U.S. NAVAL RESEARCH LABORATORY

Machine Learning Models for Systematic Errors in Different Cloud Regimes

Chuyen Nguyen[**], Jason Nachamkin[*], David. Sidoti[*], Jacob Gull[***], Adam. Bienkowski[+], Matthew Fernandez[++], and Melinda. Surratt[*]

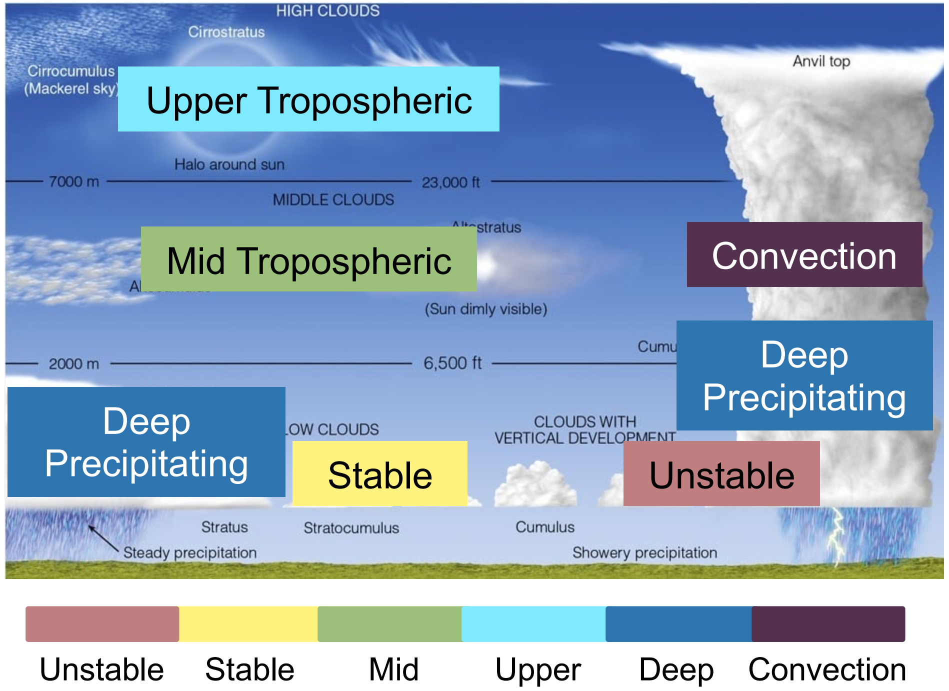
[*]Naval Research Laboratory, Monterey, CA
[**]General Dynamic Technology (GDIT)
[***]DeVine Consulting
[+]University of Connecticut
[++] SAIC

GOES data: NASA Langley Research Center (LARC)
Cooperative Institute for Research in the Atmosphere (CIRA)

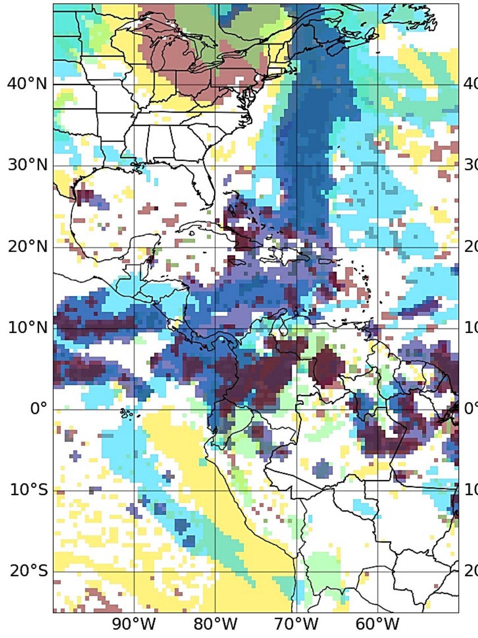
Distribution Statement A. Approved for public release. Distribution is unlimited

Motivation

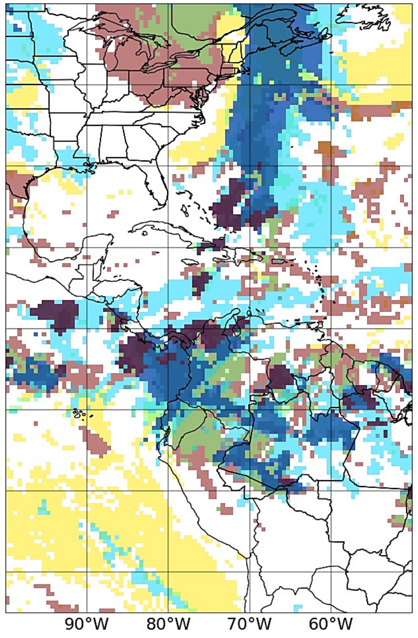
Cloud Types



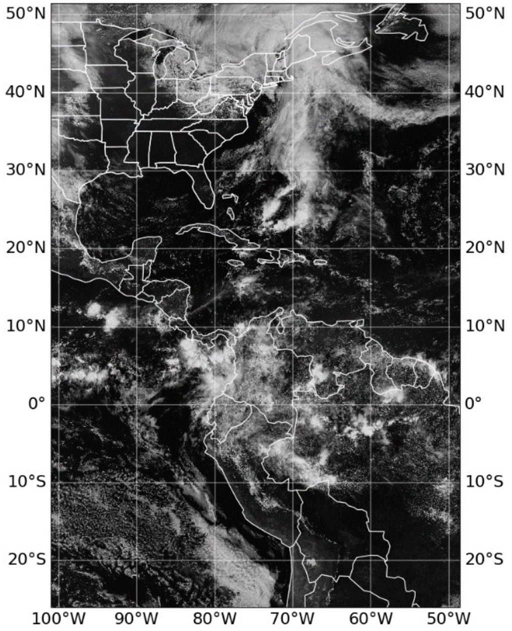
NAVGEM Cloud Type



GOES Cloud Type



GOES Reflectance



Challenge:

- Difficult to identify specific cloud types and locations

Cloud forecasts: geographical location and cloud property errors.

- **At the same atmospheric level, forcing mechanisms for different cloud types vary significantly**
- **In 3D field, different cloud types can be captured in a same pixel**

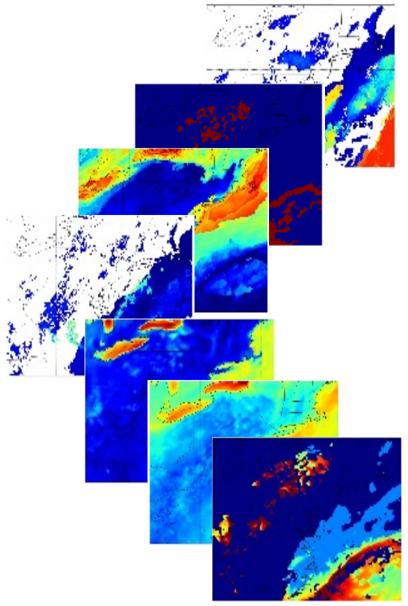
Input variables based on physics

Methodology

Feature Fusion

NWP forecast

COAMPS NAVGEM



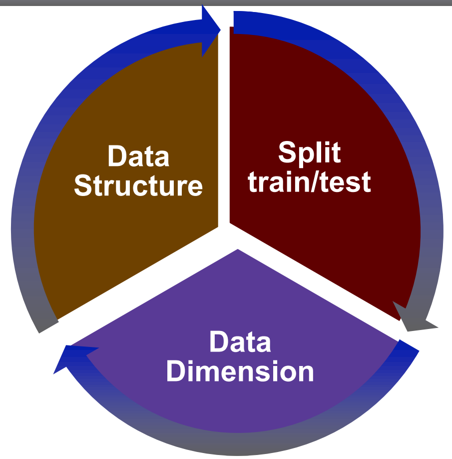
GOES

5 years of data (2018-2022)
Daily UTC 12, 15, 18, and 00

Feature Selection

- Upper tropospheric
- Mid tropospheric
- Stable
- Unstable
- Deep Precipitating
- Convection

