Third ITU/WMO/UNEP Workshop on Artificial Intelligence
for Natural Disaster Management
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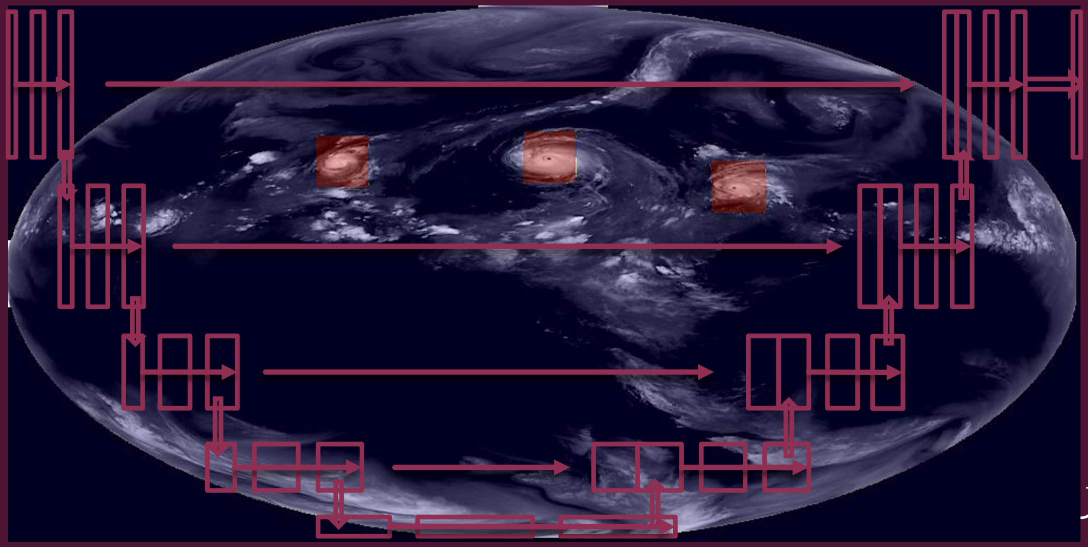
USING DEEP LEARNING TO IDENTIFY CYCLONES IN SATELLITE AND WEATHER MODEL DATA

CHRISTINA KUMLER[1], JEBB Q. STEWART[3], DAVID HALL[2], AND MARK GOVETT[3]



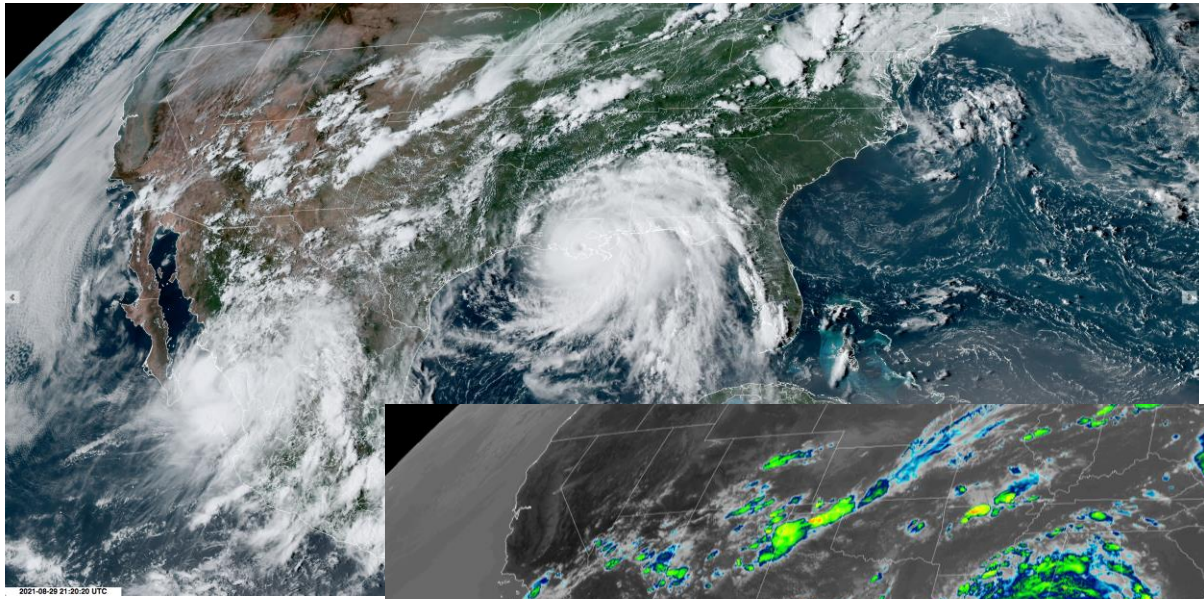
University of Colorado Boulder
[2]NVIDIA
[3]NOAA/OAR/ESRL/Global Systems Division

