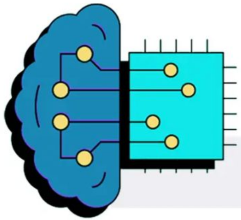
Satellite-only deep-learning model for nowcasting lightning

AI, ML, and deep learning

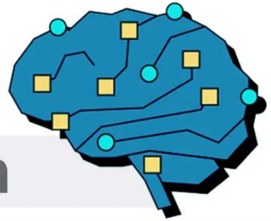


https://datawider.com/how-deep-learning-is-different-from-machine-learning/

AI, ML, and deep learning



Key Differentiation



Machine Learning	Factors	Deep Learning
Manual Extraction	Problem-Solving Approach	Minimal Human Intervention
Supervised & Reinforcement Learning	Training Methods	Autoencoders & Generative Adversarial Networks
Diverse Models	Complexity of Algorithms	Interconnected Neurons
Relatively easy	Interpretability	**Relatively difficult**
Requires relatively less data **CPU is usually fine**	Infrastructure & Data	**Requires relatively more data** **GPU is usually required (for training)**

Modified from https://nextgeninvent.com/blogs/machine-learning-vs-deep-learning/

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ENSO and convection

- U.S. National Weather Service definition:
- Storms that produce…
    - hail ≥ 1”-diameter (25 mm)
    - wind gust of ≥ 58 mph (50 kt)
        - Measured or estimated
    - tornado

zurich.com

ibm.com

livescience.com

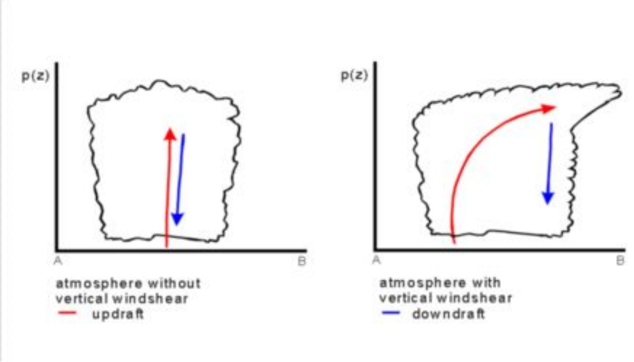
ENSO and convection

How do we get *severe* weather?

- A variety of ways, but they have 4 ingredients in common:
  - **S**hear
  - **L**ift
  - **I**nstability
  - **M**oisture
- Without these, the chance of severe weather is "SLIM".

ENSO and convection

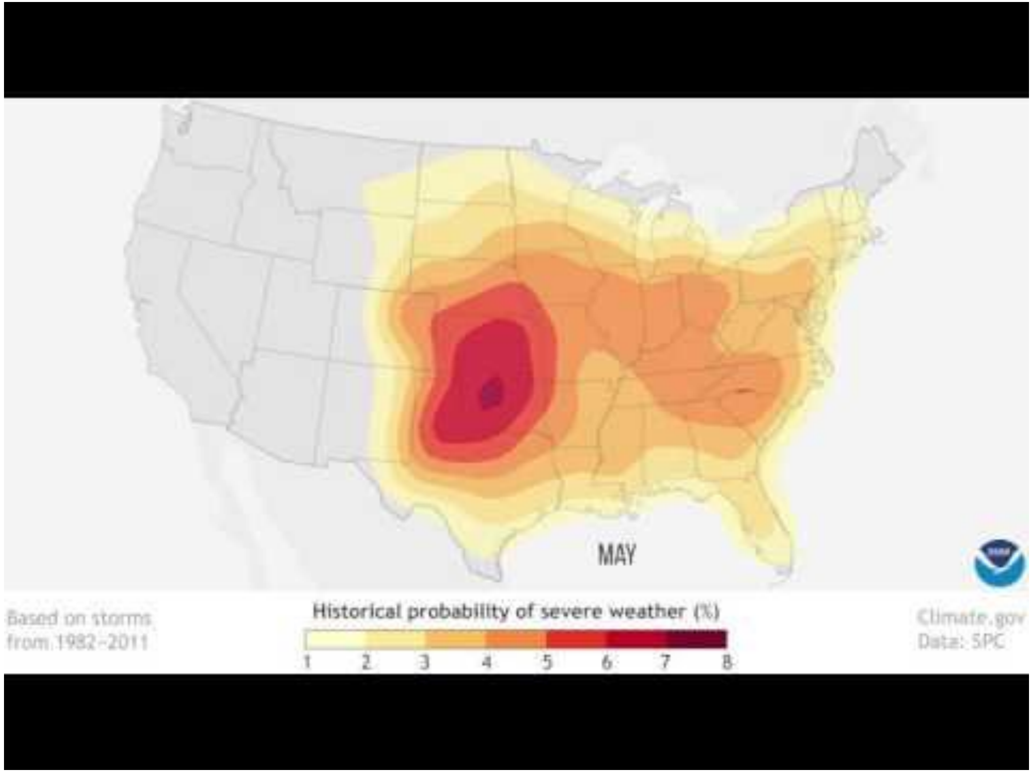
- **Instability**
  - Changes of wind speed and direction with height
  - Prevents storm updraft from collapsing on itself
  - ... under
  - supercells ... (as
  - CAPE ... potential energy
  - particularly important in the lower atmosphere
  - storms need lots of moisture to form and produce lightning
    - stronger CAPE = stronger storm **updraft**
  - strong updrafts are important for hail generation, in particular.



credit: Colorado State University

https://youtu.be/LYubHpEMTPM

ENSO and convection

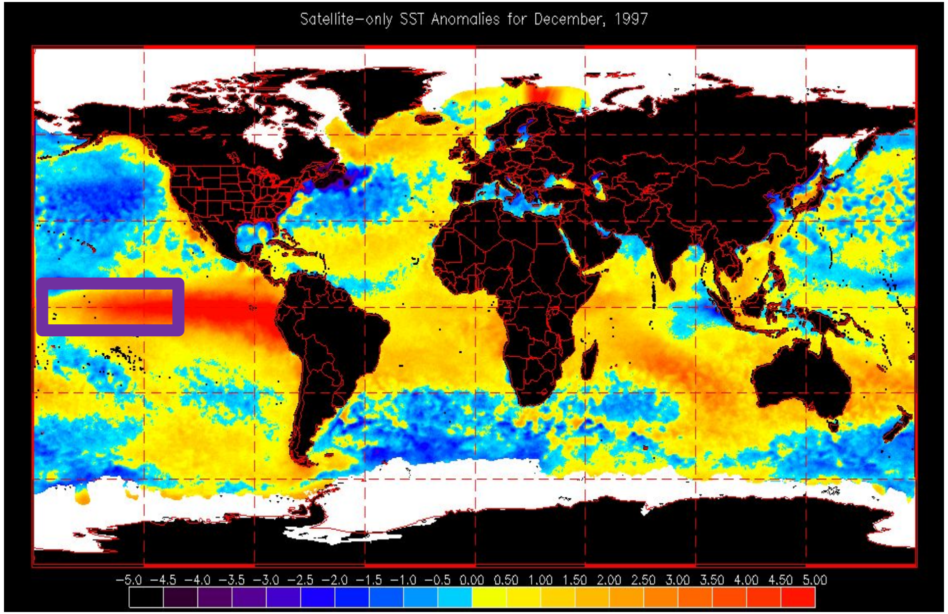


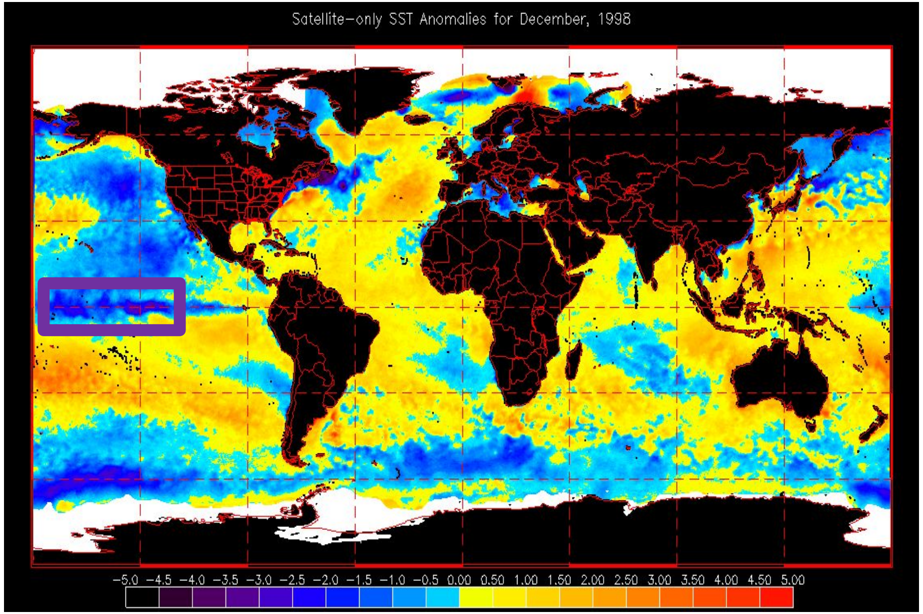
https://youtu.be/z-oijdylBcQ

- **"climatology"** – when and where do certain atmospheric conditions or phenomena occur, on average
- Severe weather can occur anywhere in the U.S., but most of it occurs in the eastern ⅔ of the country, April through August
- Different parts of the country have different severe-weather seasons

ENSO and convection

Period semi-regular shifting of SST patterns in the tropical Pacific – usually most noticeable in the cold season



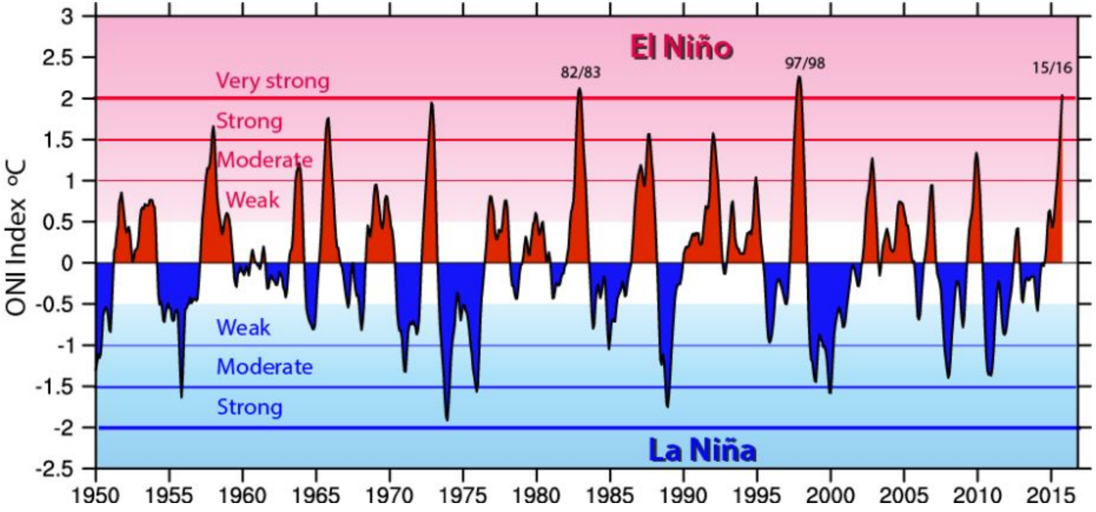


Niño 3.4 Region

https://www.ospo.noaa.gov/Products/ocean/sst/monthly_mean_anom.html

ENSO and convection

ONI – looks at SST anomaly in Region 3.4



https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php

ENSO and convection

How does all that oceanic heat wobble affect severe weather?

15 Largest Tornado Outbreaks,1880-1990
relation to ENSO Events

Date	Total Tornadoes	ENSO Phase
1. Apr 3-4, 1974	148	Cold
2. Sep 19-23, 1967	111	Neutral
3. Mar 20-12, 1976	66	Cold
4. Jun 2-3, 1990	64	Neutral
5. Apr 2, 1982	61	Neutral
6. Mar 13, 1990	59	Neutral
7. May 8, 1988	57	Warm
8. May 25-26, 1965	51	Cold
9. May 4-5, 1959	49	Neutral
10. Apr 11-12, 1965	48	Cold
11. Jan 9-10, 1975	47	Cold
12. May 15-16, 1968	46	Cold
13. Apr 21, 1967	45	Neutral
14. Jun 7-8, 1984	45	Neutral
15. May 29, 1980	44	Neutral

Source: Grazulis 1991

ENSO and convection

El Niño cold season storm track is farther south

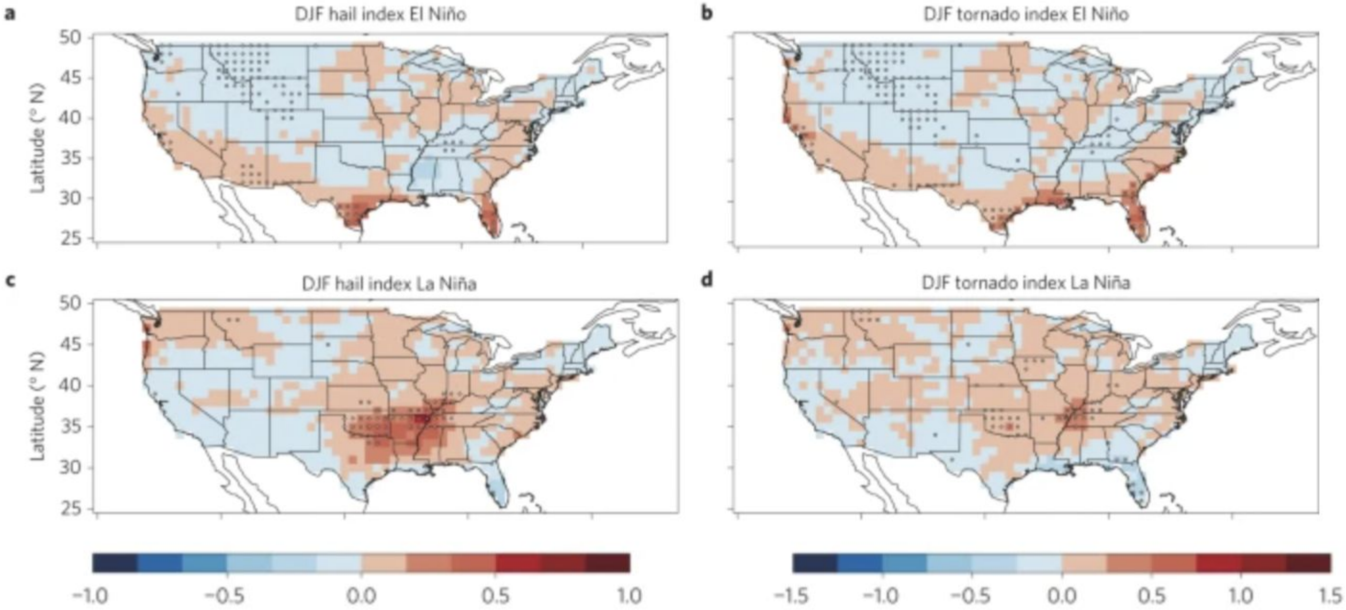
ENSO and convection

How does all that oceanic heat wobble affect severe weather?

Figure 1: Composite mean anomalies of winter (December, January, February) hail and tornadoes conditioned on the winter ENSO state.

El Niño

La Niña



Allen et al. (2015)
https://www.nature.com/articles/ngeo2385

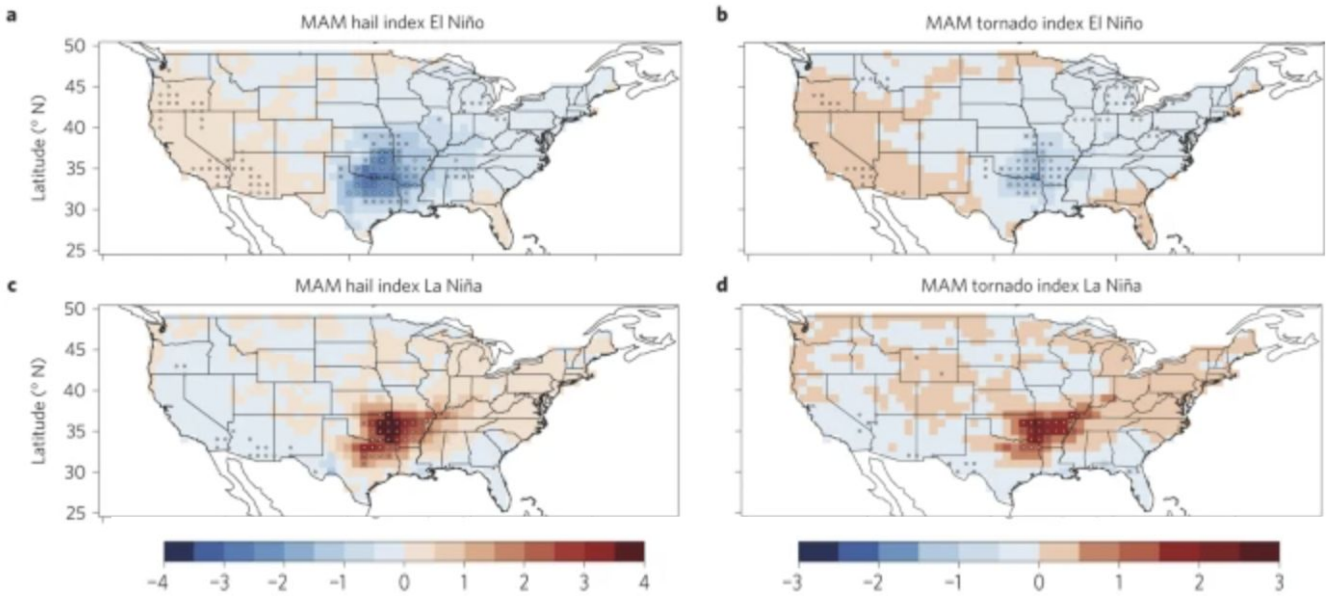
ENSO and convection

How does all that oceanic heat wobble affect severe weather?

Figure 2: Composite mean anomalies of spring (March, April, May) hail and tornadoes conditioned on the spring ENSO state.