Preprocessing



- ***Data dimension***

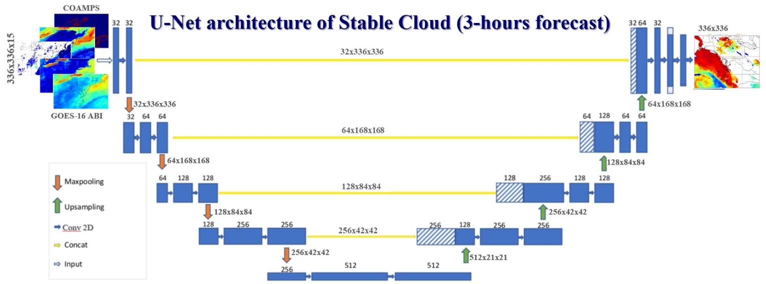
CNN: 2D images

- ***Data structure***

Samples, row, column, features

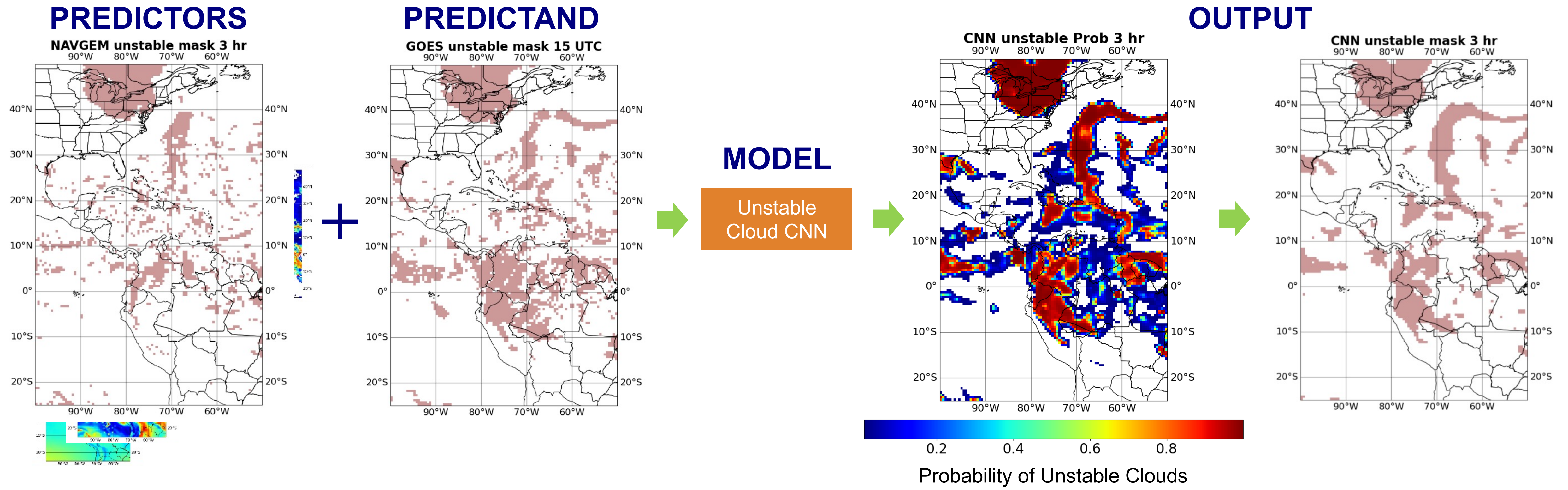
- ***Split training/testing:***
  - *2018-2020 Training*
  - *2021 Validating*
  - *2022 Independent testing*

ML Implementation



1. *Model structures*
2. *Hyper Parameter*
3. *Evaluate test results*
4. *Identify ML errors*
5. *Improve ML model*
6. *Finalize ML model*

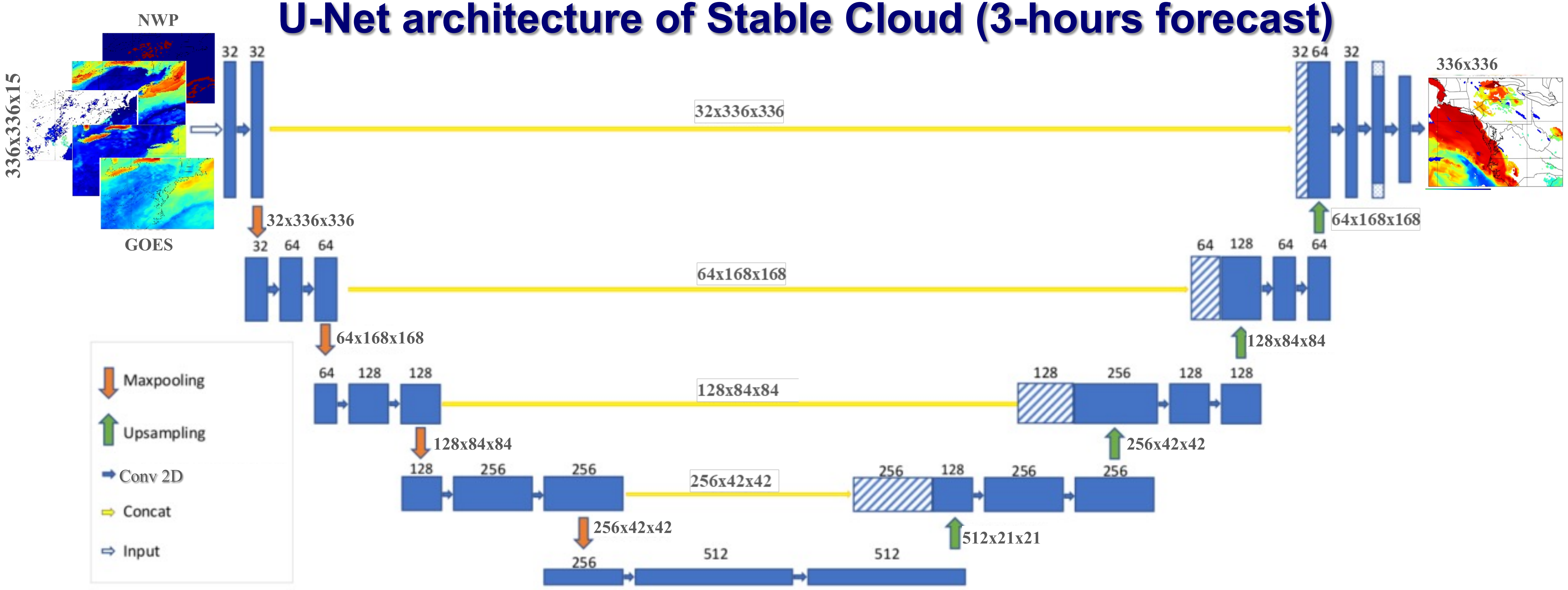
Methodology



- 3-12 hour forecasts for Stable, Unstable, Mid-Tropospheric, Upper Tropospheric, Deep Precipitating, and Convective clouds
- Separate convolutional neural network (CNN) models for each cloud type and forecast hour
- 24 machine learning models, each with its own set of predictors and predictands