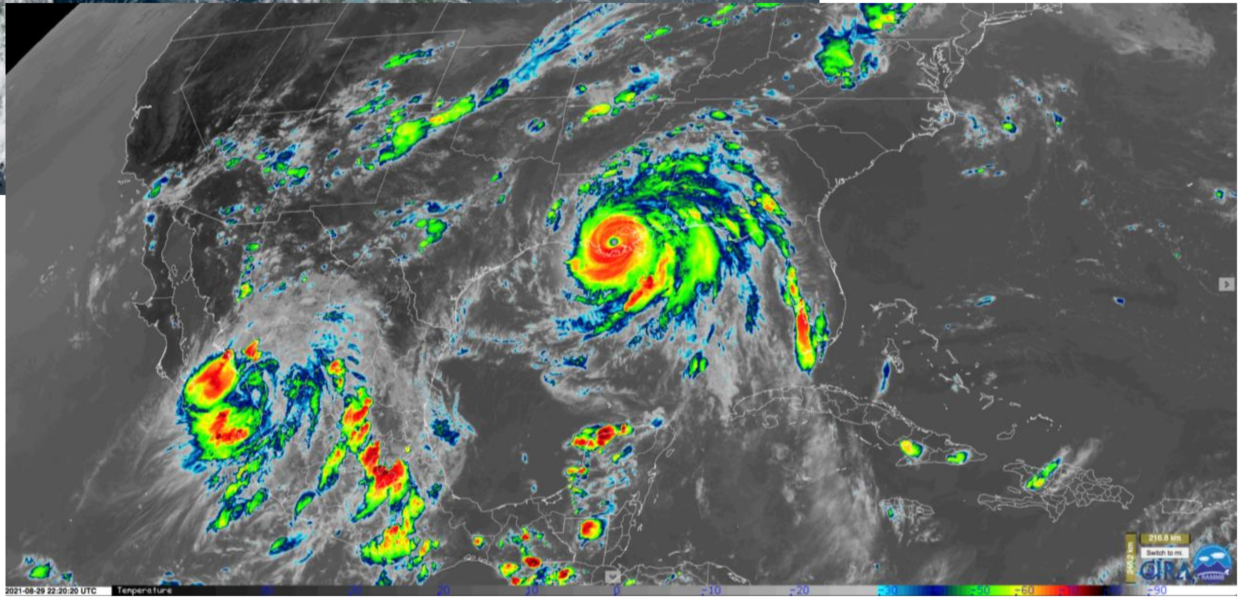
SOME MACHINE LEARNING PROJECTS AT NOAA'S GSL:

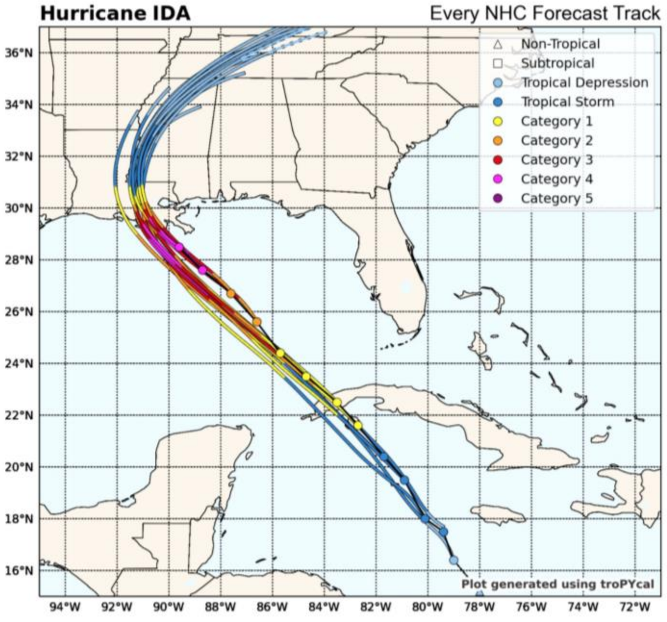
- Cyclone Detection
  - https://journals.ametsoc.org/view/journals/apme/59/12/jamc-d-20-0117.1.xml
- Parameterization
  - Estimate shortwave radiative transfer in the Rapid Refresh (RAP) model using scalars *(e.g.*, albedo, solar zenith angle, latitude, longitude) and vertical profiles (*e.g.*, temperature, humidity, liquid- and ice-water content, liquid- and ice-water path)
  - Target variables include surface downwelling flux, top-of-atmosphere upwelling flux, and the vertical profile of heating rates.
  - https://journals.ametsoc.org/view/journals/atot/aop/JTECH-D-21-0007.1/JTECH-D-21-0007.1.xml
- Convection Detection
  - U-NET to identify convection in satellite data similar to cyclone project
  - Publication to come
- Fire Radiative Power Modeling
  - Random Forest models with meteorology and satellite inputs
- More in the works…

CIRES Christina.E.Kumler@noaa.gov

MOTIVATION:



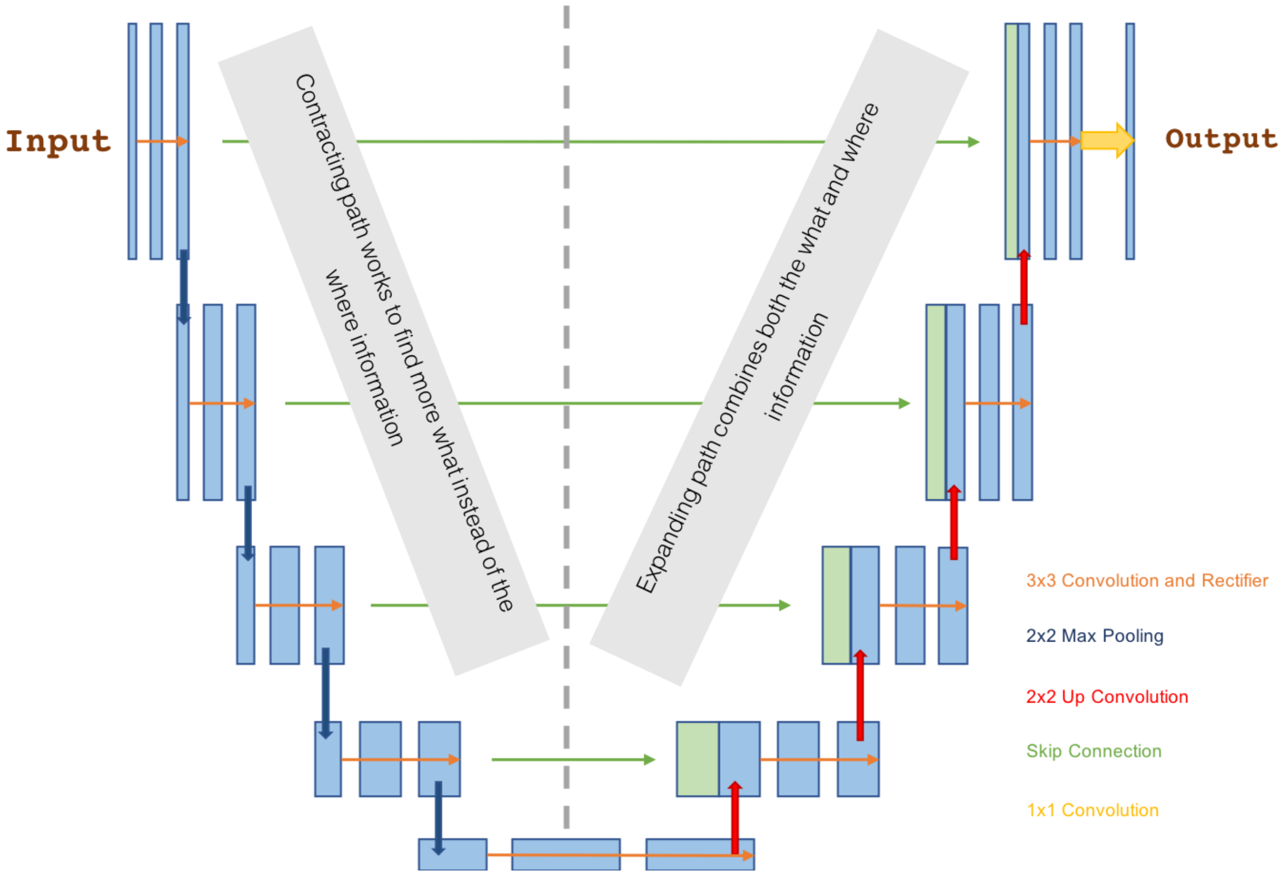




Sam Lilo, @splilo

Christina.E.Kumler@noaa.gov

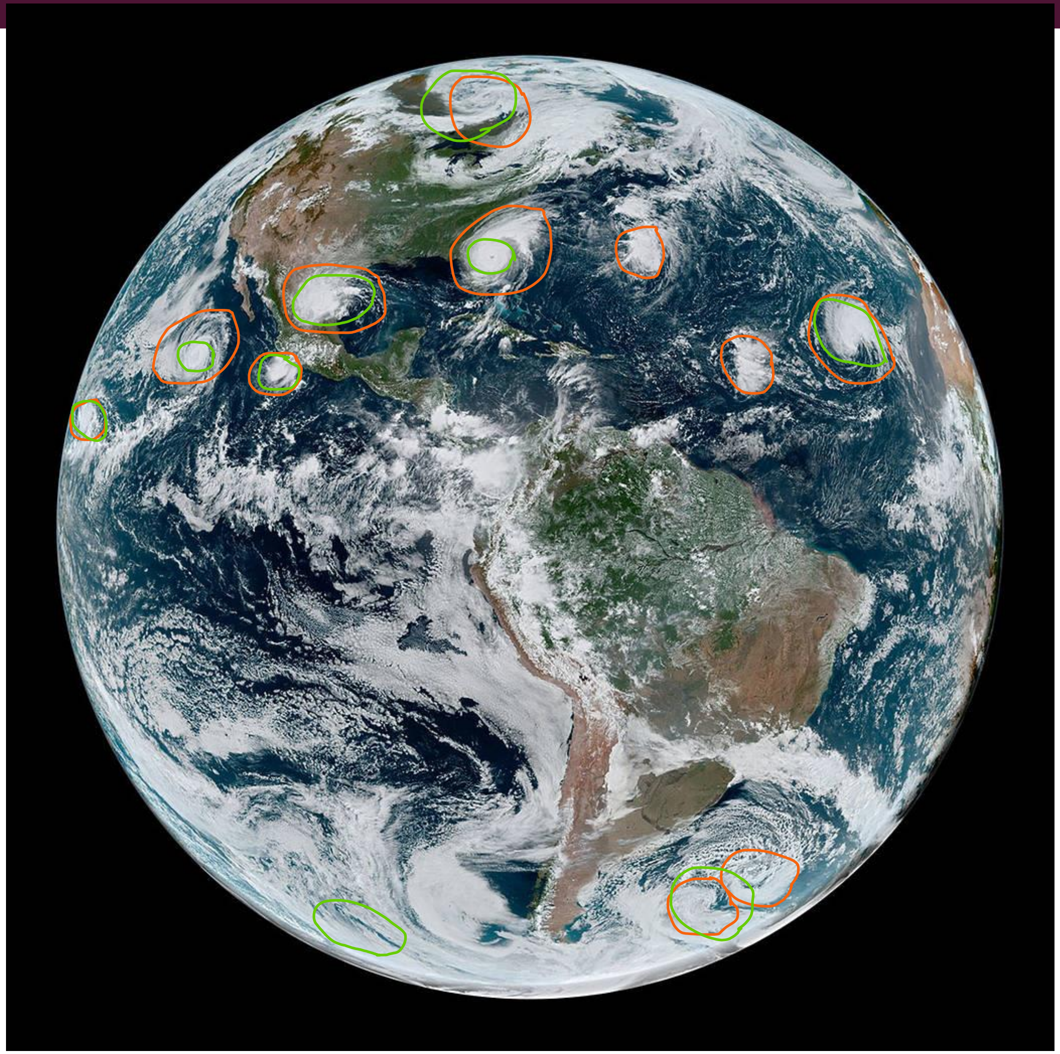
SETTING UP THE CYCLONE DETECTION PROBLEM