El Niño

La Niña



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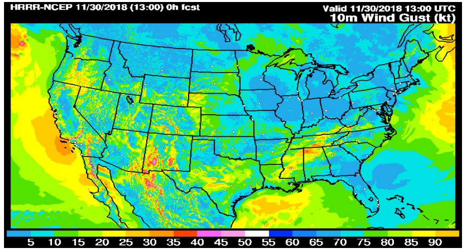
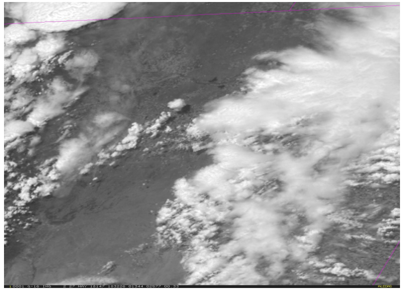
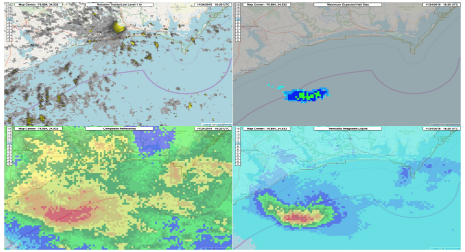
ProbSevere – "probability of severe" models



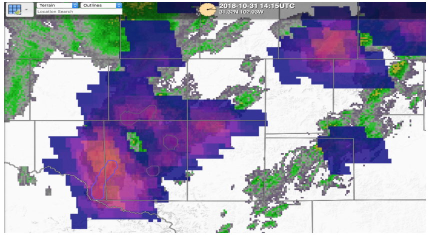
High-resolution NWP Data (HRRR)



GOES imagery and derived parameters



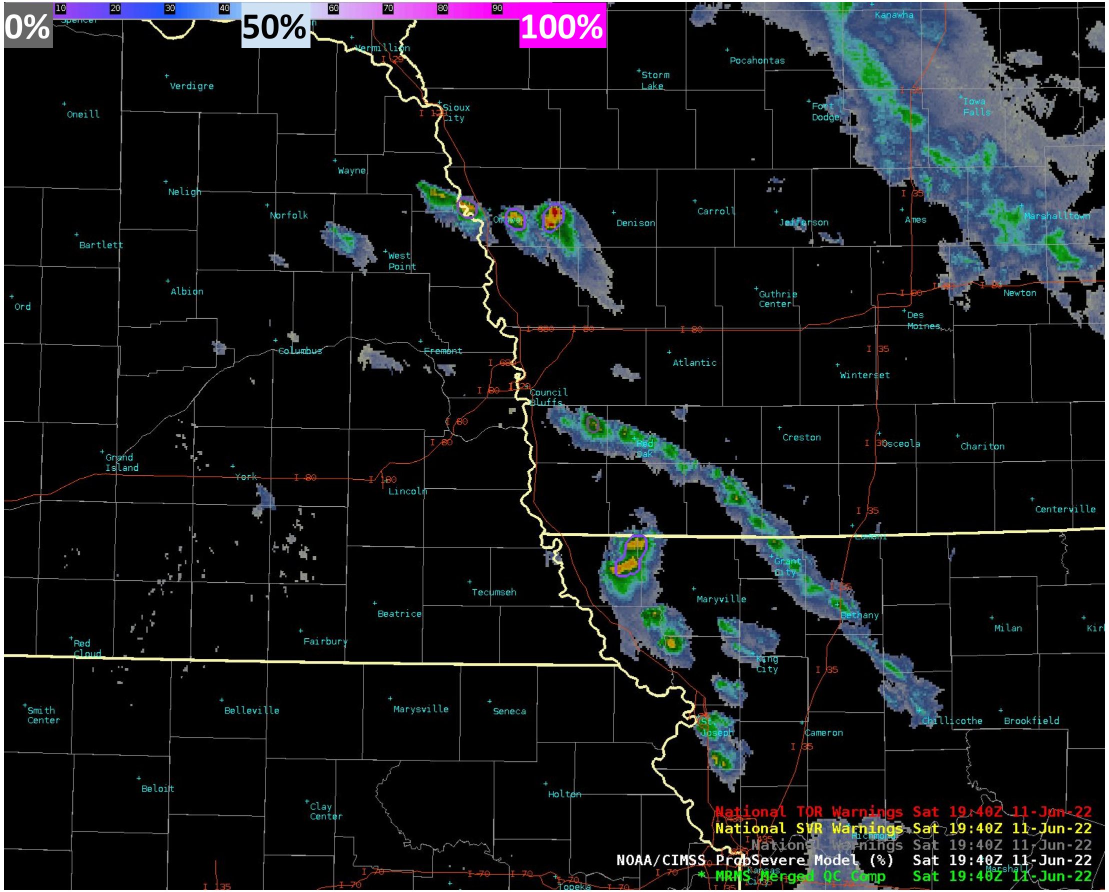
MRMS products



Total Lightning (terrestrial and spaceborne)

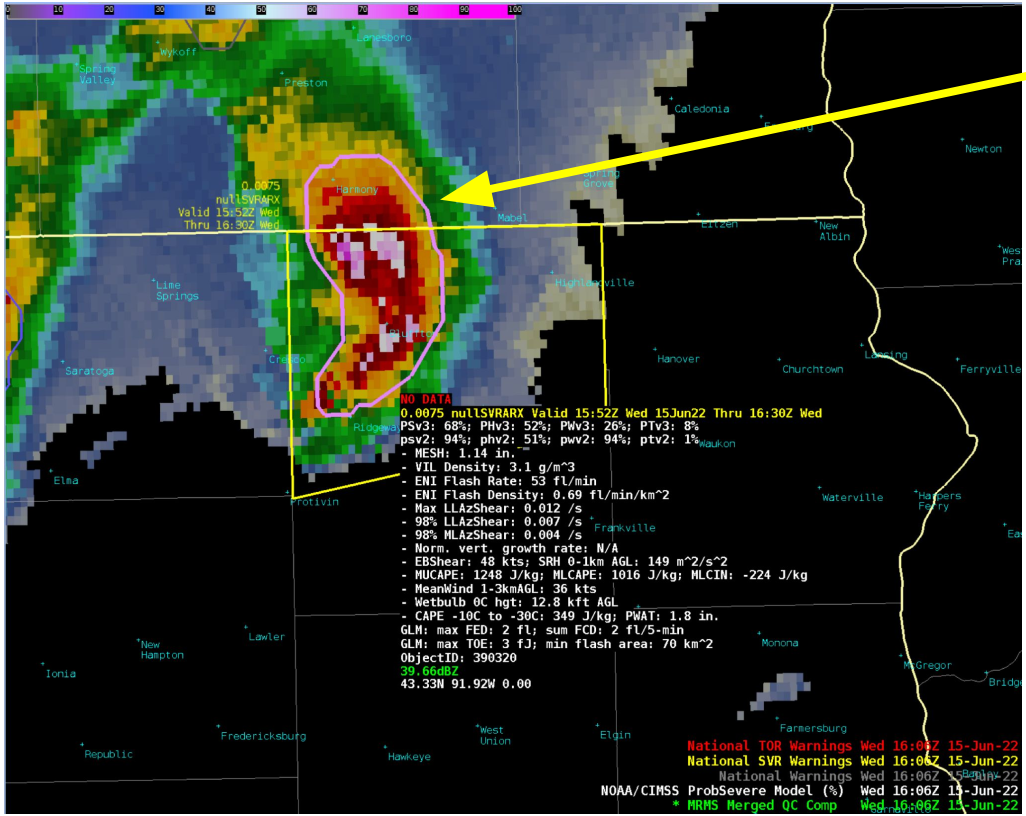
Probability a thunderstorm will produce severe hail, wind, or a tornado in the future (up to 60 minutes)

ProbSevere v3



- **ProbSevere** uses **radar**, **satellite**, **environmental**, and **lightning** data to predict *next-hour severe-weather probabilities*.
- ProbSevere models *(gradient-boosted decision trees)*:
  - probability of any severe weather
  - probability of severe hail
  - probability of severe wind
  - probability of tornado
- ProbSevere identifies and tracks storms in both radar and satellite imagery across the lower 48 U.S. states
- Extracts features or predictors within storm objects from meteorological data
- Used operationally throughout the NWS
  - a “decision aid” to help forecasters issue severe-weather warnings

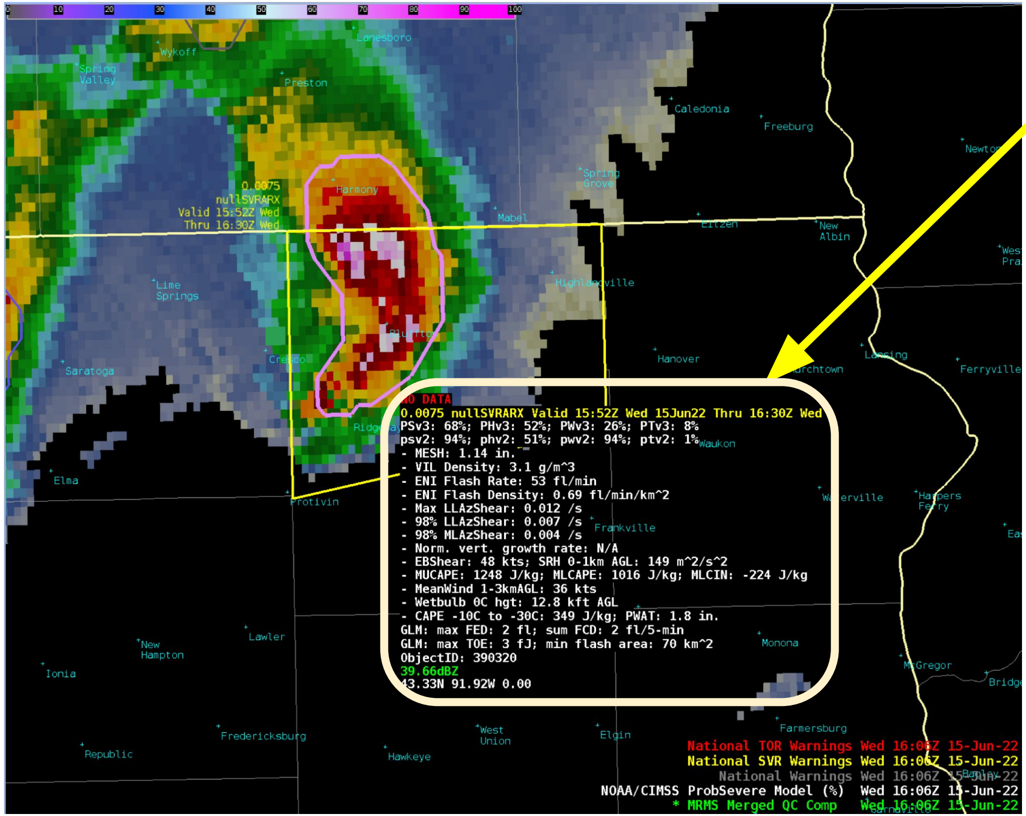
ProbSevere v3



- Storm objects contoured around radar data
  - colored by probability of severe
  - allows forecasters to monitor radar/satellite data and still get the ProbSevere probabilities

Display is AWIPS, used by U.S. National Weather Service

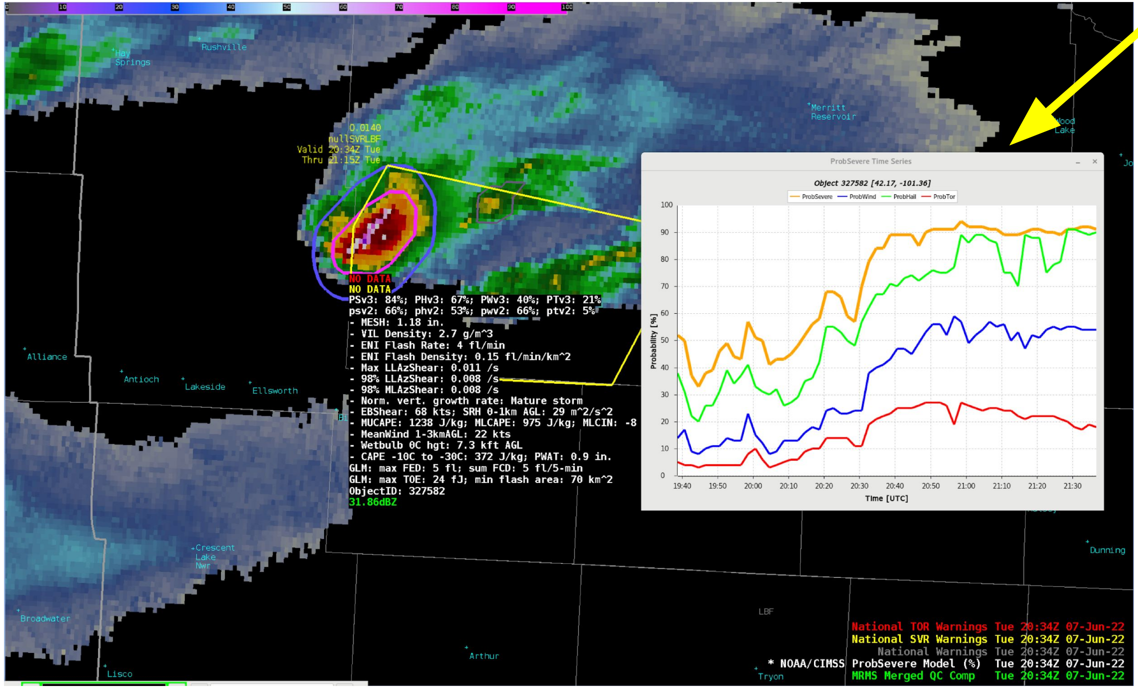
ProbSevere v3



- If a forecaster hovers over a storm with their cursor, they can see the specific severe-weather probabilities and predictor values
  - Radar, satellite, lightning, and environmental information about the storm
  - This helps forecasters understand how changes in the storm data affect changes in the probabilities.
    - helps unpack the “black-box” of ML models.

Display is AWIPS, used by U.S. National Weather Service

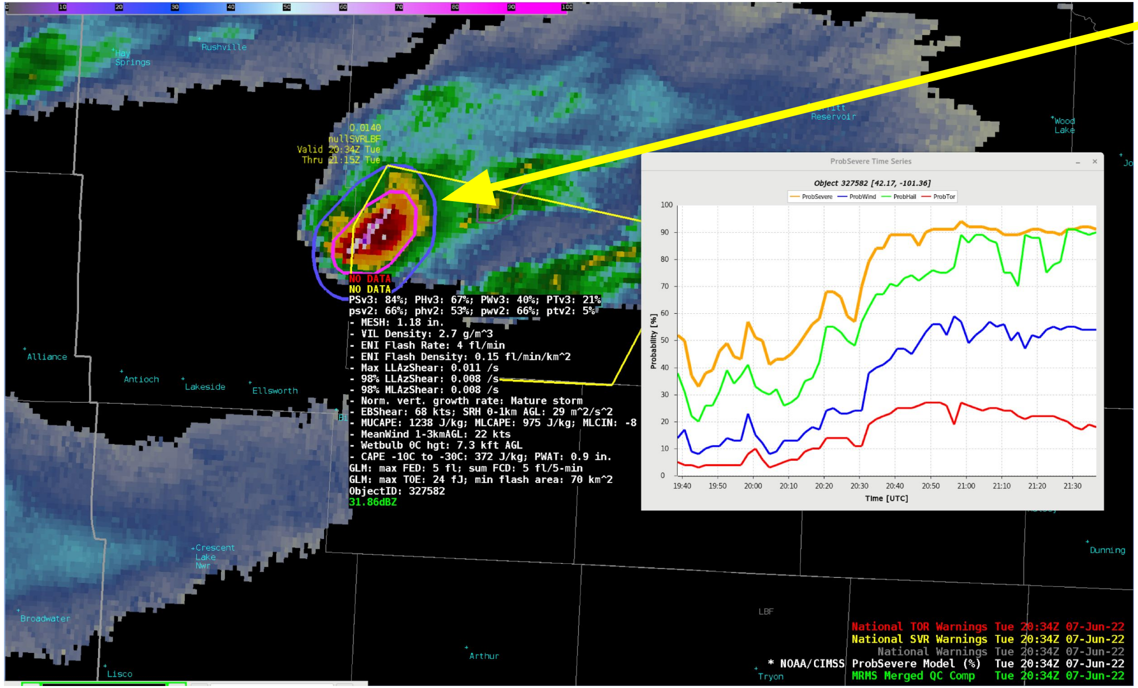
ProbSevere v3



- Forecasters can click on a storm and get a recent history of the ProbSevere models' probabilities
- ProbSevere trends in storms can help forecasters decide to issue or not issue a severe-weather warning.