Unet-CNN Architecture

U-Net architecture of Stable Cloud (3-hours forecast)

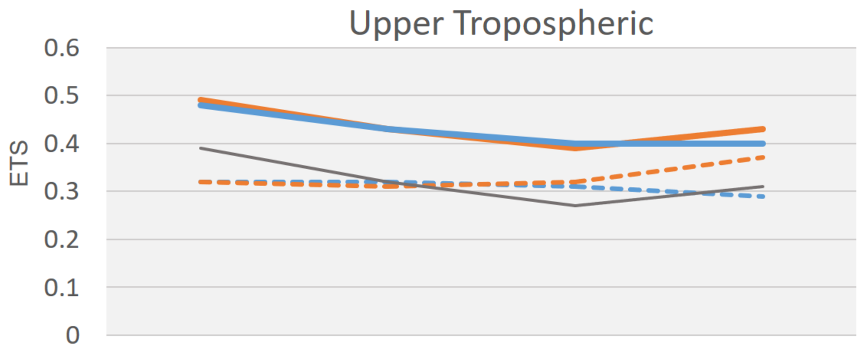


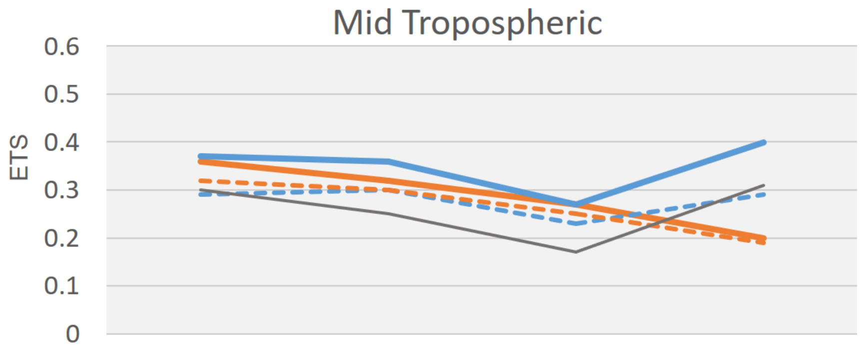
The model comprises an encoder and a decoder pathway, with skip connections between the corresponding layers.

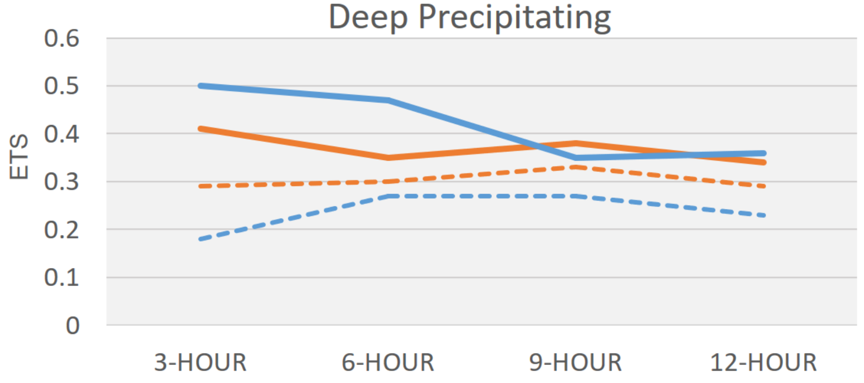
- 3 × 3 convolution kernels, followed by a max-pooling operation of 2 × 2 and stride of 2
- Loss function: binary_cross entropy
- Optimizer: Adam
- Activate function: Sigmoid

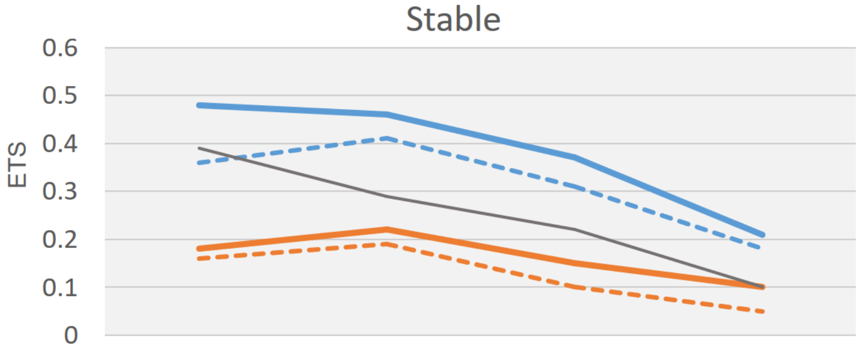
Results and Discussion

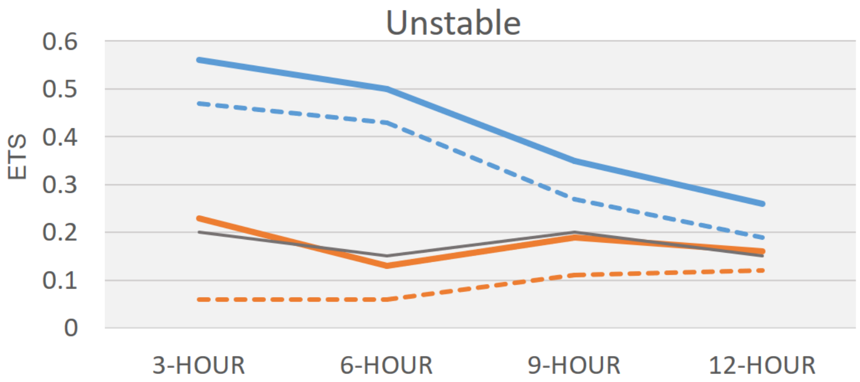
NAVGEM – COAMPS Comparison









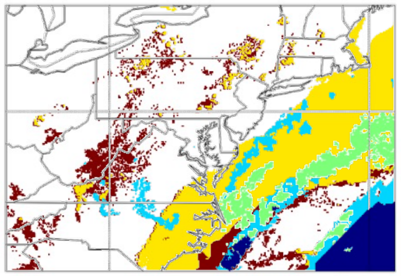


Run same machine learning infrastructure with different set of input variables and grid size.

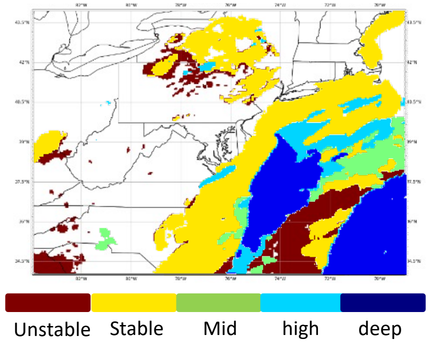
Comparing COAMPS and NAVGEM to see of potential "Transferable"

- NAV-CNN improve ETS score of all hours and cloud types
- COAMPS improve ETS score of all hours and cloud types