- The problem: Object Detection
  - Lots of data available to atmospheric scientists and if ever used, it's almost exclusively in some form of post-processing
  - Look for innovative ways to organize and utilize this data for real-time uses
- A solution: Deep Learning with the U-NET
  - ✓ Lots of data
  - ✓ Runs fast
  - ✓ Works in other fields
- The Challenges
  - ⚔ Not many labeled datasets in atmospheric science
  - ⚔ Rare events
  - ⚔ How to measure success

LABELS FOR CYCLONE DETECTION

- LABELING IS OFTEN AN ISSUE
  - Hand identification takes a long a time and is inconsistent
  - Depends on our own set of rules and we make "human errors"
  - Heuristic, or rule-based, models risk missing events that break rules occasionally
  - …And we all know that weather has and can break the rules
  - IBTrACS
  - Kumler – Bonfanti's Heuristic Labels
    - https://ieeexplore.ieee.org/document/8455276



CIRES
Christina.E.Kumler@noaa.gov

SETTING UP THE CYCLONE DETECTION PROBLEM

- Four models built that identify many cyclone ROI
  - IBTrACS on GFS analysis total precipitable water
  - Kumler-Bonfanti heuristic on GFS analysis total precipitable water
  - IBTrACS on GOES water vapor
  - Kumler-Bonfanti heuristic on GOES water vapor
- IBTrACS models
  - Both numerically and qualitatively
  - Slightly better with GFS than GOES inputs
- Kumler-Bonfanti heuristic models are unique and new tools that detect potential cyclonic regions for immediate updates

QUANTITATIVE RESULTS FOR CYCLONE DETECTION U-NET MODELS

UNET Model Results								
Model Labels	**Model Input**	**Accuracy**	**Loss Score**	**Dice Coefficient**	**Tversky Coefficient**	**Optimizer**	**Dropout or Noise**	**Batch Normalization**
IBTrACS	GFS	0.991	0.237	0.763	0.750	rms 0.00008	noise 0.2	yes
Heuristic	GFS	0.807	0.351	0.58	0.649	rms 0.00001	dropout 0.1	yes
IBTrACS	GOES	0.996	0.311	0.689	0.680	rms 0.0001	noise 0.1	yes
Heuristic	GOES	0.901	0.442	0.511	0.558	rms 0.00001	dropout 0.1	yes

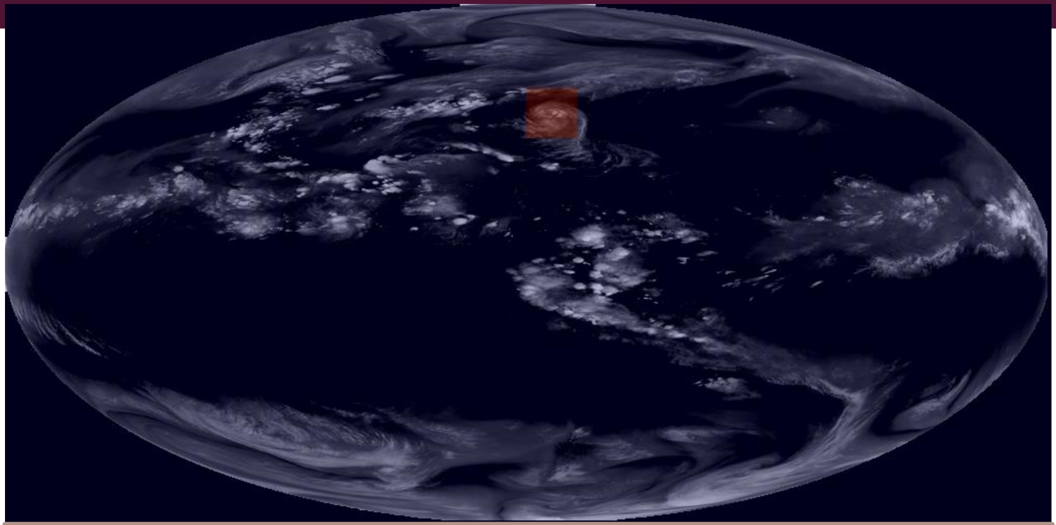
We looked at the *Tversky coefficient* to measure how well our model performed against our truth because this compares "likeness" as opposed to accuracy's binary comparison. We set $\alpha = 0.3$ and $\beta = 0.7$:

$$\frac{|\mathbf{X} \cap \mathbf{Y}|}{|\mathbf{X} \cap \mathbf{Y}| + \boldsymbol{\alpha}|\mathbf{X} - \mathbf{Y}| + \boldsymbol{\beta}|\mathbf{Y} - \mathbf{X}|}$$

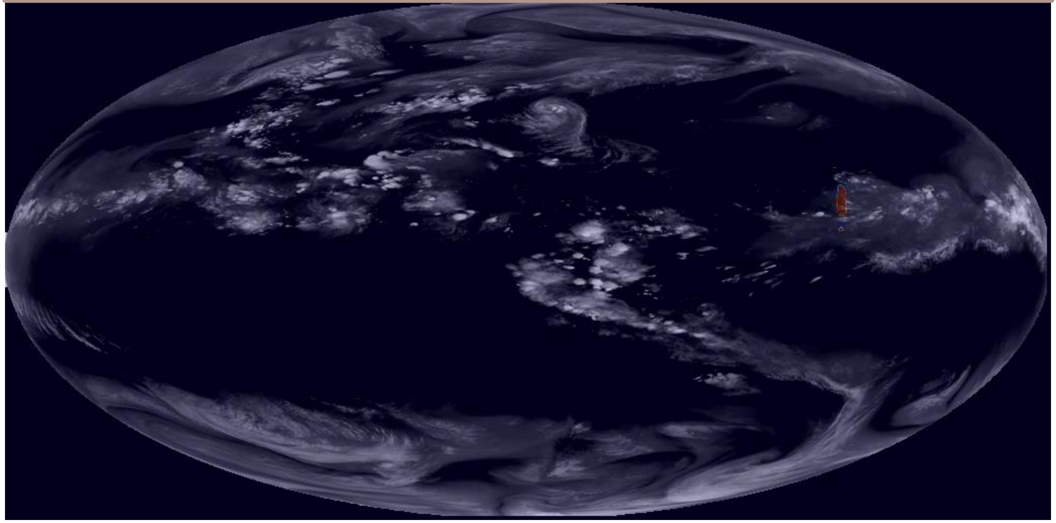
CIRES Christina.E.Kumler@noaa.gov

QUALITATIVE RESULTS FOR CYCLONE DETECTION U-NET MODELS

Truth Label:



UNET Label:



Note:

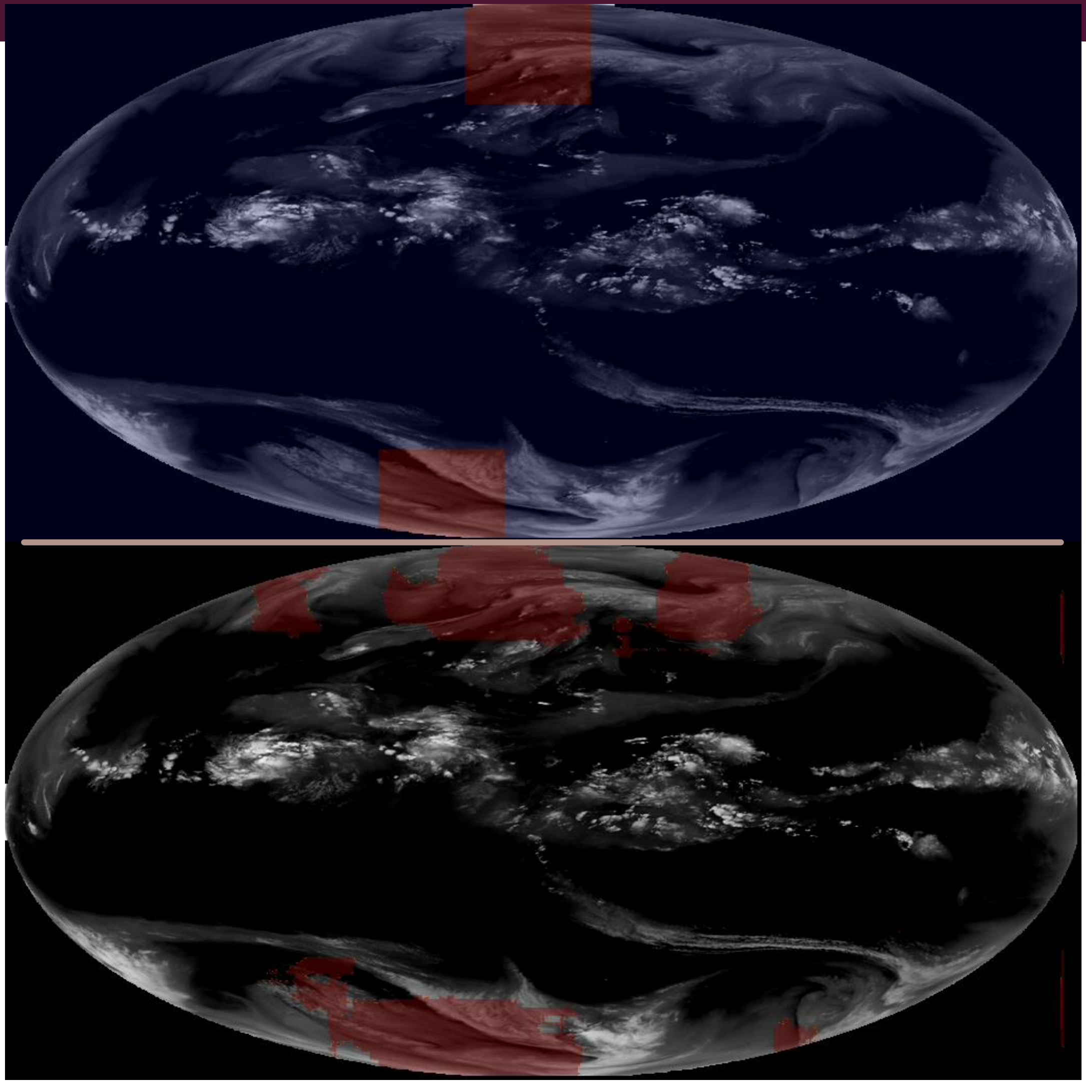
- Confidence threshold of at least 70%
- False labels in ITCZ are short-lived
- Identification of events that don’t have a truth label
    - ➢ Early detection
    - ➢ Catching diverse storms

Christina.E.Kumler@noaa.gov

QUALITATIVE RESULTS FOR CYCLONE DETECTION U-NET MODELS

Truth Label:

UNET Label:



Note:

- Confidence threshold of at least 70%
- Identification of events that don’t have a truth label
    - Early detection
    - Catching diverse storms
- More storms in Southern Hemisphere

Christina.E.Kumler@noaa.gov

CONCLUSIONS, DISCUSSIONS, QUESTIONS

- How do we measure success:
  - I argue it depends on the application of the problem
    - What problem is this machine learning method trying to solve
    - It must be measured in relation to the labels that trained the model
    - A model will only ever be as good as the labels provided
- What can be learned from the UNET outputs
  - Understand which features were most important to determining the ROI
- Use these ROI to perform analysis on weather ensemble members in these regions
- Test if using more data in assimilation helps or hurts the ROI forecast
- Further improvements in labels and future models – **new** hybrid-labels idea for future ML
  - Expert-verified labels with UNET model outputs to provide a hybrid labeled dataset to train new ROI models

Xkcd.com

Christina.E.Kumler@noaa.gov