Display is AWIPS, used by U.S. National Weather Service

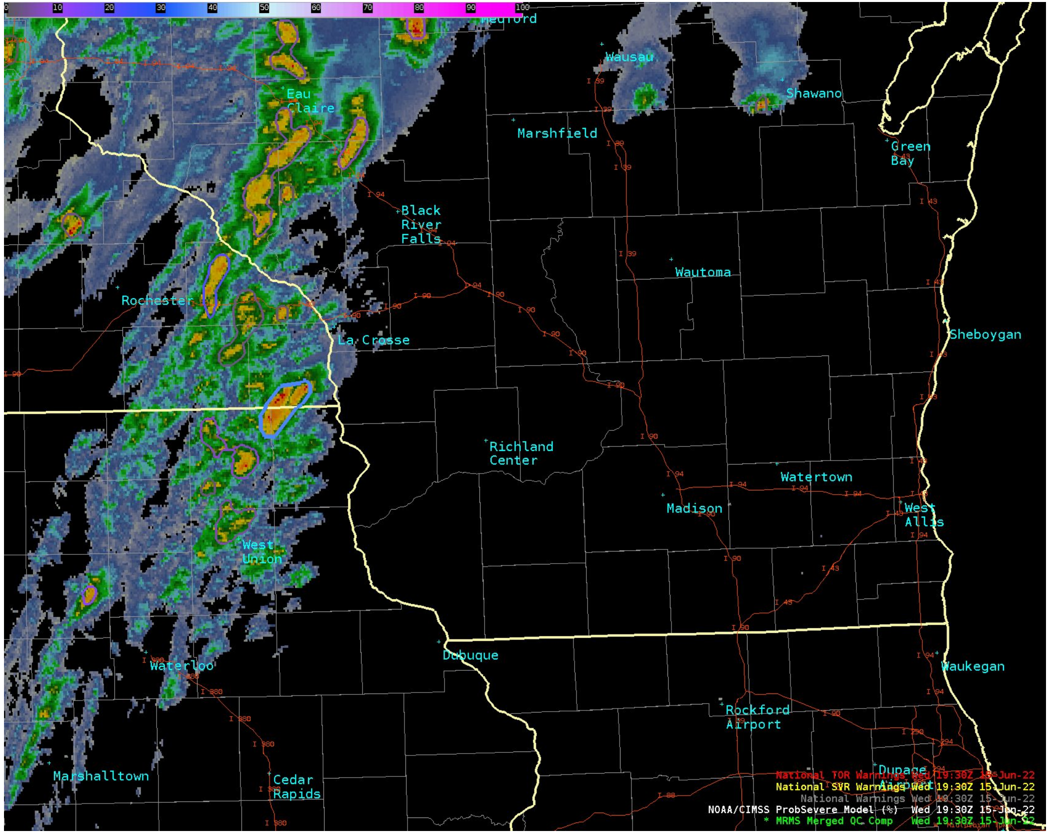
ProbSevere v3



- Outer storm-object contour is colored by **probability of tornado**
  - Only appears when above some threshold
- Enables forecasters to see both the severe threat (hail or wind) and the tornado threat at the same time.

Display is AWIPS, used by U.S. National Weather Service

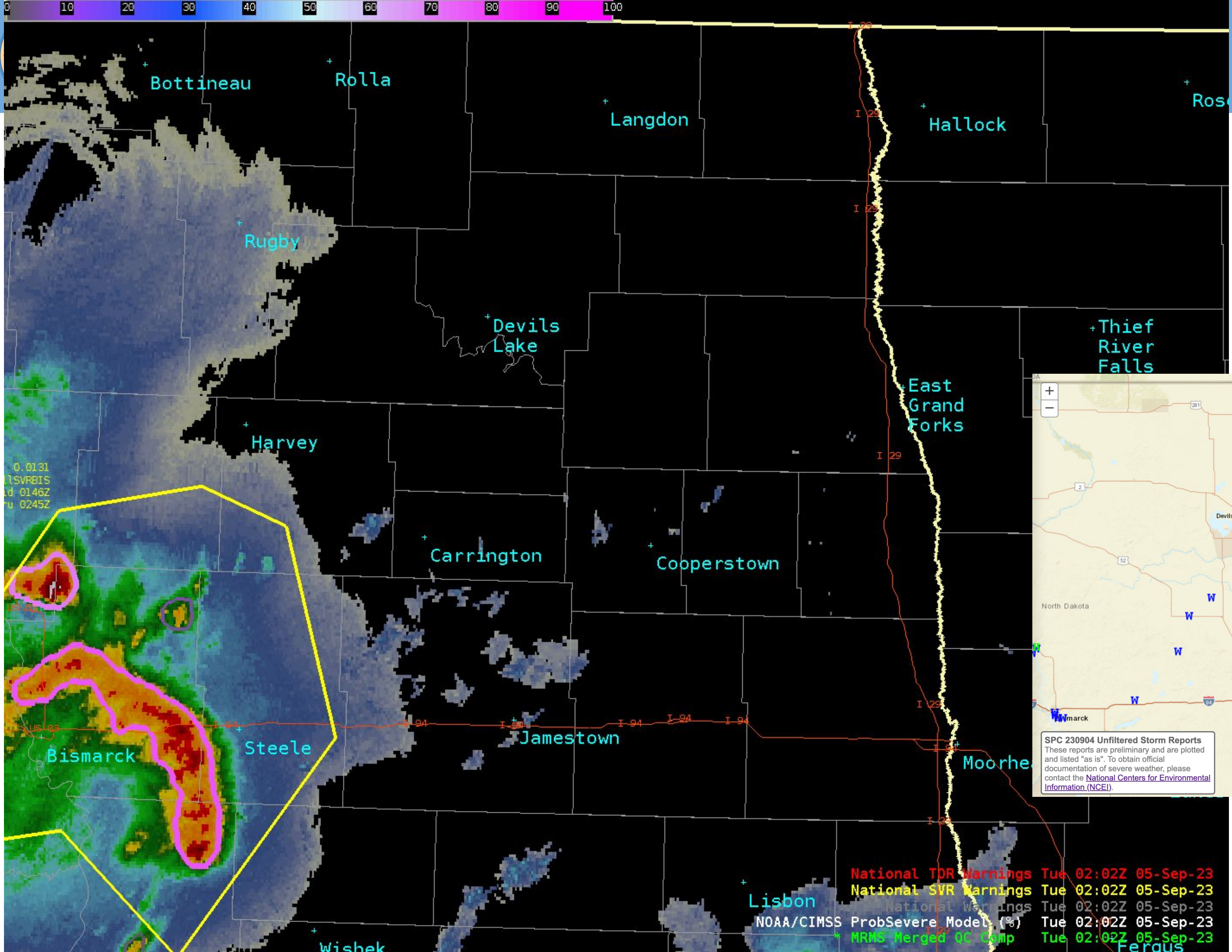
ProbSevere v3



Tornadic, severe, and non-severe storms in Wisconsin, USA

- Decision aids like ProbSevere can help forecasters perform **triage** in busy situations, that is, prioritize threatening storms to investigate and make warning decisions.

Display is AWIPS, used by U.S. National Weather Service


0
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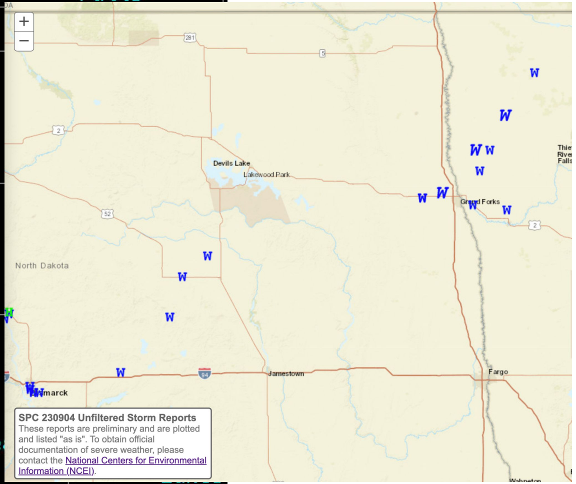
Bottineau
Rolla
Langdon
Hallock
Ros
Rugby
Devils Lake
Thief River Falls
East Grand Forks
Harvey
Carrington
Cooperstown
Steele
Bismarck
Jamestown
Moorhe
Lisbon
Wishek
Fergus
I 29
I 94
0.0131
llSVRBIS
id 0146Z
ru 0245Z
National TOR Warnings Tue 02:02Z 05-Sep-23
National SVR Warnings Tue 02:02Z 05-Sep-23
National Warnings Tue 02:02Z 05-Sep-23
NOAA/CIMSS ProbSevere Model (%) Tue 02:02Z 05-Sep-23
MRMS Merged QC Comp Tue 02:02Z 05-Sep-23


Devils Lake
Lakewood Park
North Dakota
Grand Forks
Jamestown
Fargo
SPC 230904 Unfiltered Storm Reports
These reports are preliminary and are plotted and listed "as is". To obtain official documentation of severe weather, please contact the National Centers for Environmental Information (NCEI).

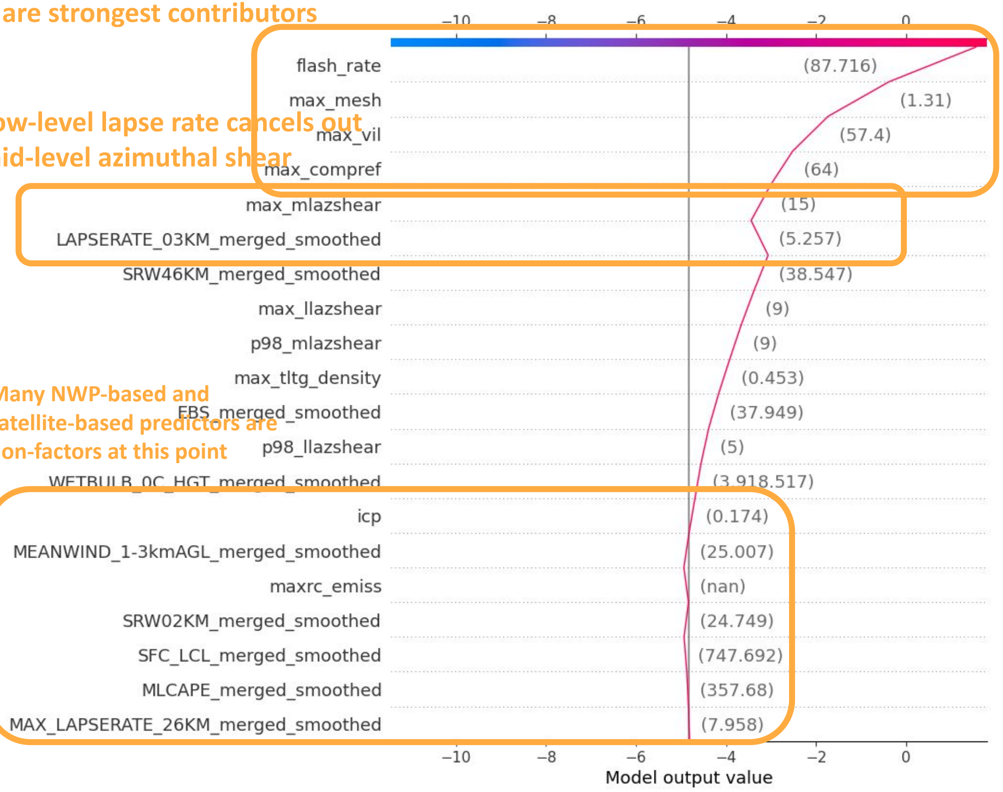
ProbSevere v3

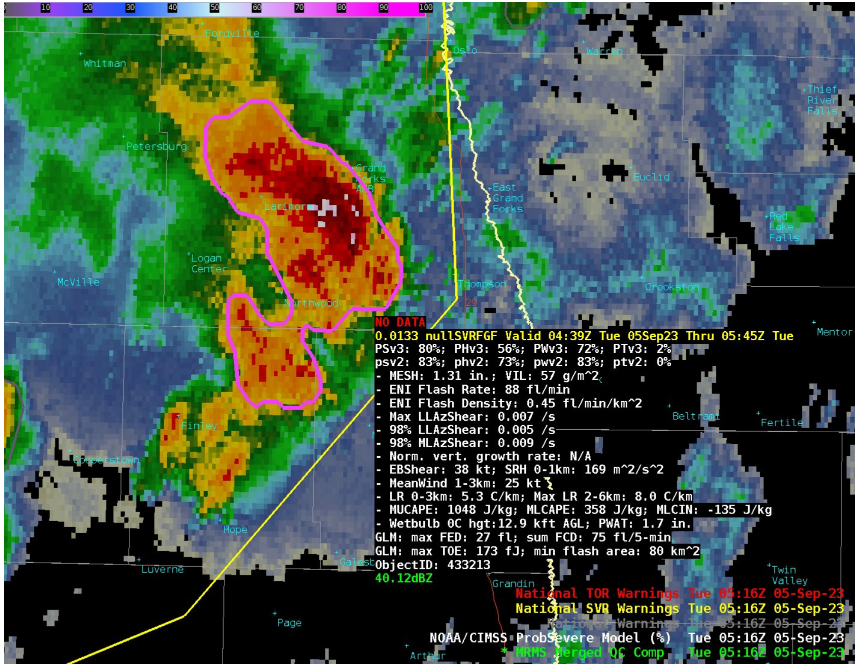
Decision plots

Lightning and radar predictors are strongest contributors

Low-level lapse rate cancels out mid-level azimuthal shear

Many NWP-based and satellite-based predictors are non-factors at this point





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IntenseStormNet

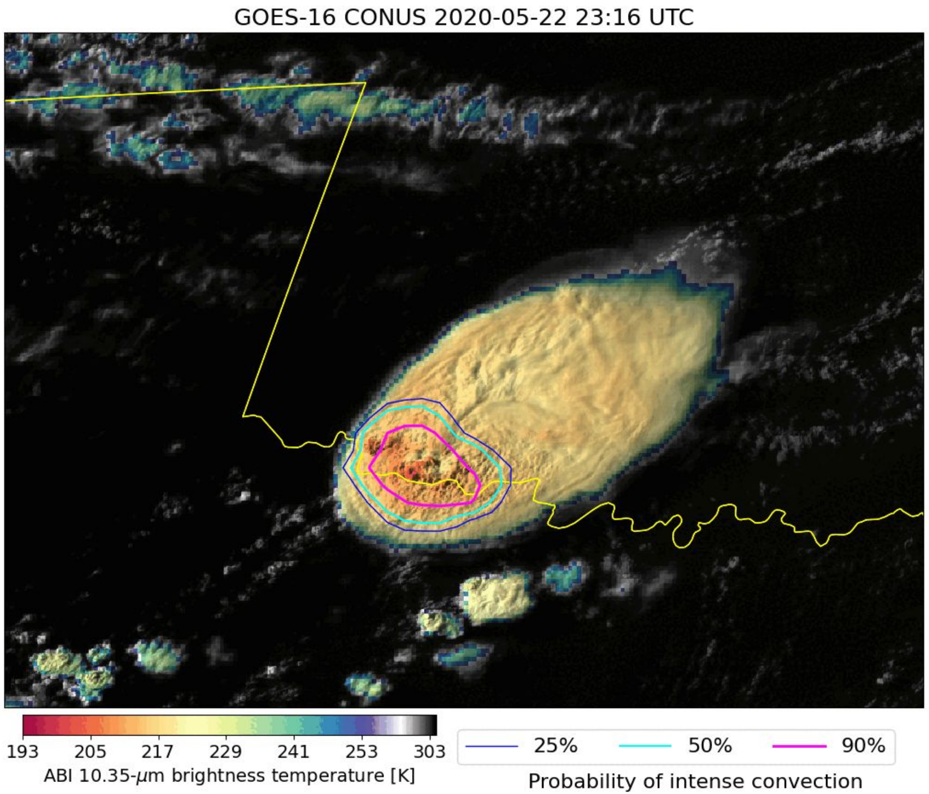
Objective: identify convective regions with one or more visual indicator of an intense updraft (satellite indicators often precede other indicators)

Labeled data: >200K human expert labels

Input data: ABI (0.5-km visible and 2-km IR window) and GLM flash-extent density imagery

Output data: intense convection probability maps

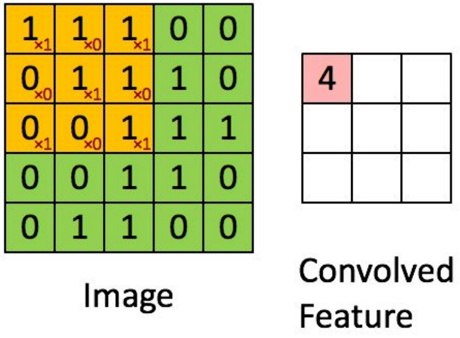
Applications: utilized in ProbSevere v3, satellite-only nowcasting tool, process and climate studies

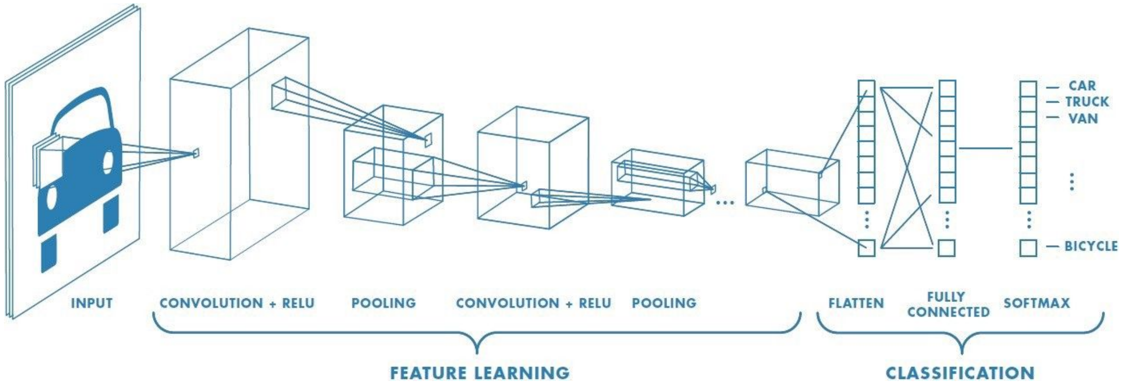


WAF Cintineo et al. 2020

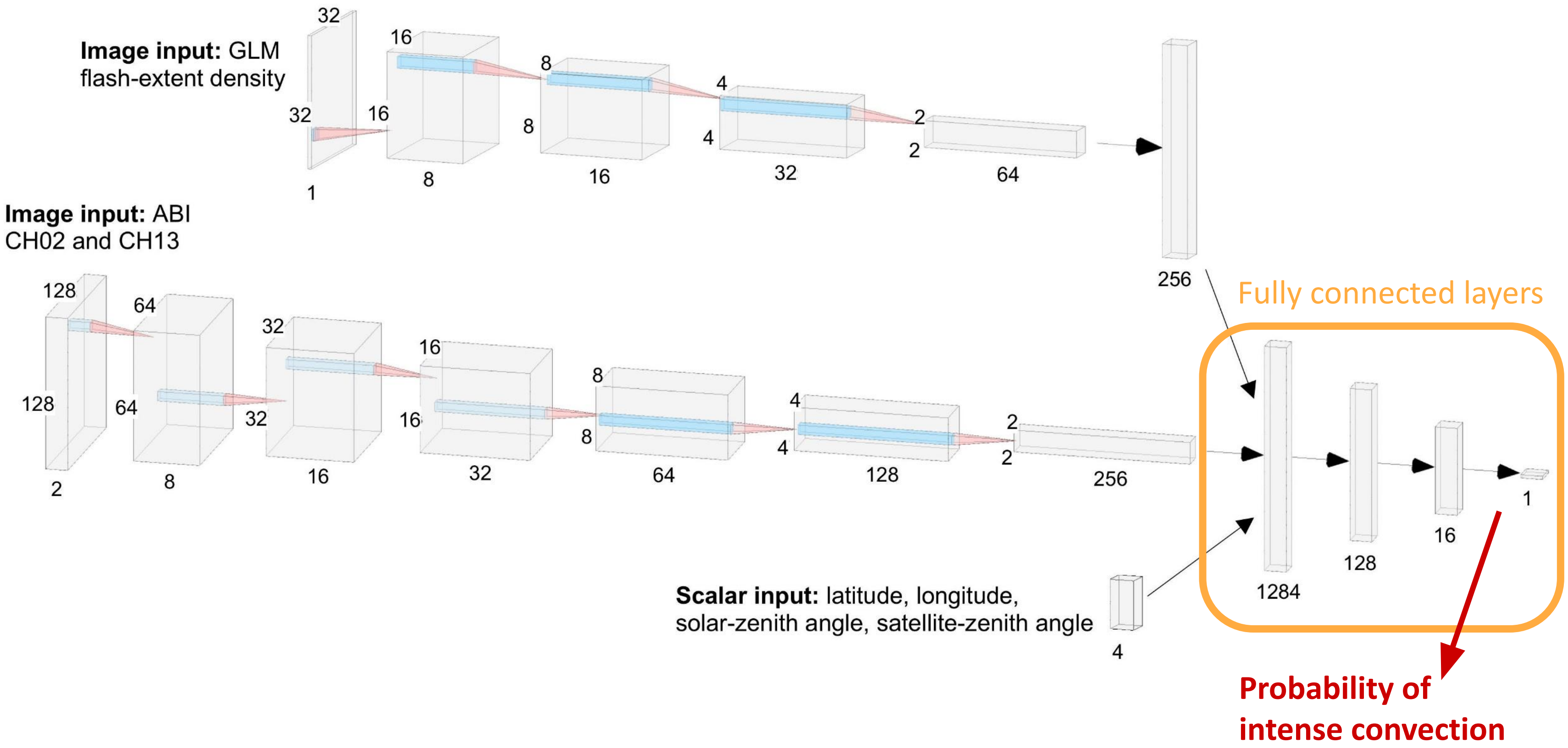
What is a convolutional neural network (ConvNet) and how does it work?