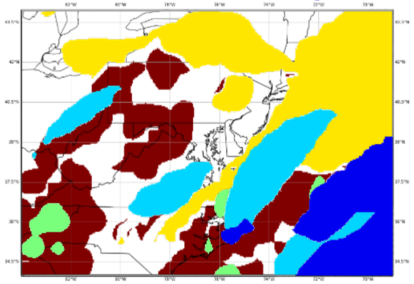
GOES Cloud Types



COAMPS Cloud Types

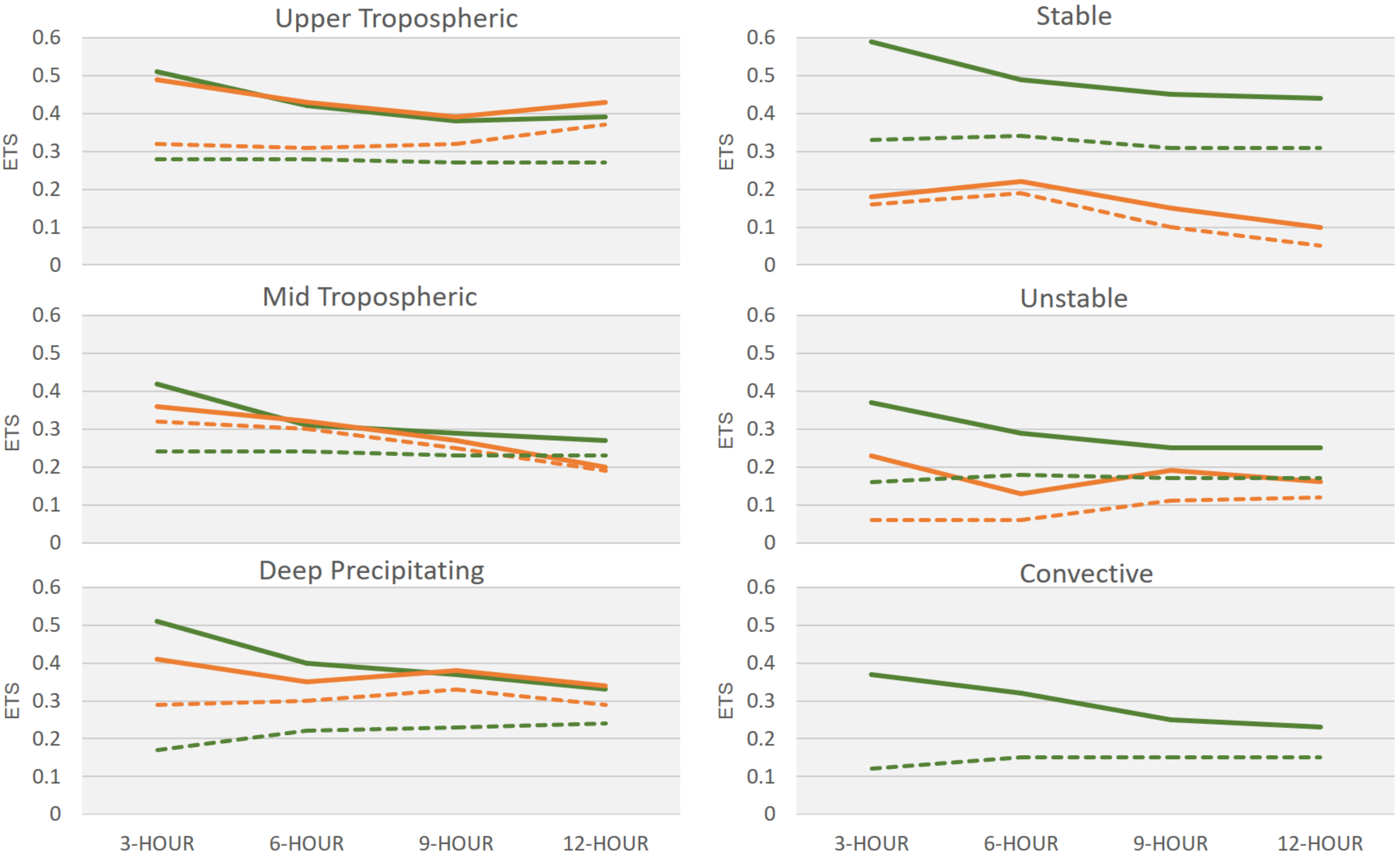


NAVGEM Cloud Types



Results and Discussion

Overall ALFS Performance



- Latest ALFS predictions on the larger grid.
- ALFS improvements are larger.
- NAVGEM stable, unstable forecasts are better.
- Coarse resolution results in smoother features that are easier to correct.

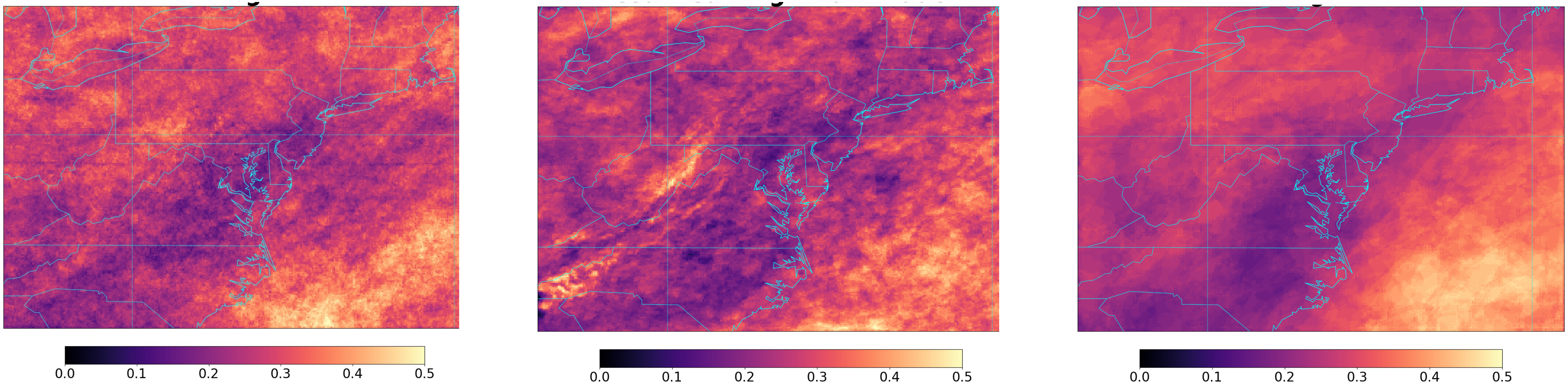
Results and Discussion

Seasonal Effects: Warm Season

Upper tropospheric: Mean Cloud Fraction

5 Apr. – 13 Oct

GOES Observations | COAMPS 6-hour forecast | Unet-CNN 6-hour forecast



Cloud Fraction

	ETS	Bias	POD	FAR
COAMPS	0.28	0.83	0.54	0.35
Unet-CNN	0.43	0.92	**0.69**	**0.25**

Aggregate Statistics NDTG = 85

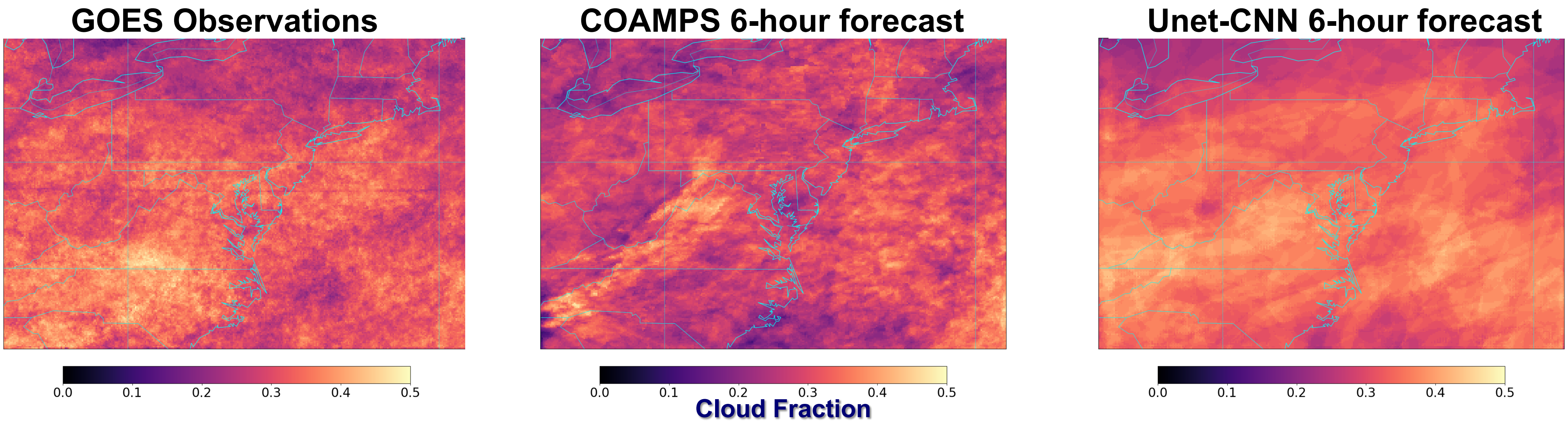
Unet-CNN improved warm season high cloud forecast significantly

Results and Discussion

Seasonal Effects: Cold Season

Upper tropospheric: Mean Cloud Fraction

14 Oct. – 14 Apr.



	ETS	Bias	POD	FAR
COAMPS	0.46	0.90	0.69	0.23
Unet-CNN	0.61	1.06	**0.85**	0.20

Aggregate Statistics NDTG = 81

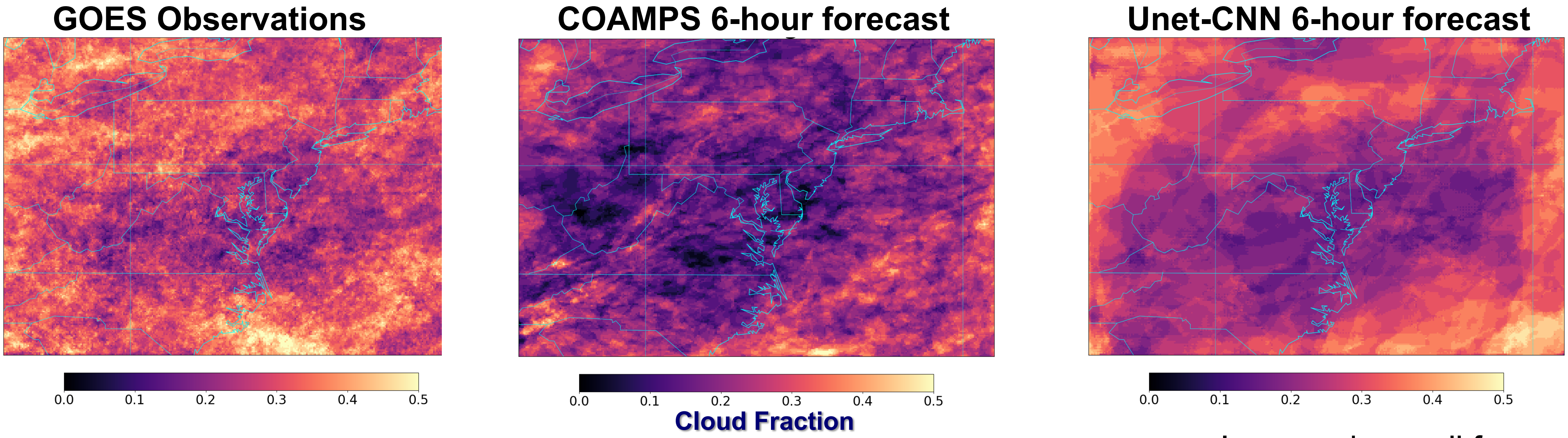
Improved overall forecast quality: ETS, bias, and correct hits
Reduced false alarm rates

U.S. NAVAL RESEARCH LABORATORY

Results and Discussion

Systematic Error: Extreme under predicted

Upper tropospheric: COAMPS (Bias ≤ 0.75)



	ETS	Bias	POD	FAR
COAMPS	0.24	**0.66**	0.44	0.33
Unet-CNN	0.37	**0.88**	0.63	0.28

Aggregate Statistics NDTG = 38

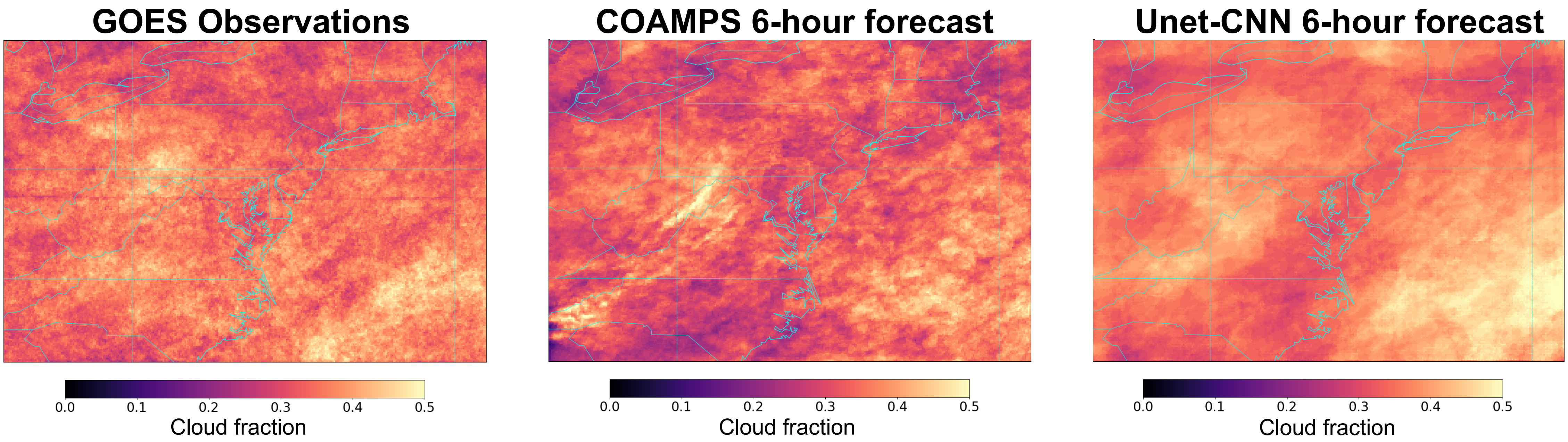
Improved overall forecast quality:

- Improve ETS, bias, and correct hits
- Reduce false alarm ratio

Results and Discussion

Systematic Error: Typical well-predicted

Upper tropospheric: COAMPS (0.75 < Bias < 1.5)