- Deep-learning algorithm that uses *images* as input, and assigns importance (learnable weights and biases) to various aspects/objects/features in the image and is able to differentiate between classes (in our case).
- With enough training data, ConvNets have the ability to learn filters/characteristics.
- **ConvNets learn salient <u>spatial</u> *and* <u>multispectral</u> features in images.**
- [“The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction”]



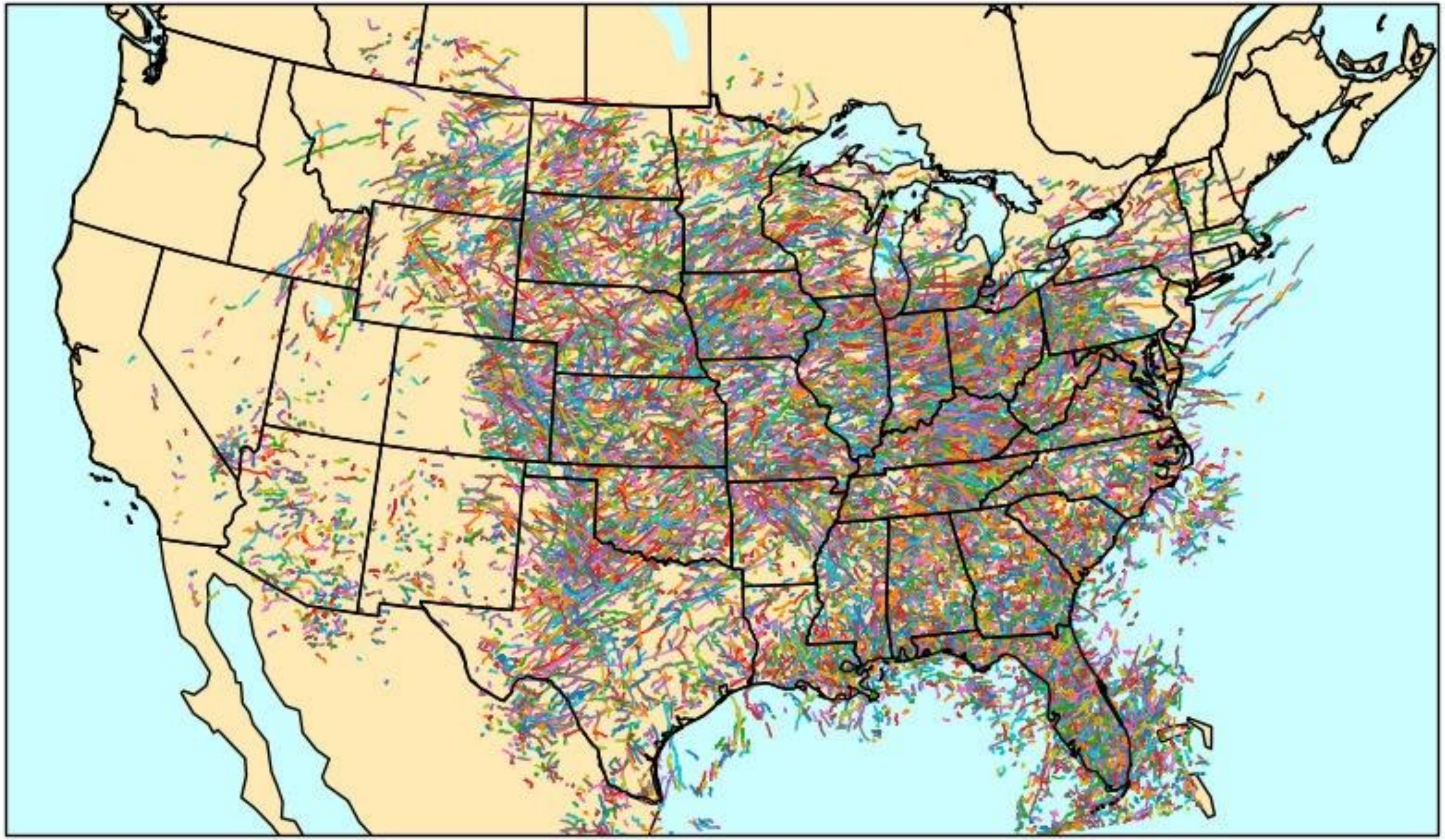


IntenseStormNet



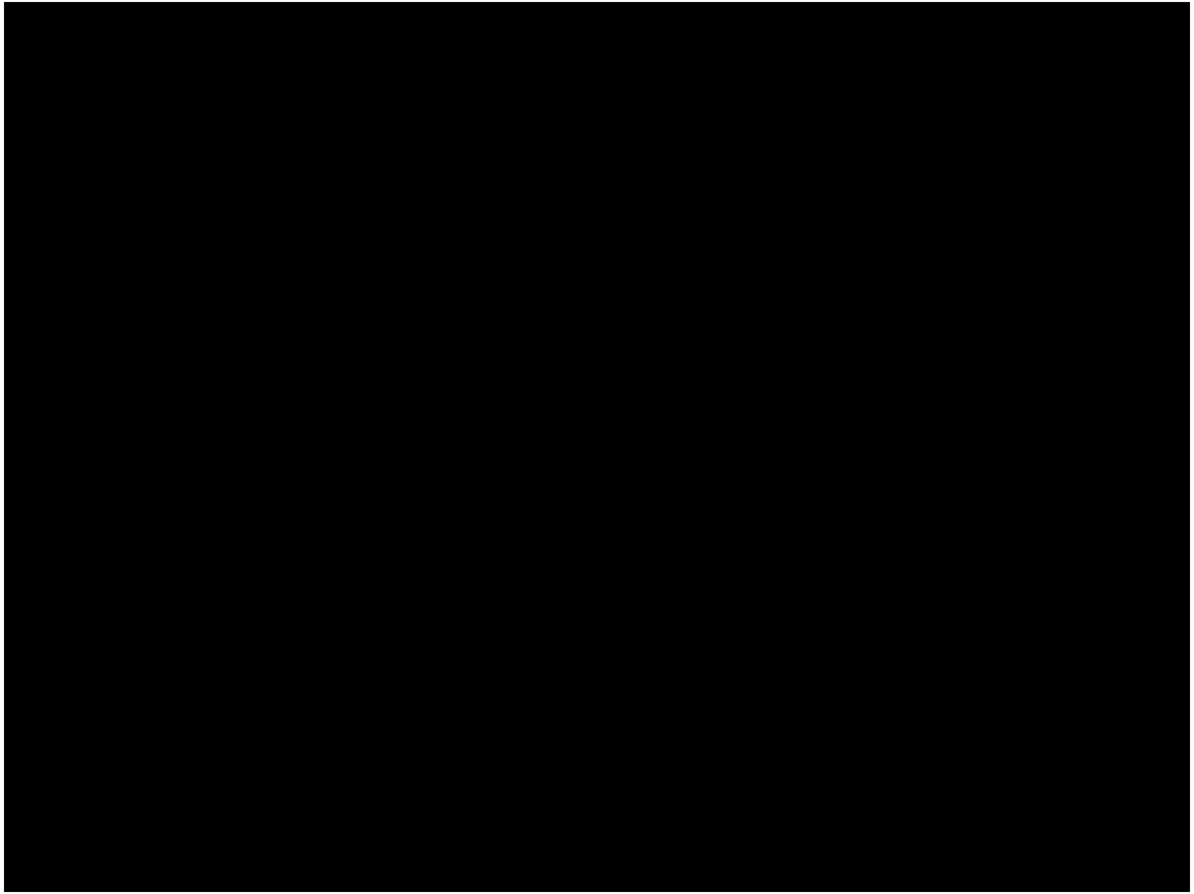
IntenseStormNet

Storm tracks of training database



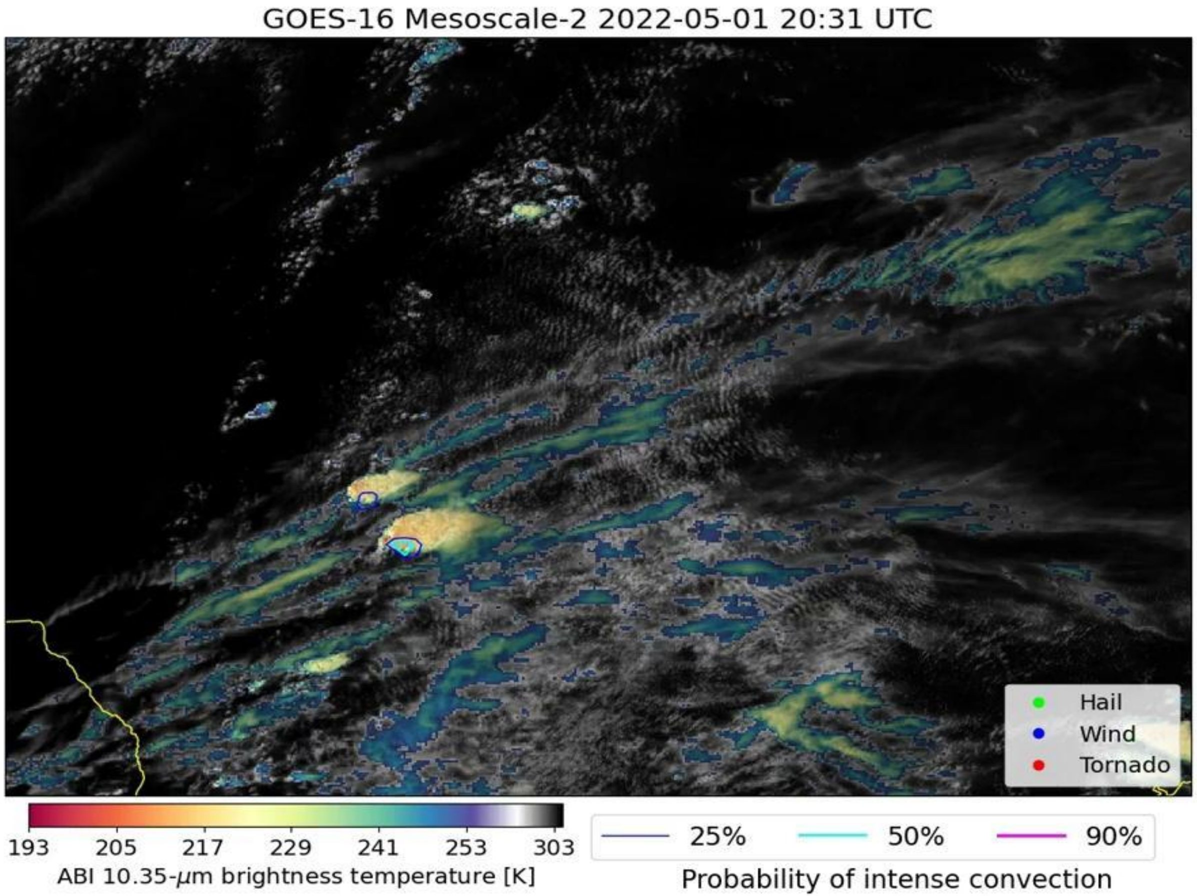
IntenseStormNet

- Works day and night
- CONUS or Meso scans
- GOES-East or -West
- Doesn’t require radar
- Near-real-time output available at CIMSS



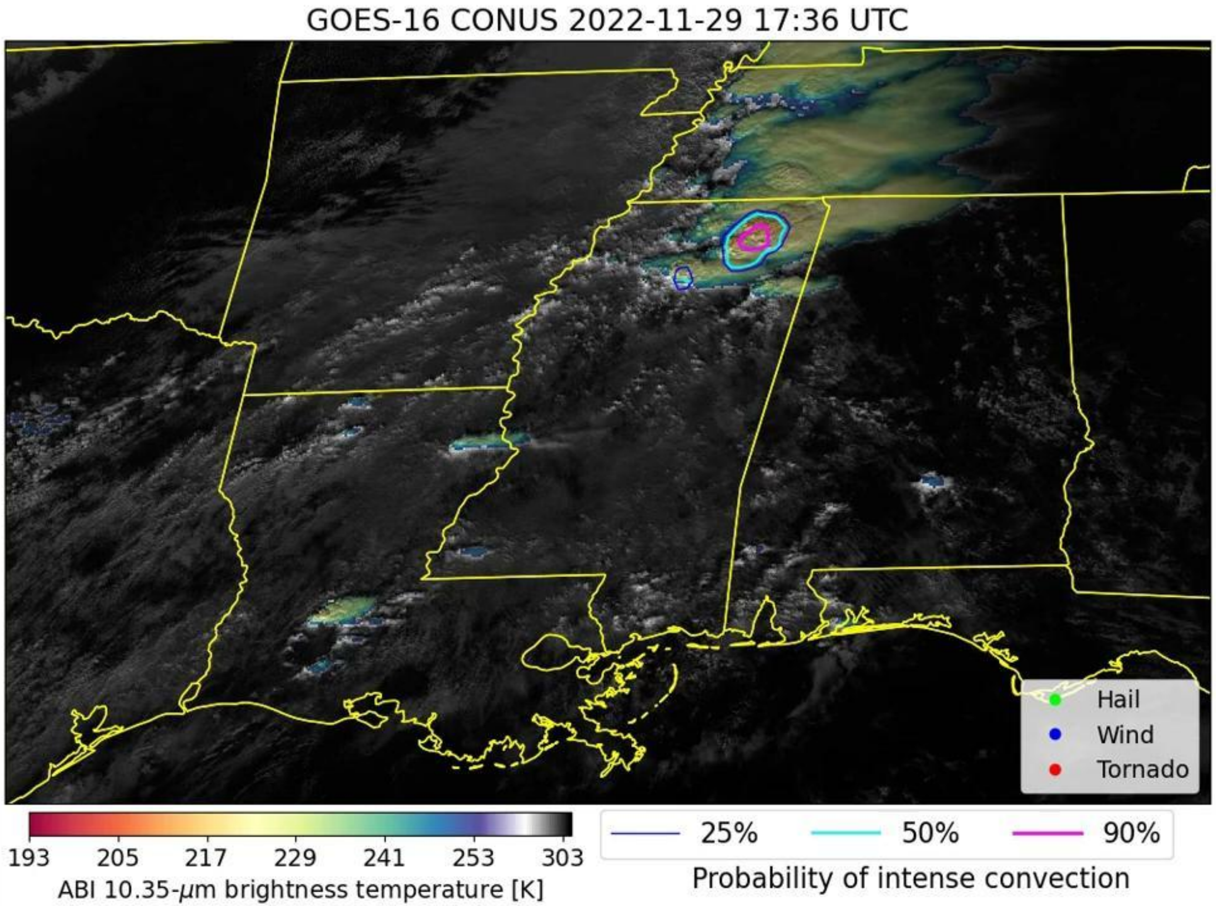
IntenseStormNet

- 1-min Meso sector
- South/central Texas
- Shows good correspondence with reports
    - hail ≥ 25mm diameter
    - wind ≥ 50 kt or property damage
    - tornado