	ETS	Bias	POD	FAR
COAMPS	0.35	0.94	0.66	0.29
Unet-CNN	0.46	1.05	**0.78**	0.26

Improved overall forecast quality: ETS, bias, and correct hits

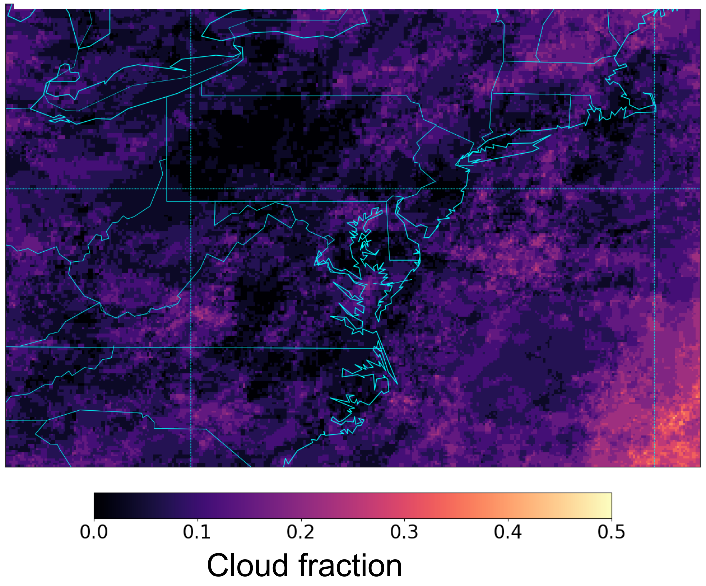
Aggregate Statistics NDTG = 101

Results and Discussion

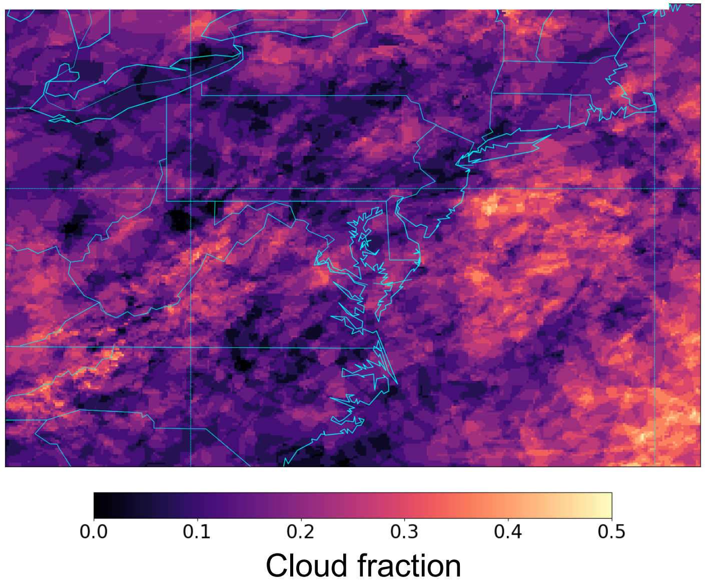
Systematic Error: Extreme over predicted

Upper tropospheric: COAMPS (Bias ≥ 1.5)

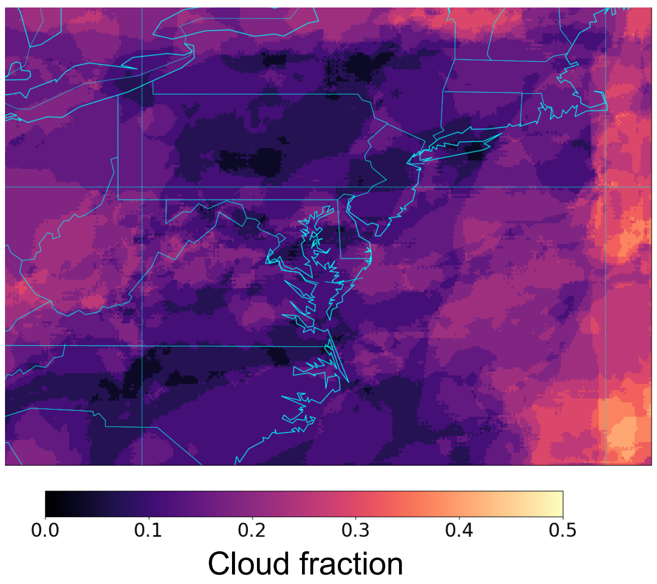
GOES Observations



COAMPS 6-hour forecast



Unet-CNN 6-hour forecast



	ETS	Bias	POD	FAR
COAMPS	0.19	2.02	0.60	0.70
Unet-CNN	0.24	1.89	**0.66**	0.65

Small improvement of overall forecast quality, when COAMPS data contain extreme Bias ≥ 1.5

Aggregate Statistics **NDTG = 27**

Next Steps

The initial results indicate that ML application: Unet-CNN able to capture the complexity, improve "systematic errors", and "transferable"

LSTM –Unet CNN

Incorporate: Temporal information

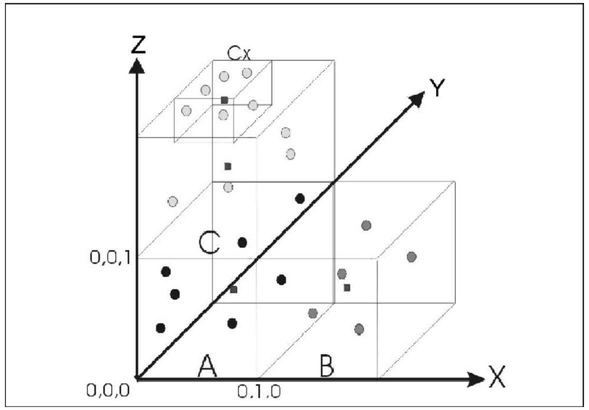
Broad-LSTM –Unet CNN Ensemble

Solving image scale problems and regional errors

Identify:
- **Cloud top base**
- **Cloud base height**

Boundary for 3D cube

3D cloud forecast ML system



U.S. NAVAL RESEARCH LABORATORY

EXTRA Slides

U.S. NAVAL RESEARCH LABORATORY

Highlights of the Approach

Low Unstable

- Unstable boundary layer (CCL, LCL)
- Weak inversion (EIS)
- Surface-based (cloud base ≤ 4 km)

Low Stable

- Stable boundary layer (CCL, LCL)
- Moderate Strong inversion(EIS)
- Surface-based (cloud base ≤ 4 km)

Mid Tropospheric

- Cloud top between 4 and 8 km
- LWP > 25 g m^2 if ice cloud (GOES)
- LWP > 350 g m^2 if top > 8 km

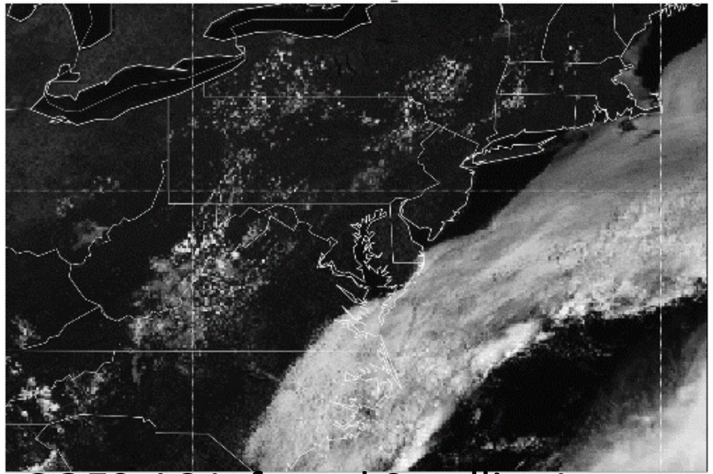
Deep Precipitating

- Cloud top ≥ 9.5 km
- Within 100 km of rainfall ≥ 3 mm/hr
- Cloud area ≤ 10 times size of rain area