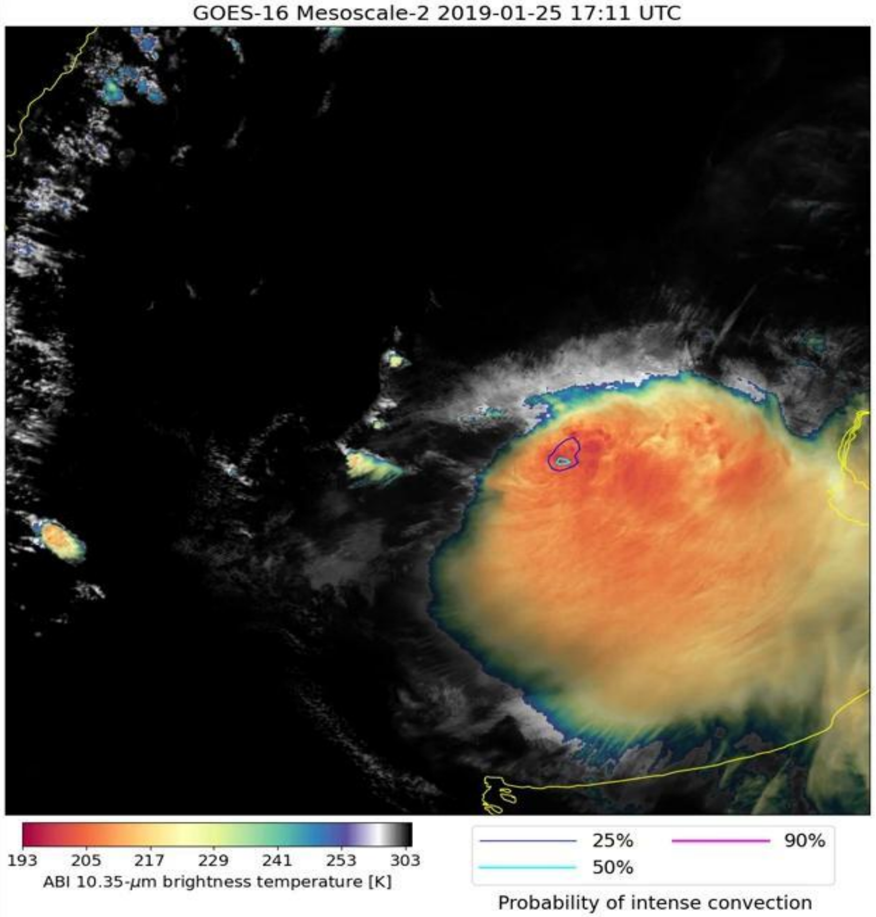
IntenseStormNet

- Southeast U.S.
- Some linear convective structures mixed with supercells
- Good transition to night (i.e., loss of 0.64-µm reflectance)
- Underestimation where zero or very low lightning

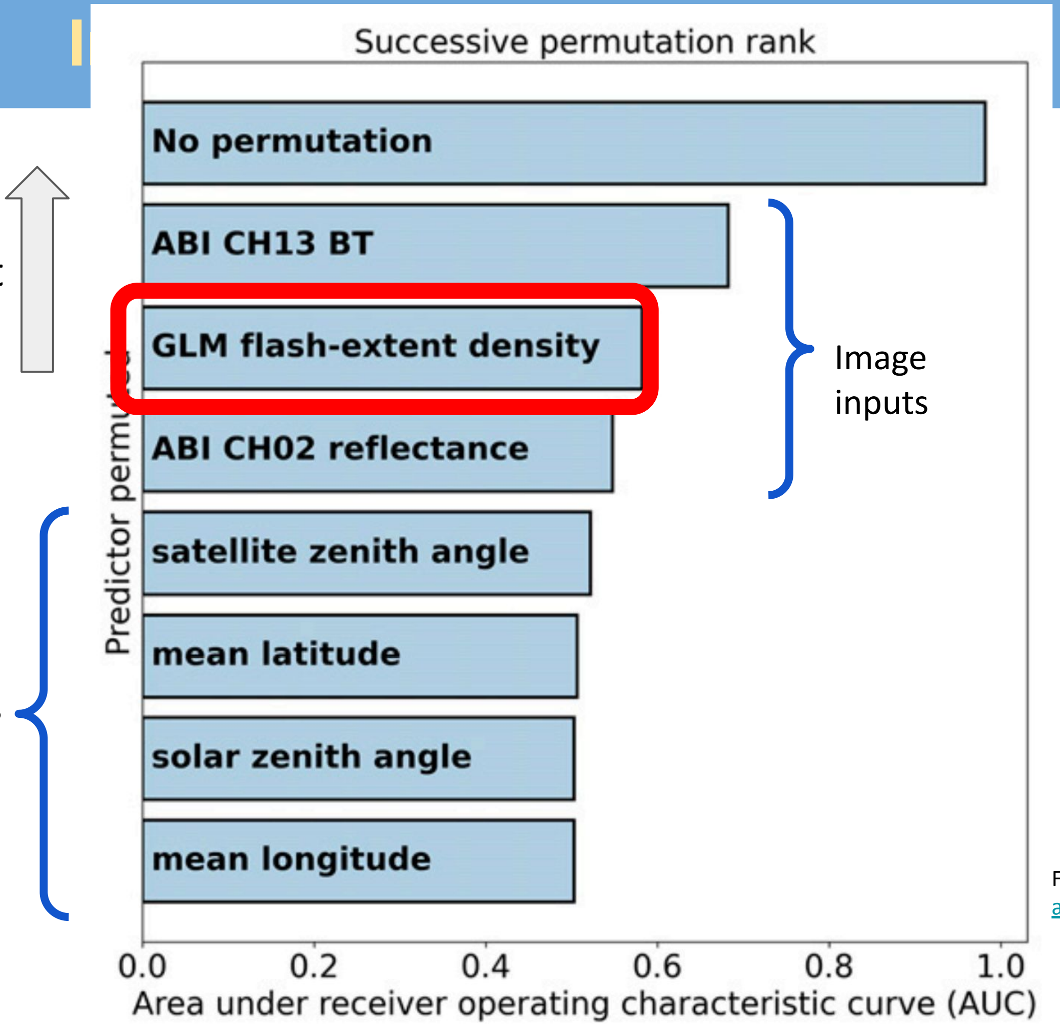


IntenseStormNet

- 1-min Meso sector
- Argentina
- Hail, wind damage, and widespread flash flooding
- 50-dbZ echo top ~20 km on storm near Córdoba



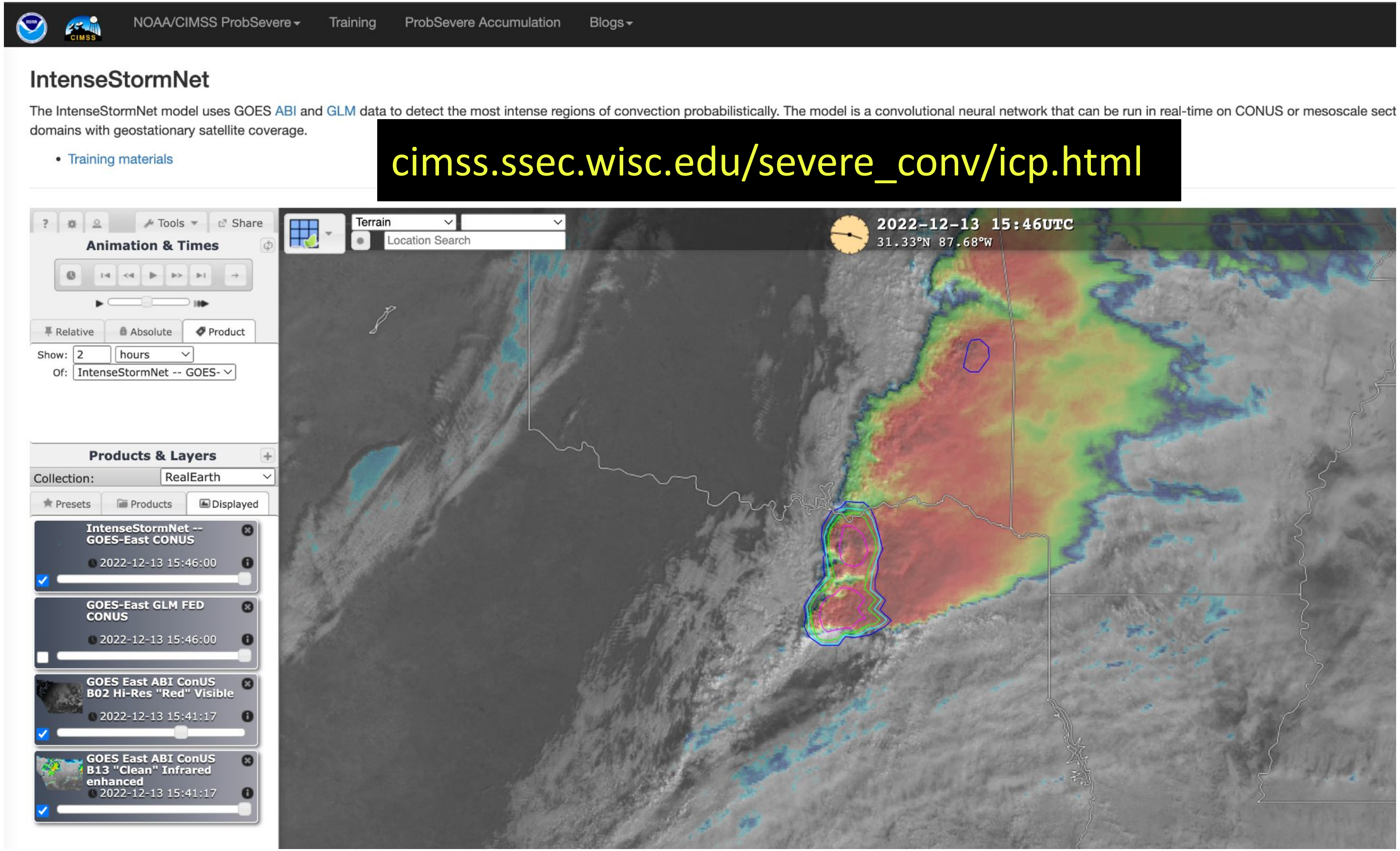
More important



- daytime-only sample
- GLM flash-extent density more important than ABI 0.64-µm channel

From [Cintineo et al. 2020 (WAF)]

IntenseStormNet



cimss.ssec.wisc.edu/severe_conv/icp.html

*Only run over CONUS, currently

- IntenseStormNet geoJSONs available through RealEarth API

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LightningCast

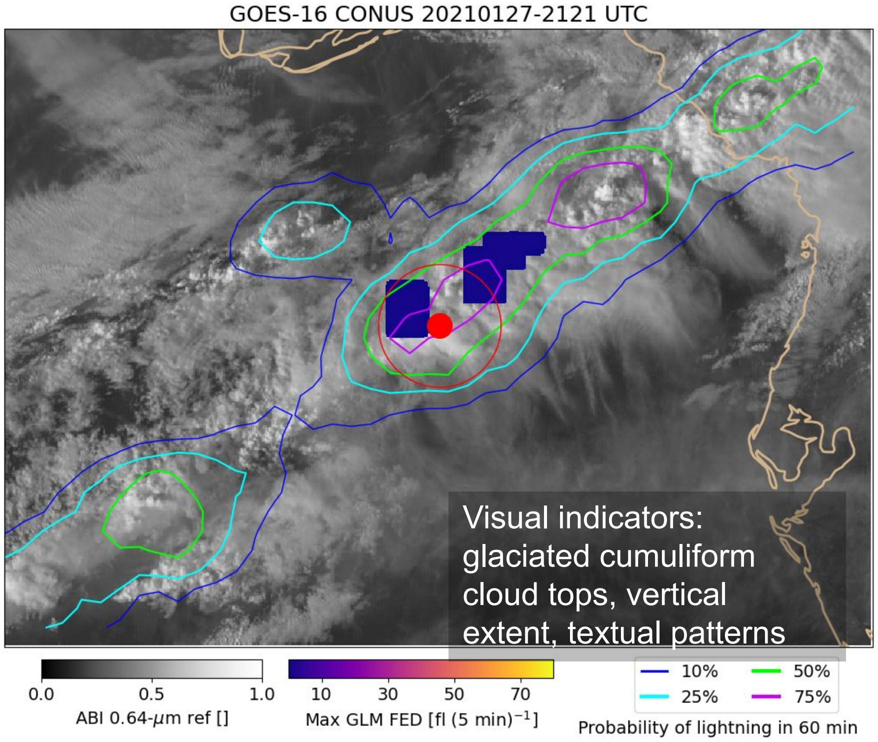
Objective: determine where lightning is most likely to occur within a forecast time interval

Labeled data: millions of GLM lightning records

Input data: ABI (0.5-km visible, 1-km SWIR, and 2-km IR window)

Output data: location-specific, probabilistic lightning nowcasts

Applications: satellite-only nowcasting tool for protection of life and property, process and climate studies



WAF Cintineo et al. 2022

LightningCast

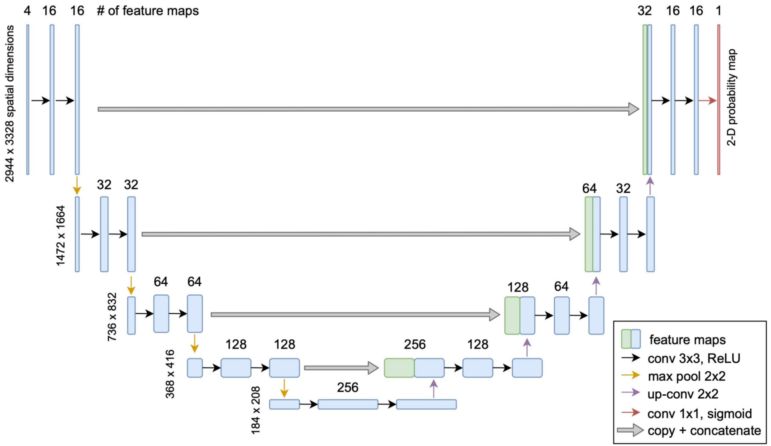
- Use an image-based AI model: convolutional neural network
  - LightningCast model is “U-net”
  - Learns salient spatial and multispectral features
- **Predictors (GOES-16 ABI):**
  - **0.64-µm reflectance (0.5 km)**
  - **1.6-µm reflectance (1 km)**
  - **10.3-µm BT (2 km)**
  - **12.3-µm BT (2 km)**

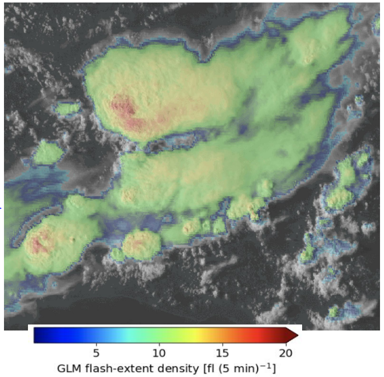
Day-cloud-phase RGB (0.64-µm and 1.6-µm reflectance)

Split-window difference (10.3-µm and 12.3-µm BT)

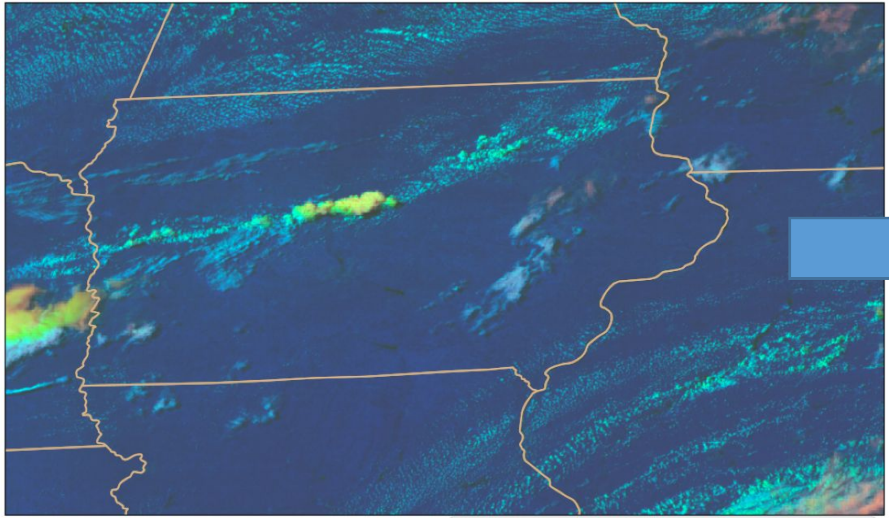
- **Target / Truth (GOES-16 GLM):**
  - next-hour maximum accumulation of **GLM flash-extent density** (≥ 1 flash)
  - Optical sensor (single band: 777.4 nm)
  - 8-km resolution
- **Output:** Probability of lightning at any location within the next 60 minutes
  - 2-km spatial resolution

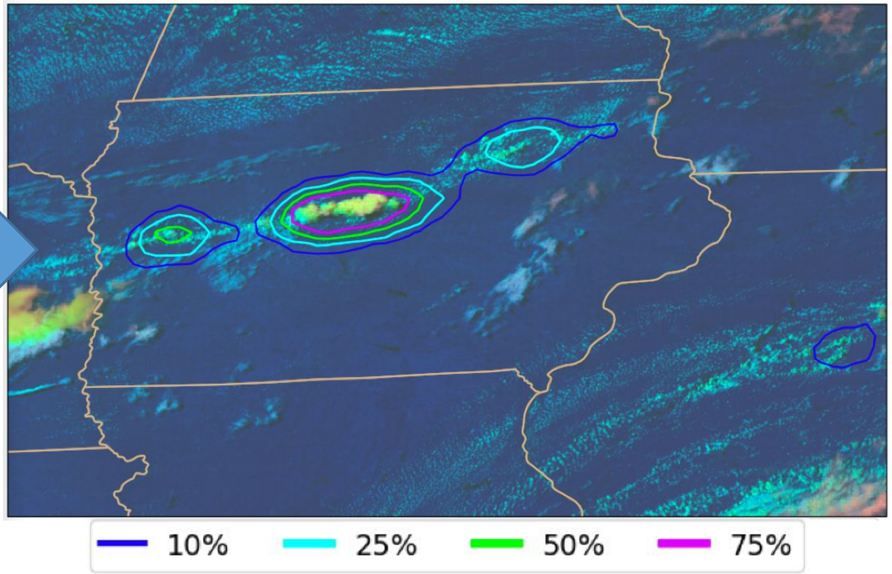
WAF Cintineo et al. 2022





LightningCast

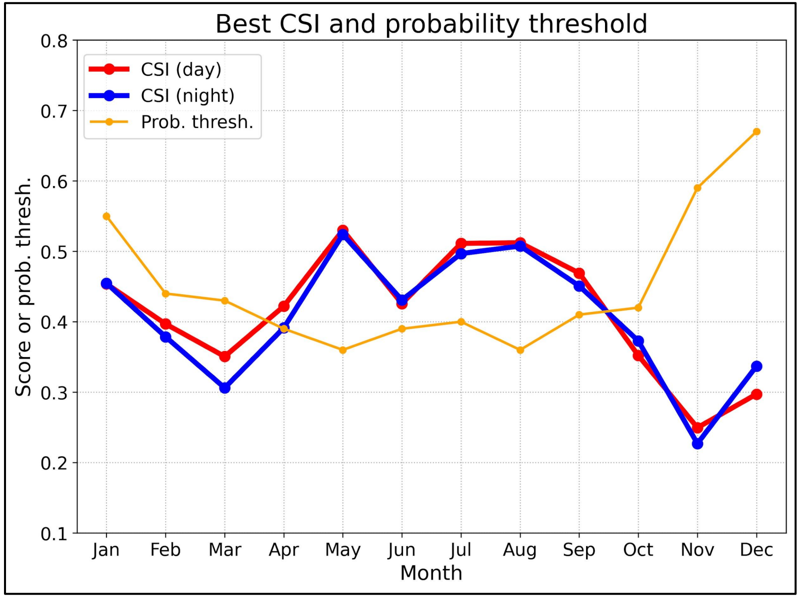




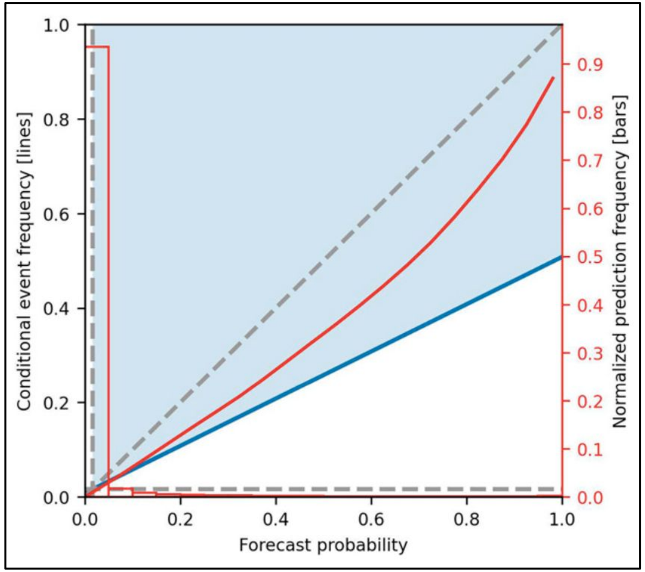
Probability of lightning in 60 min

- Objectively quantify the day-cloud-phase RGB and split-window difference.

LightningCast



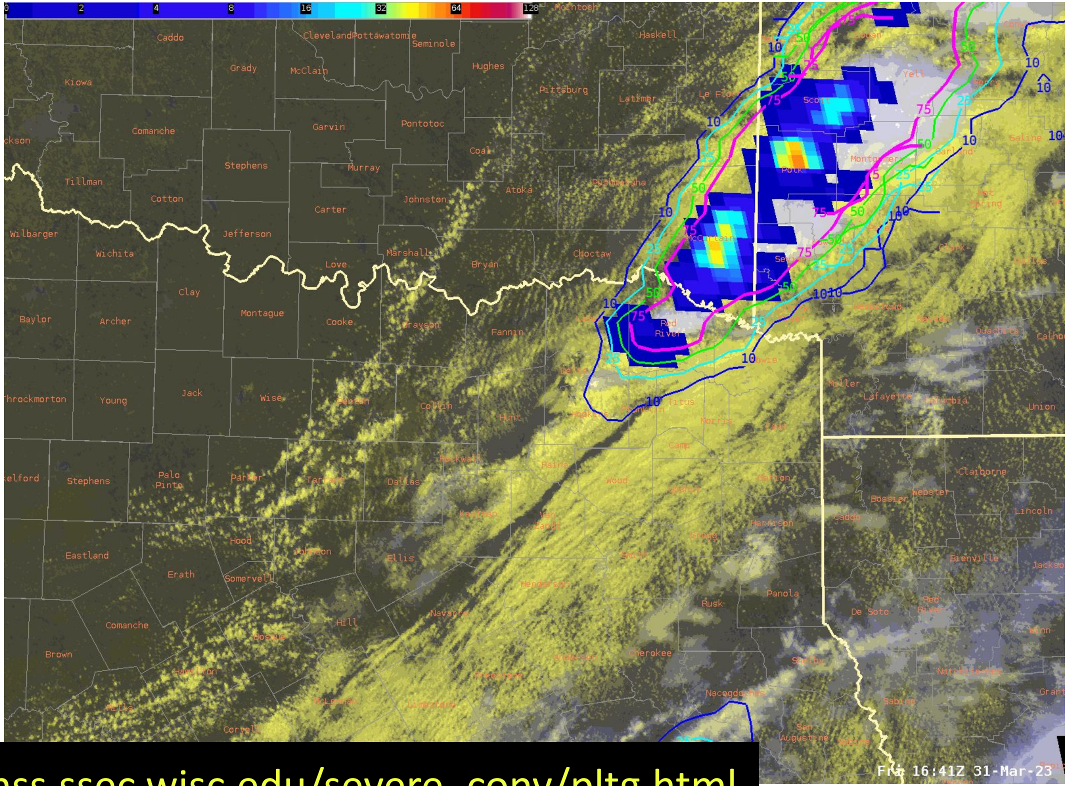
- Better performance better during the day (still predicts initiation well at night)
- Better performance April ⟶ October
  - Higher "most skillful" probability threshold November ⟶ February (50-60%)



- Some over-forecasting bias
- **Primary goal of LightningCast:** predict lightning initiation
- Lead time to *first* GLM flash
  - First quartile: **5-10 min**
  - median: **15-20 min**
  - Third quartile: **30-35 min**
  - Similar stats for 30-60% prob. thresholds

LightningCast

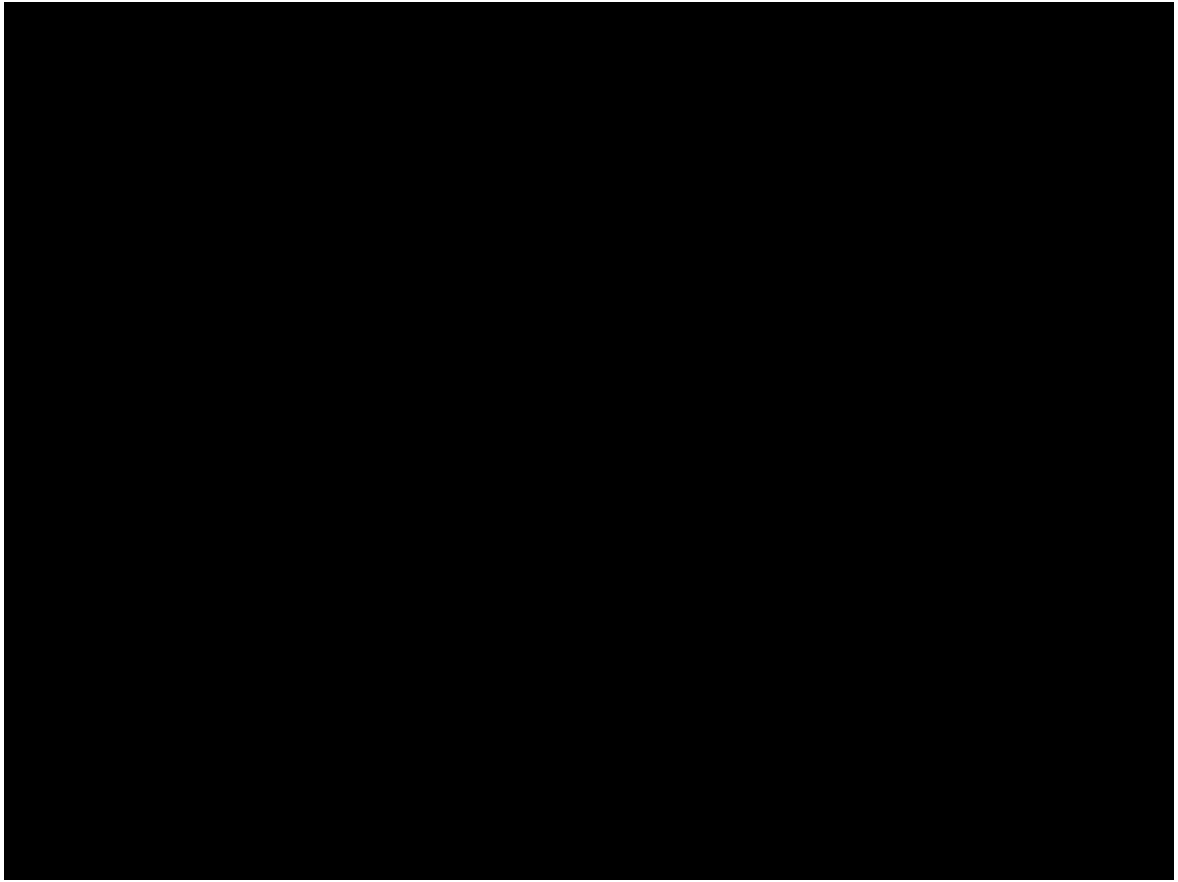
- **Available in AWIPS, GRLevelX, internet**
  - AWIPS: parallax-corrected and uncorrected
  - GRLevelX: parallax-corrected only
- **GOES-East**
  - CONUS (5 min)
  - MESO1 and MESO2 (1 min)
  - OPC/TAFB offshore zones (10 min)
- **GOES-West**
  - PACUS (5 min)
  - MESO1 and MESO2 (1 min)
  - Alaska and western Canada (10 min)
  - American Samoa (10 min)
- **Himawari AHI**
  - Guam area-of-responsibility (10 min)
- **Dashboards** (via internet)
  - TAF airports
  - D1 college football stadiums



cimss.ssec.wisc.edu/severe_conv/pltg.html

LightningCast

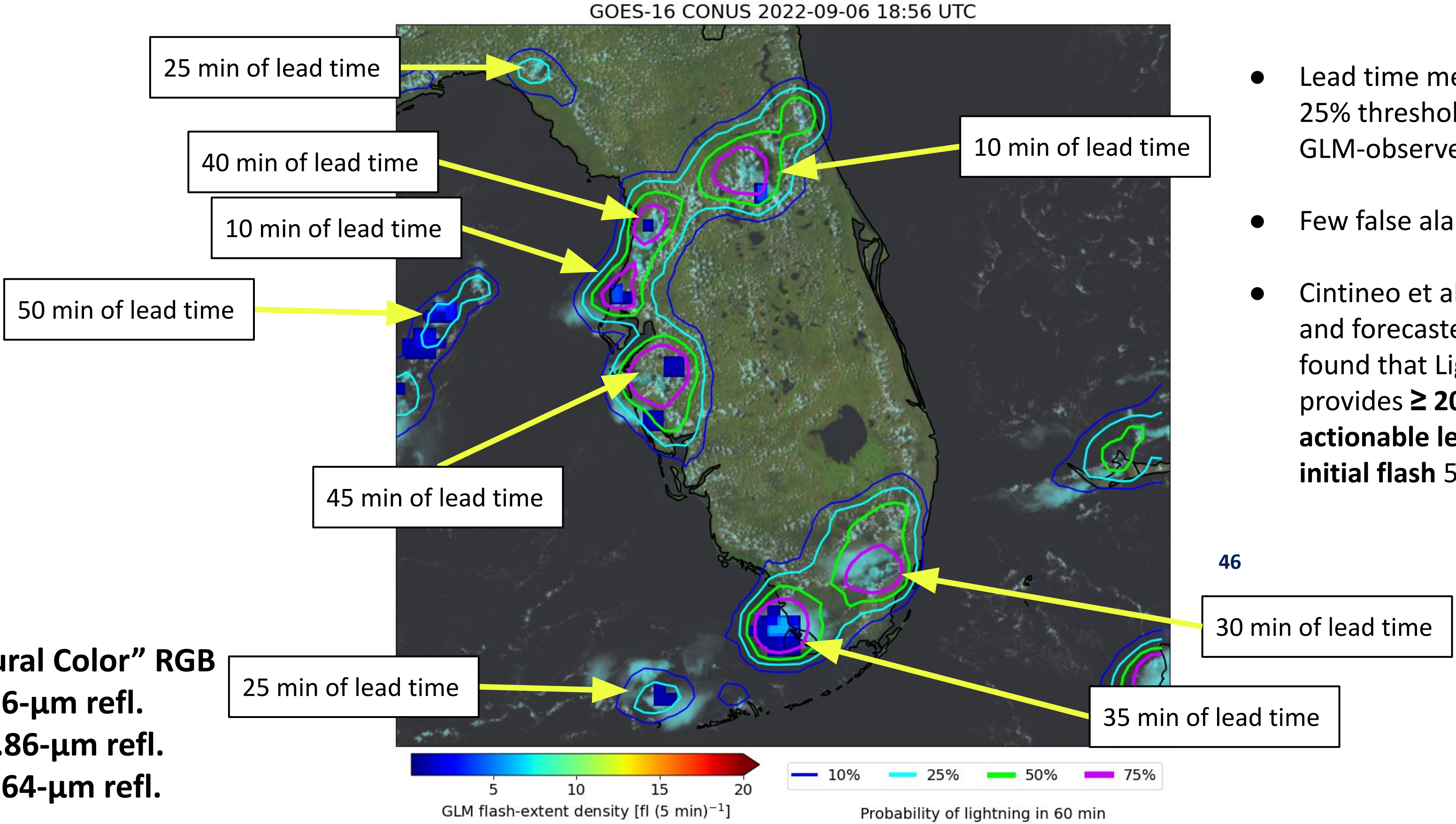
Example 1: Florida peninsula



“Natural Color” RGB
R = 1.6-µm refl.
G = 0.86-µm refl.
B = 0.64-µm refl.

LightningCast

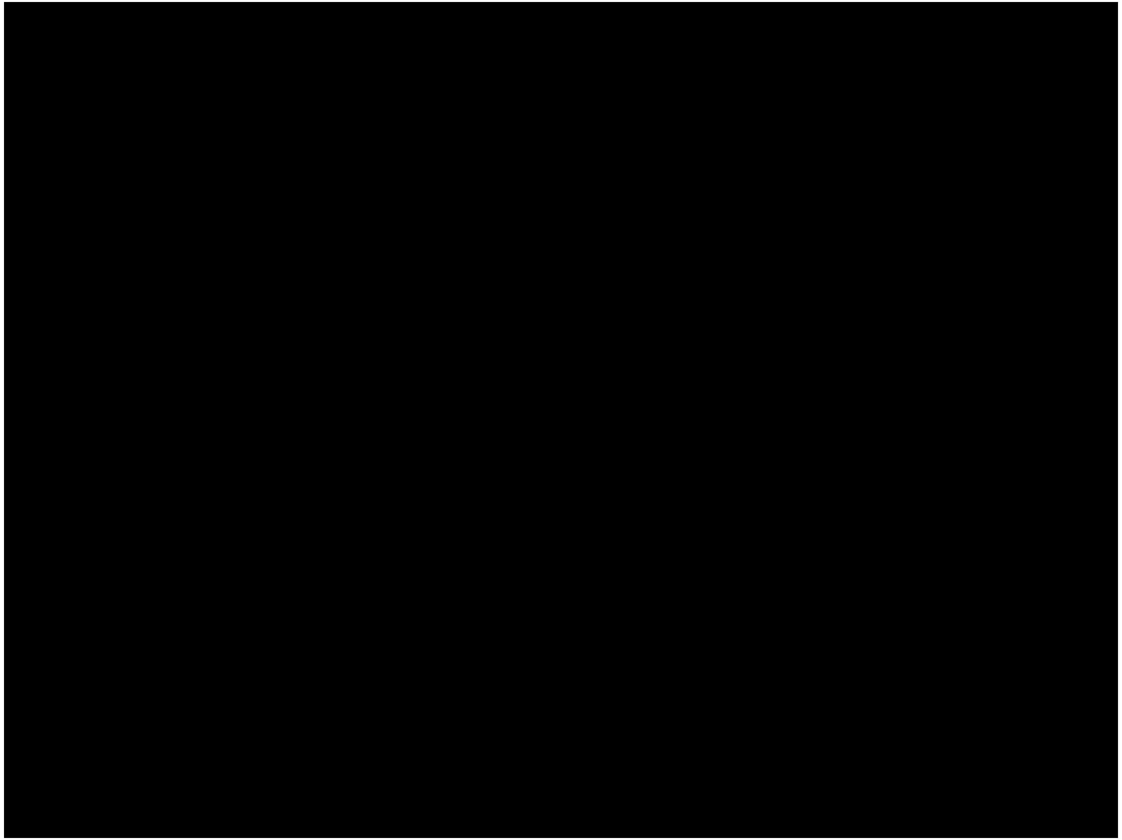
Example 1: Florida peninsula



"Natural Color" RGB
R = 1.6-µm refl.
G = 0.86-µm refl.
B = 0.64-µm refl.

- Lead time measured from 25% threshold to 1st GLM-observed flash
- Few false alarms
- Cintineo et al. (*WAF* 2022) and forecaster testbeds found that LightningCast provides **≥ 20 min of actionable lead time to initial flash** 50% of the time.