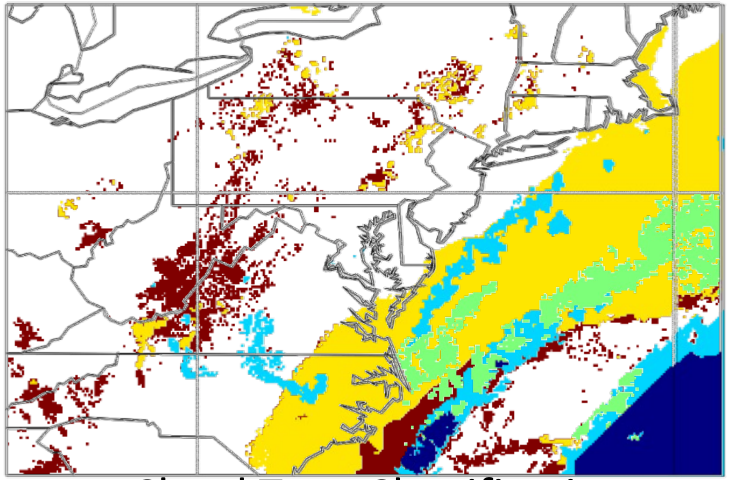
Upper Tropospheric

- Cloud top ≥ 8 km
- Thin ice clouds (GOES)

8 May 2018 1500Z



GOES-16 Infrared Satellite Image

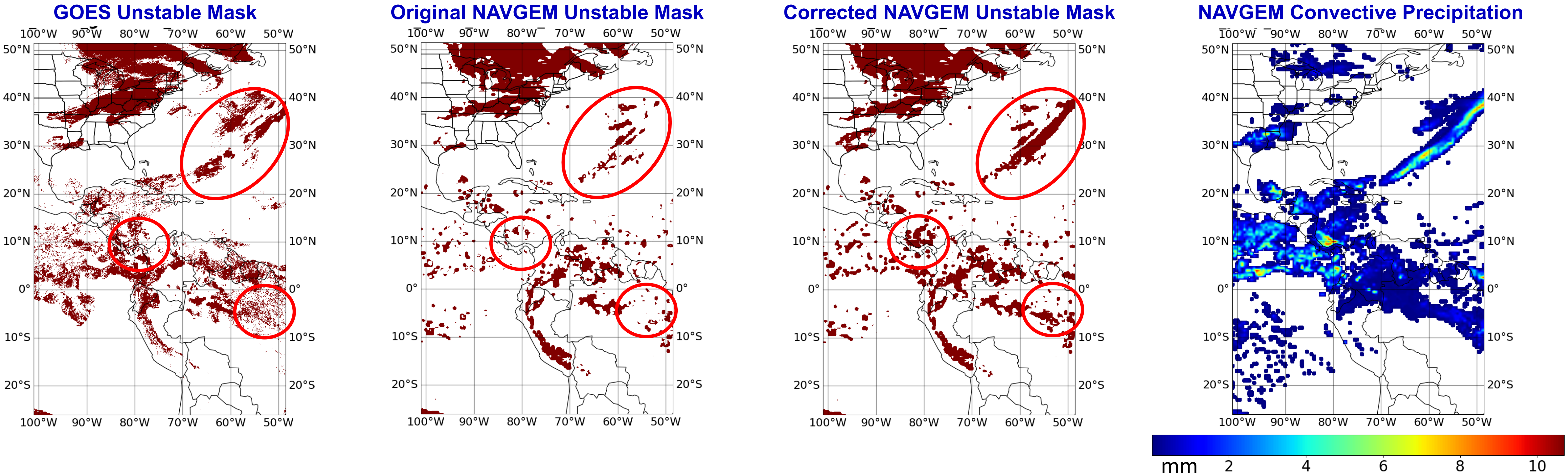


Cloud Type Classifications

U.S. NAVAL RESEARCH LABORATORY

Feature Engineering

Example: May 8th 2020 at 15 UTC



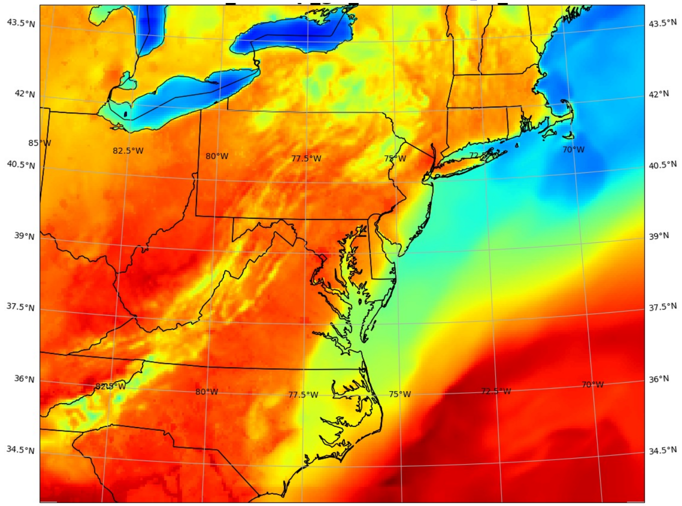
- NAVGEM Forecasts are used as one of input variable.
- Convective parameterization scheme over-stabilizes the boundary layer, Stable and unstable clouds are incorrectly labeled in the forecasts.

- Applied a correction augment algorithm: the stable and unstable probabilities.
- Improve/ correct NAVGEM bias
- Corrected NAVGEM cloud mask better correlated with GOES observation