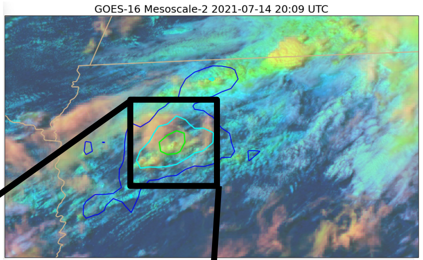
Example 2: Central U.S. (1-min updates)



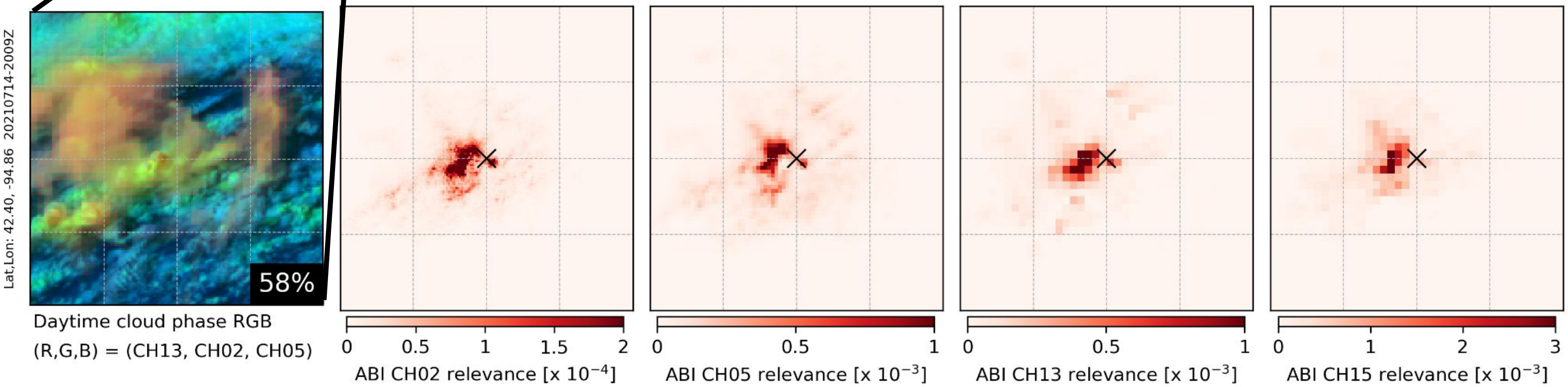
Day Cloud-Phase RGB
R = 10.3-µm BT
G = 0.64-µm refl.
B = 1.6-µm refl.

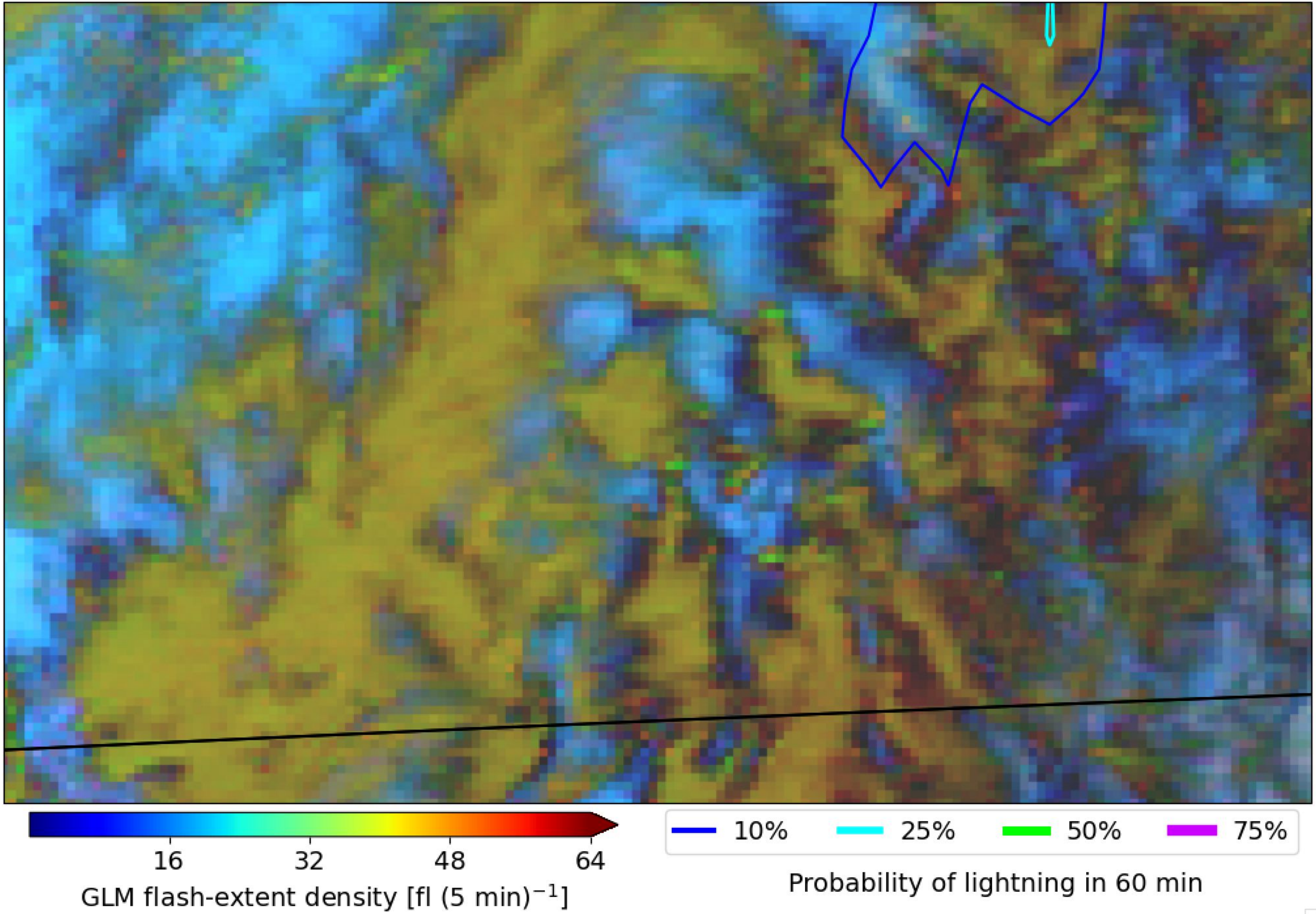
LightningCast

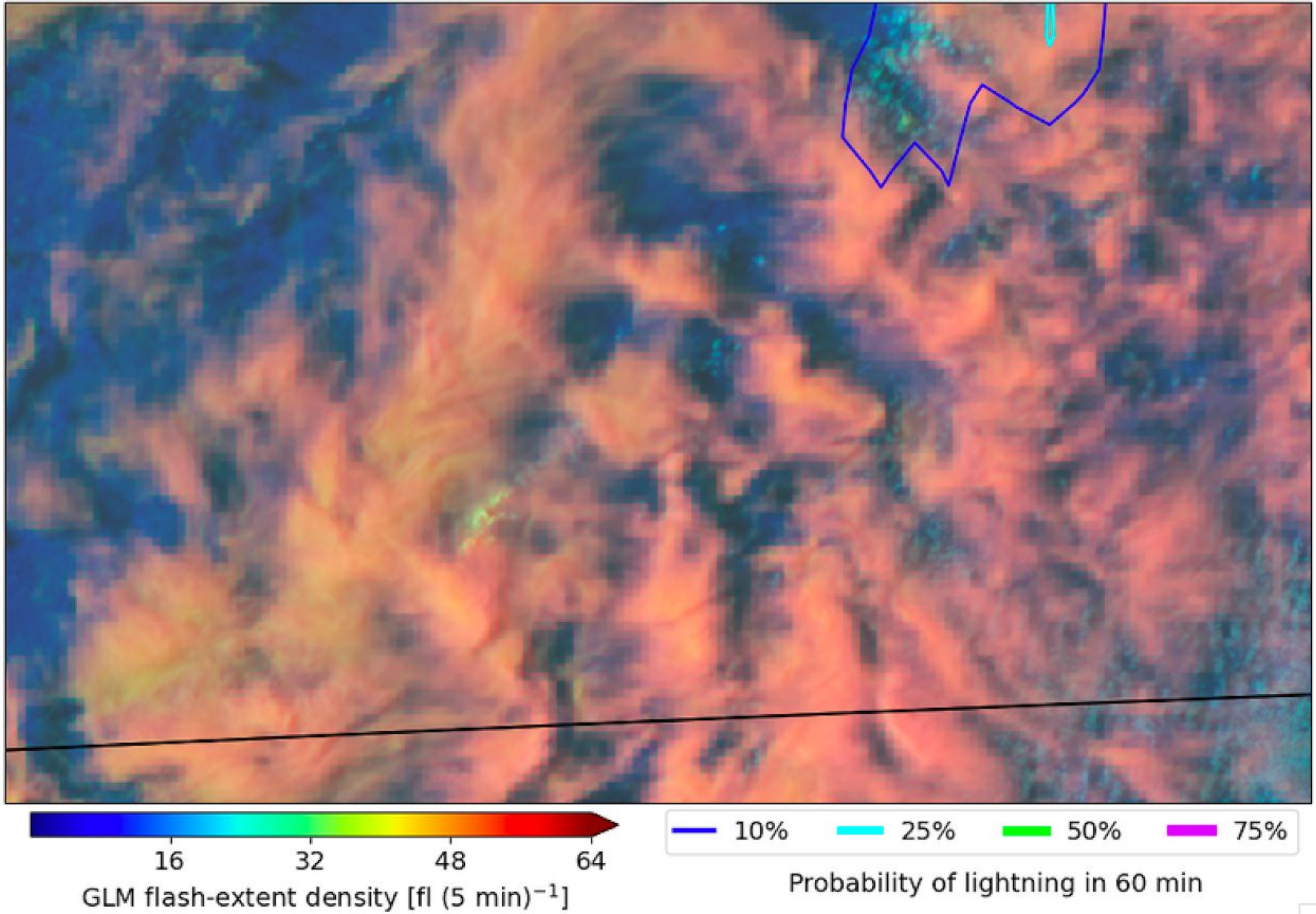
Example 2: Central U.S. (1-min updates)



- Layerwise relevance propagation (LRP)
- Outputs “relevance” of each pixel for each input channel
- Shows which pixels contribute or detract from the prediction
- Used iNNvestigate Python package: https://github.com/albermax/innvestigate
  - Used LRPZPlus rule (Alpha=1, Beta=0)




16
32
48
64
GLM flash-extent density [fl (5 min)$^{-1}$]
10%
25%
50%
75%
Probability of lightning in 60 min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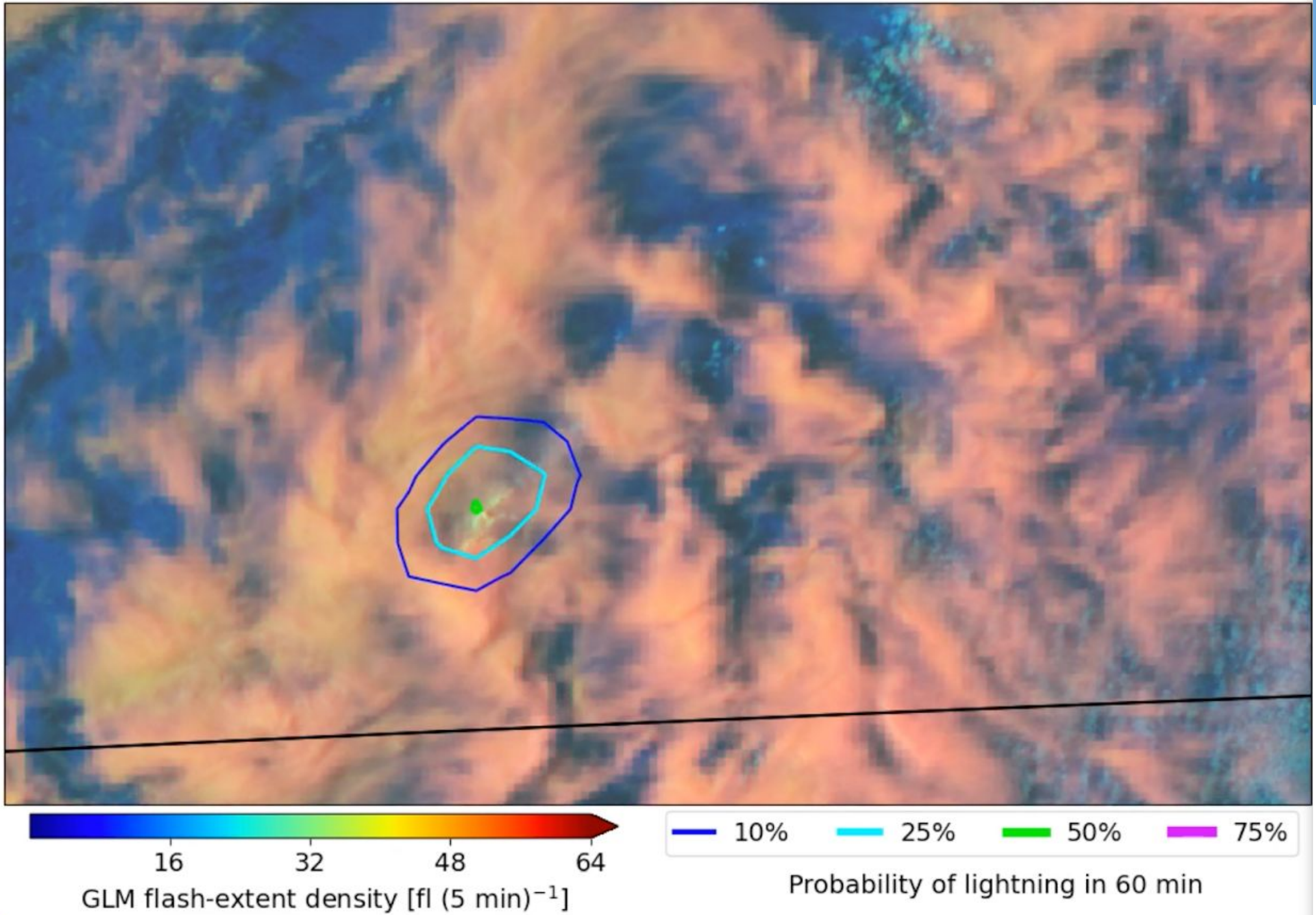
16
32
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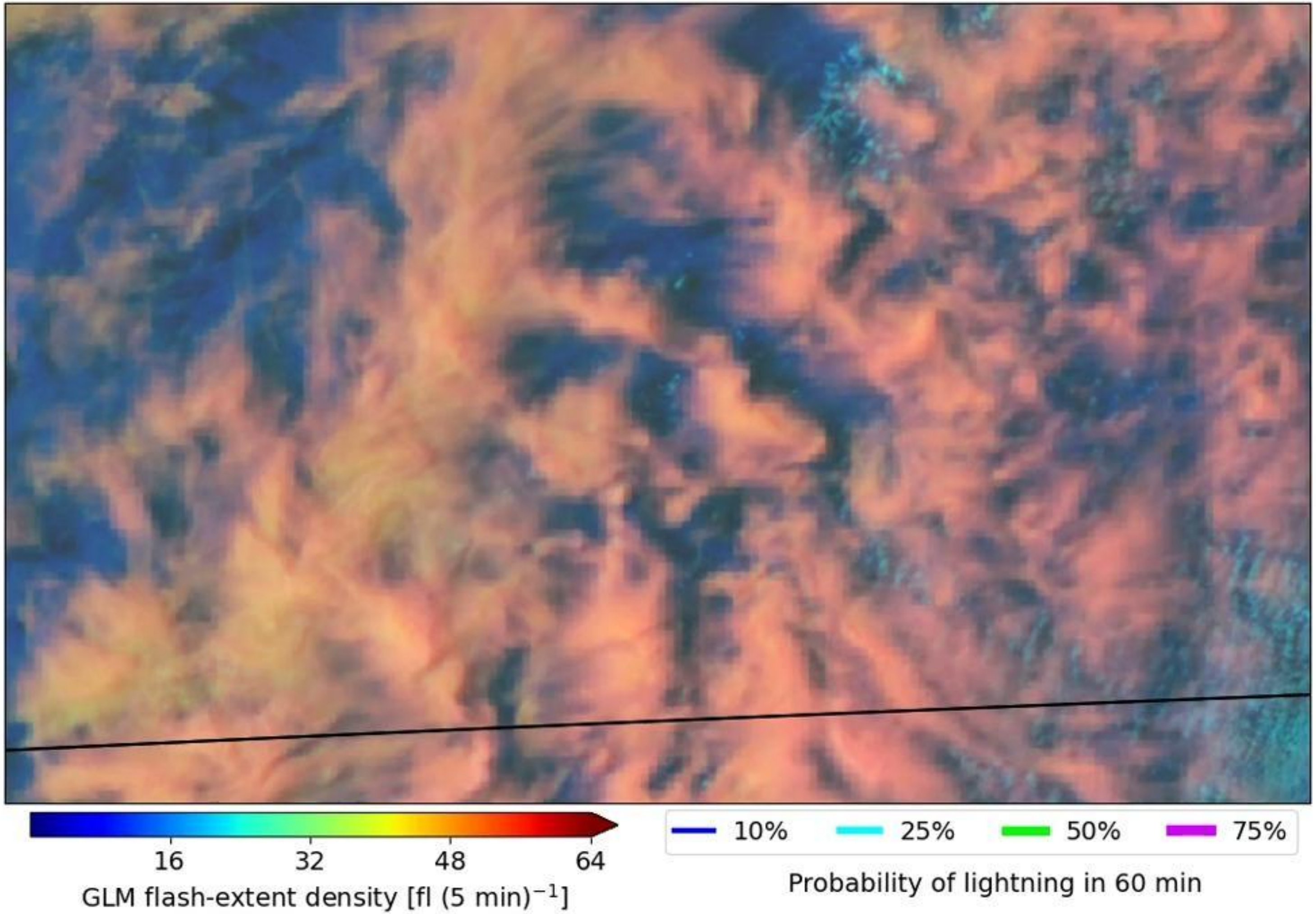
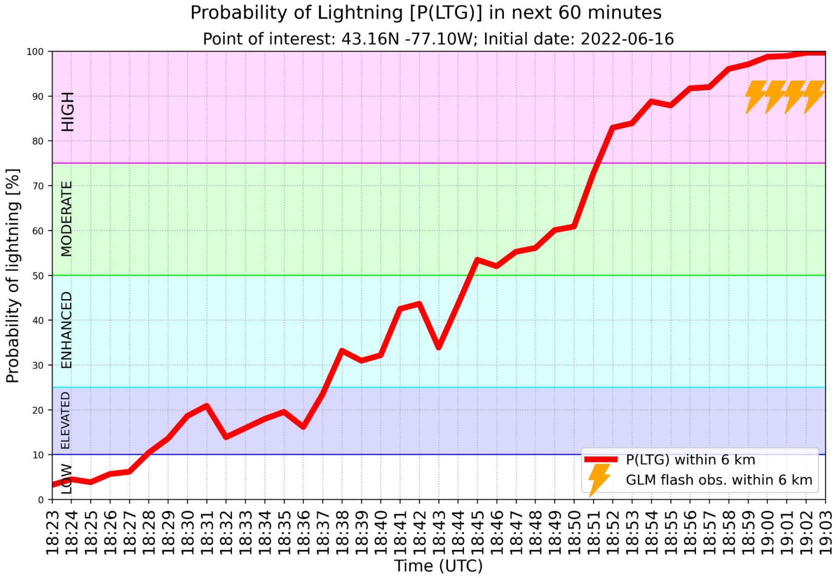
64
GLM flash-extent density [fl (5 min)$^{-1}$]
10%
25%
50%
75%
Probability of lightning in 60 min

GOES-16 Mesoscale-1 2023-04-19 21:16 UTC

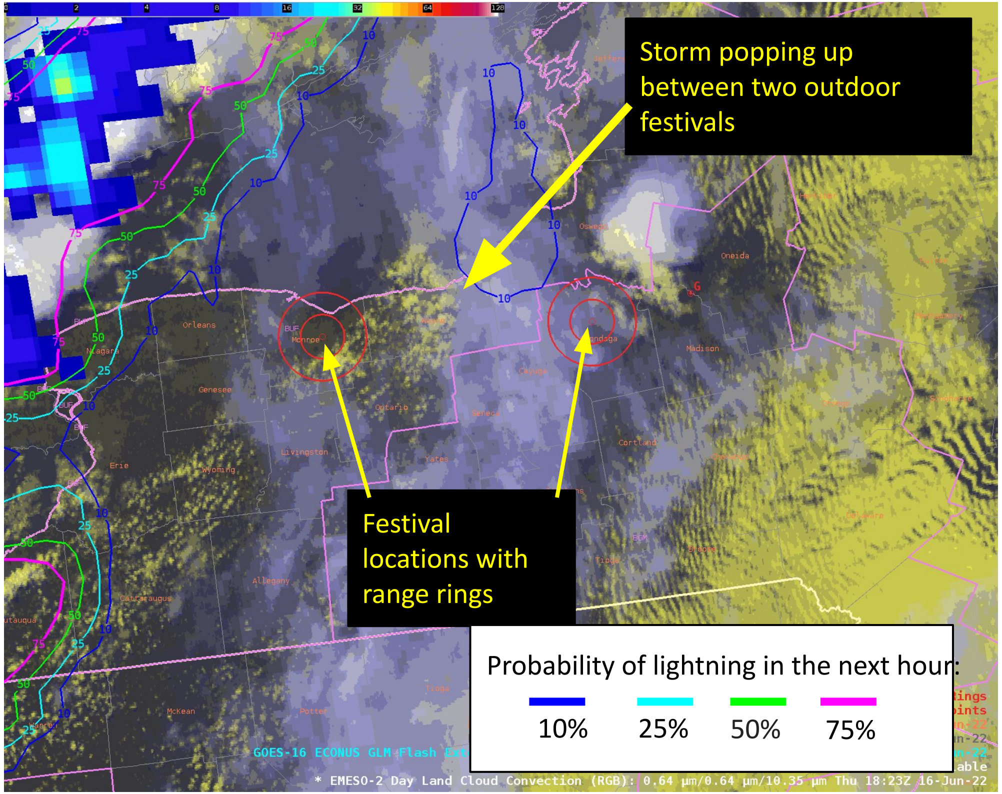


LightningCast

DSS example from 2022 HWT. Lightning initiation between outdoor festivals in Rochester and Syracuse, NY.

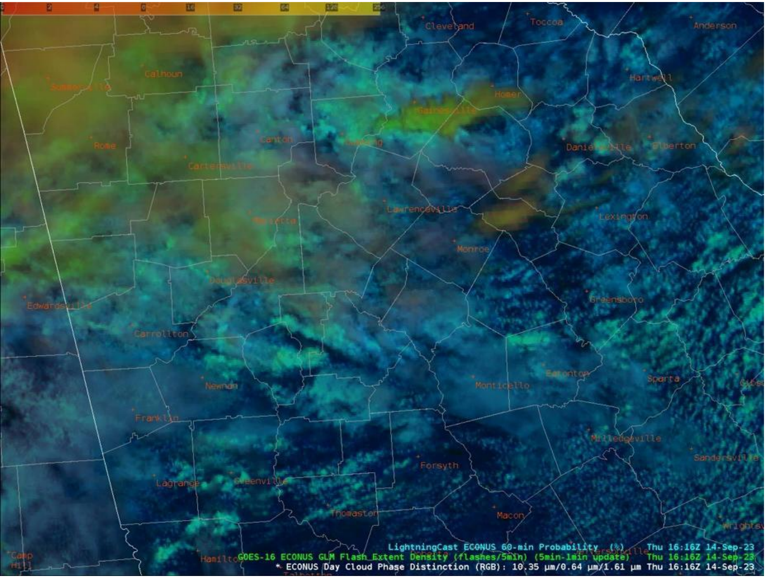


Satellite scan update frequency: 1 minute



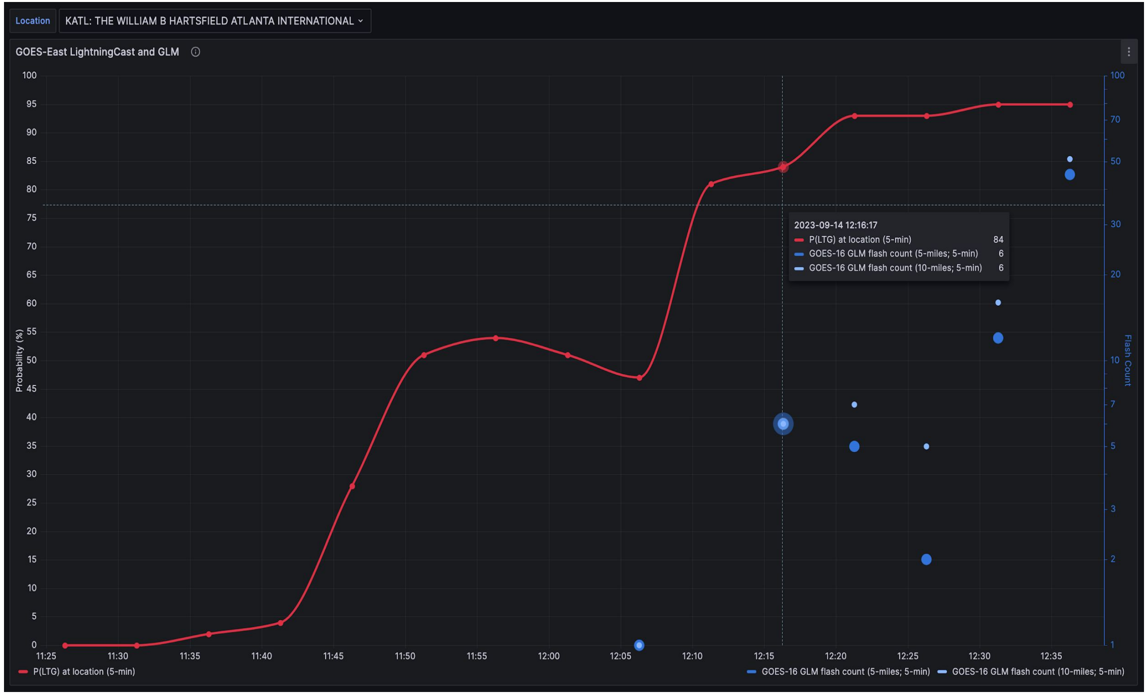
LightningCast

Satellite scan update frequency: 5 minutes

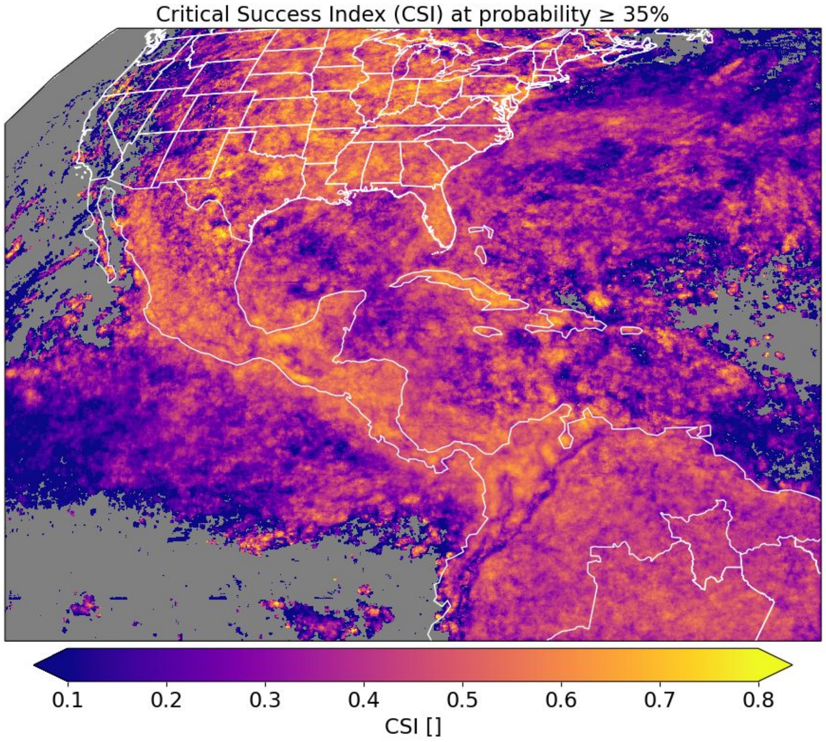


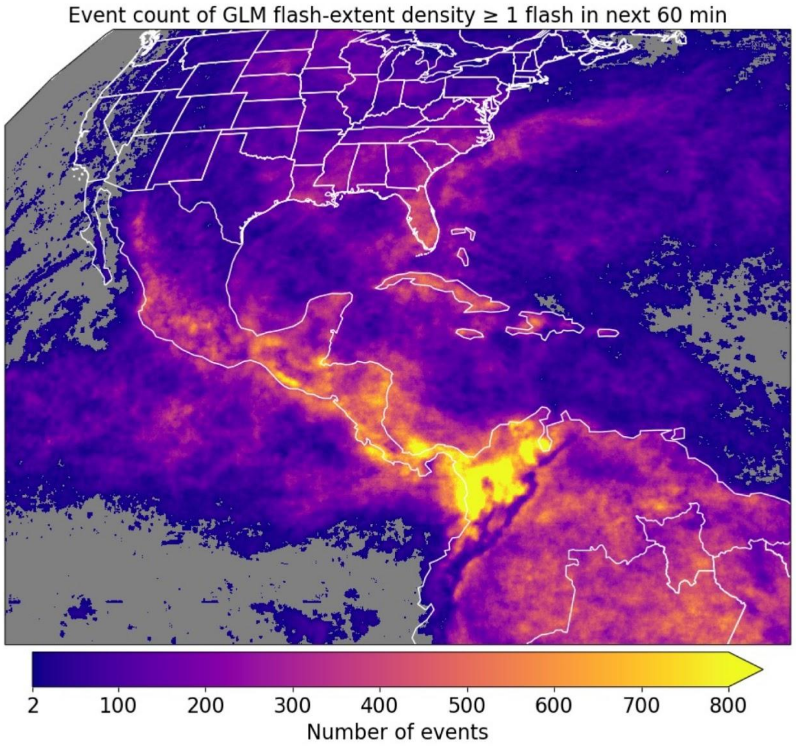
Probability of lightning in the next hour:

10% 25% 50% 75%



LightningCast



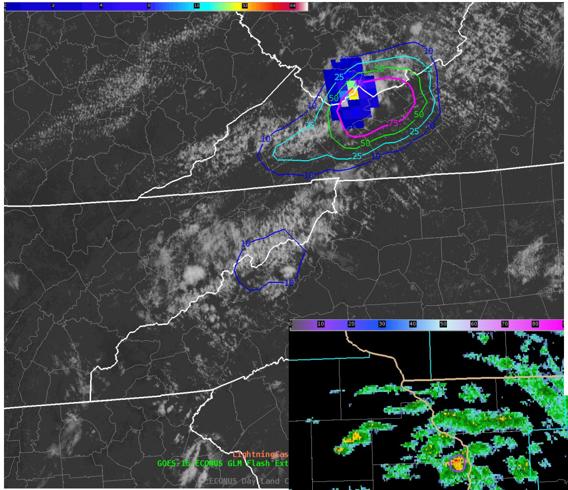


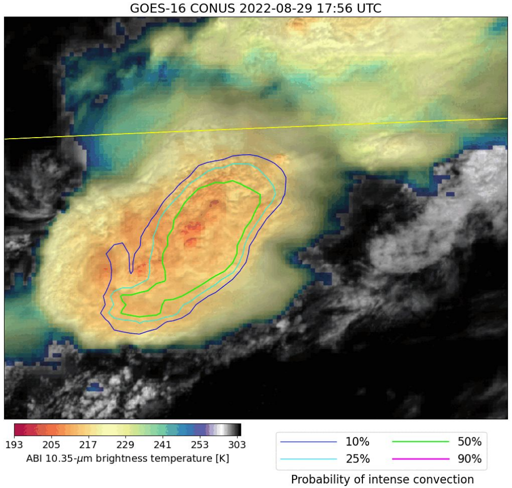
Outline

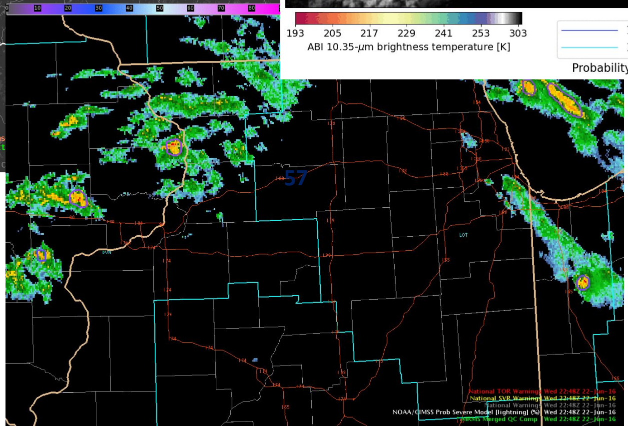
- Overview of ProbSevere
- ENSO and convection
- ProbSevere v3 models
- ProbSevere IntenseStormNet (satellite only)
- ProbSevere LightningCast (satellite only)
  - Deep-learning notebook introduction
- **Summary**

Summary

- **ProbSevere v3** (gradient-boosted decision trees)
  - Uses multi-sensor storm tracking
  - Fuses radar, satellite, lightning, NWP data
  - Guidance used throughout U.S. NWS
- **IntenseStormNet** (convolutional neural network)
  - Stand-alone satellite-only convective nowcasting tool
  - Used within PSv3
  - Exploring utility for “convection reanalysis”
- **LightningCast** (convolutional neural network)
  - Satellite-only lightning prediction
  - Excels at lightning-initiation forecasts
  - GLM serves as the truth/target data



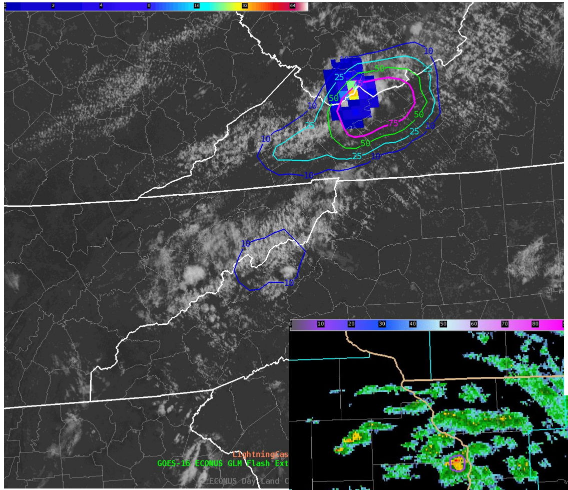


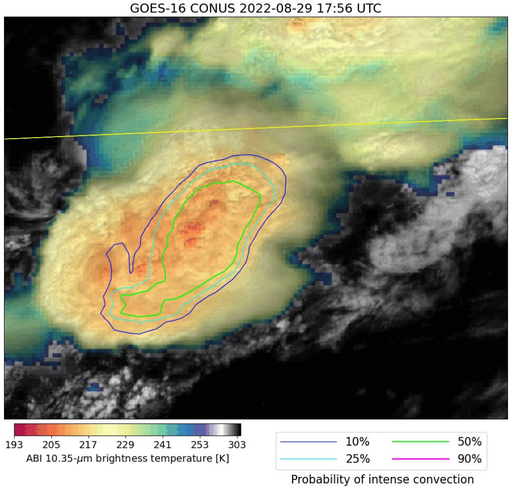


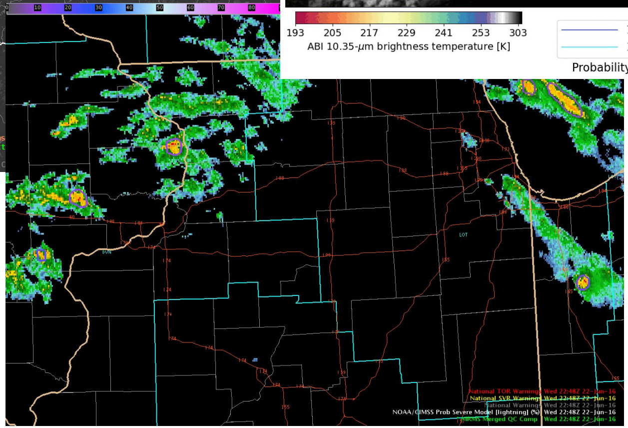
Summary

- When building machine-learning models, there are a few important steps:

1. Identify a problem
2. Choose your predictor data and truth data
   a. Knowledge and expertise about the data and problem are essential here
3. Choose your ML model
   a. Based on the problem and data
   b. Good rule of thumb is start with a simple model and increase complexity if needed
4. Collect and process the data
   a. Generally performed with computer programming
   b. Fix or exclude bad data
5. Train your model
   a. Several easy-to-use APIs
6. Evaluate your model on new data
7. Visualize your model output to users
   a. **This is a very important component that often gets overlooked or neglected!**
8. Collect user feedback and make changes if necessary







Summary

Plan:

- **Break**
- Notebook for deep-learning for lightning prediction (20-30 minutes)
    - Link will be in the chat
- **Break**
- Notebook on ProbSevere model predictor importance (60-75 minutes)
    - Link will be in the chat