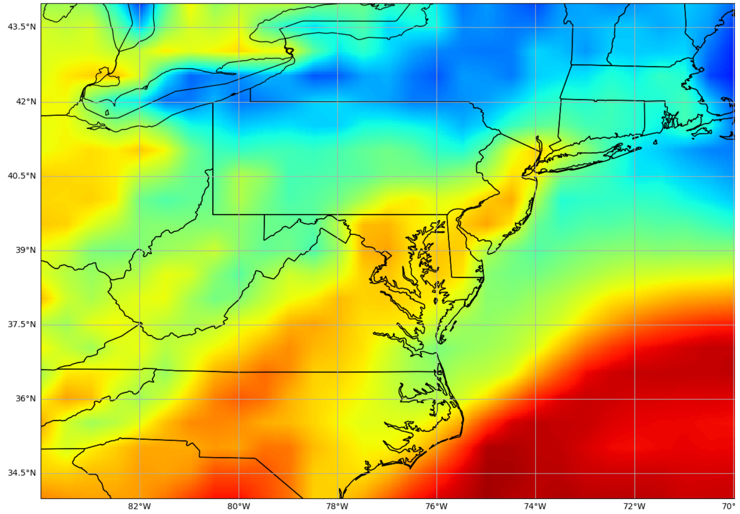
Feature Engineering

Example: May 8th 2020 at 15 UTC

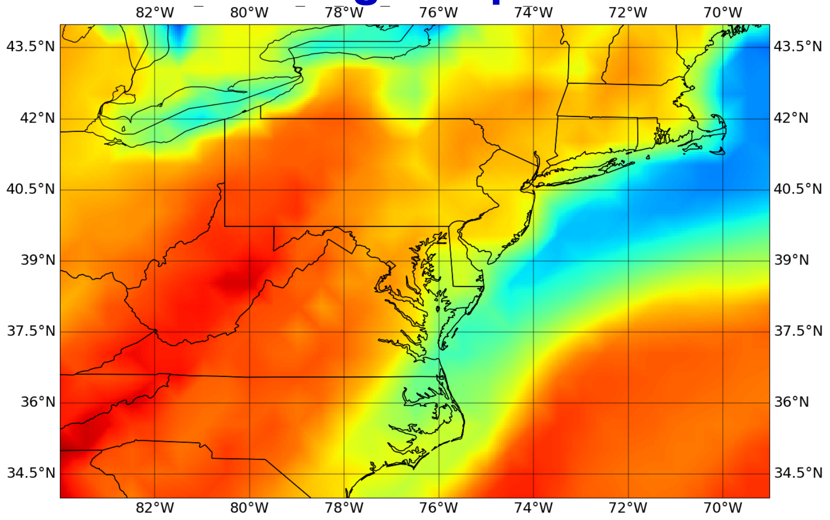
COAMPS 5 km Temperatures



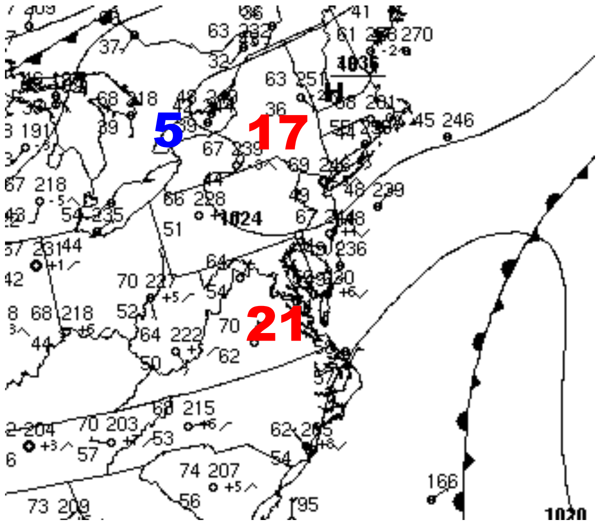
NAVGEM 0.5 Deg Temperatures



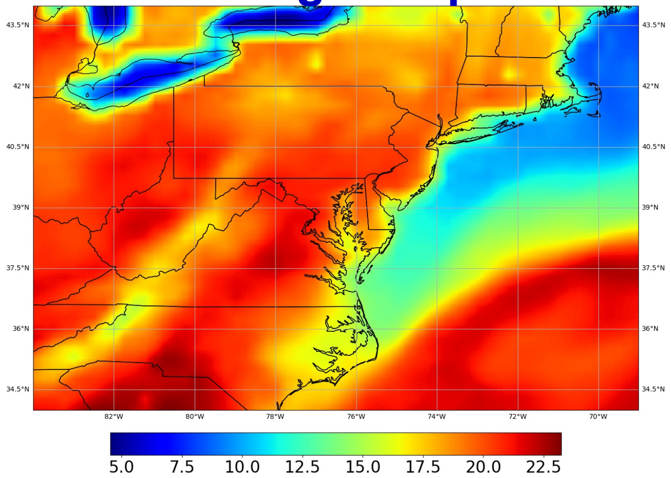
GFS 0.5 Deg Temperatures



Surface Observations



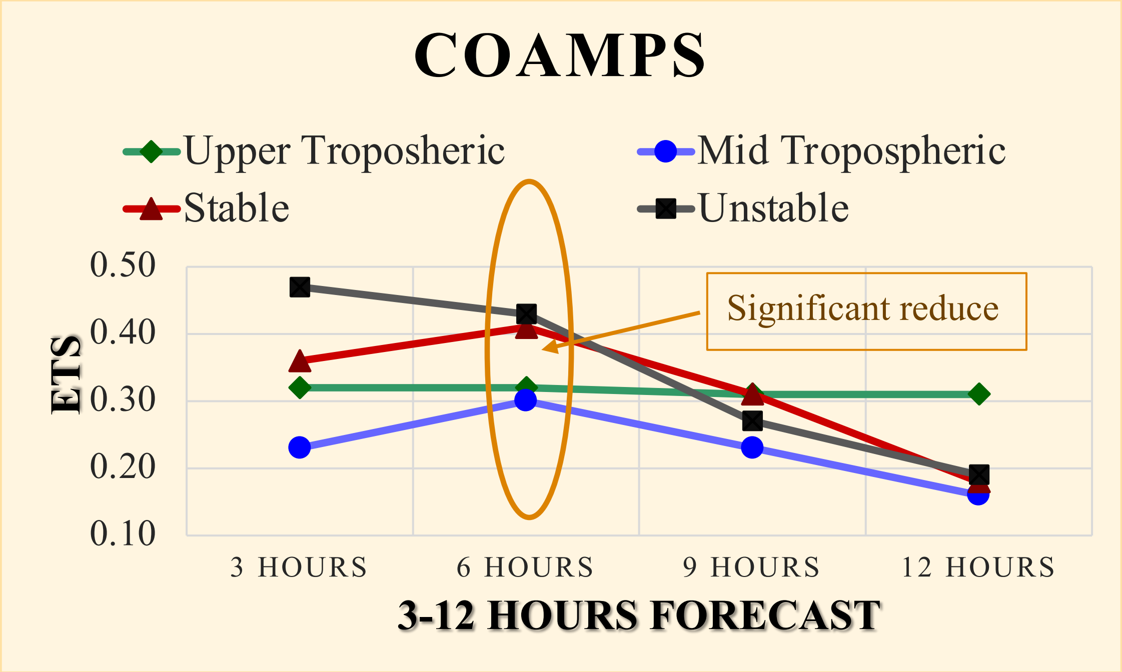
ERA5 0.25 Deg. Temperatures

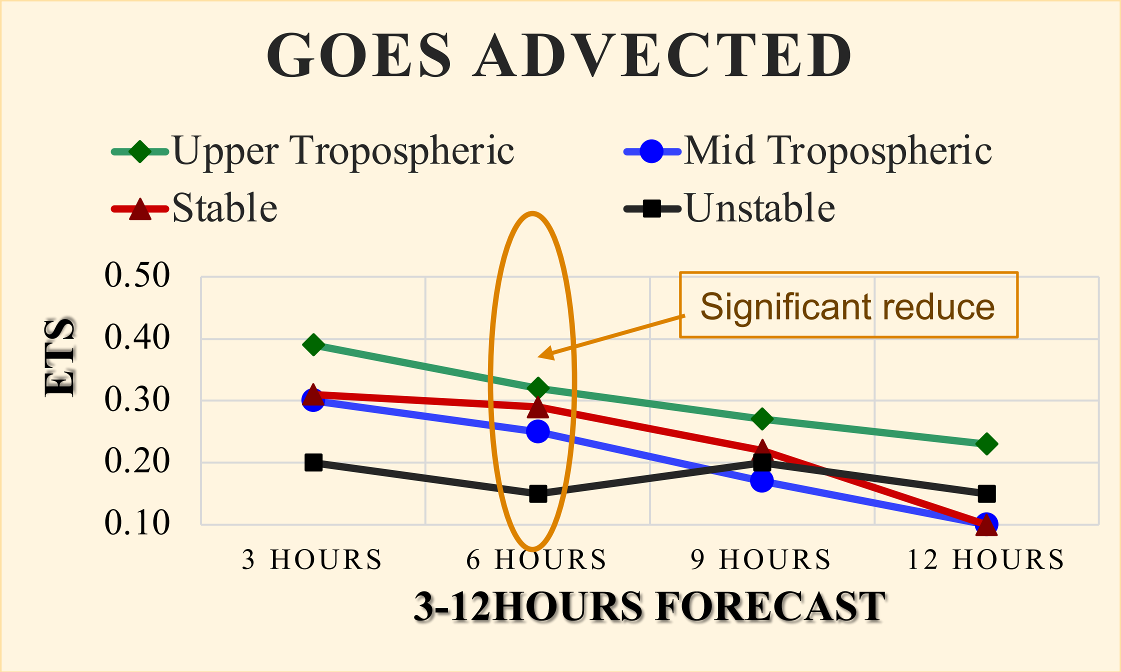


- Accurate temperatures is important input feature
- Expert of the field Jason Nachamkin evaluate all resources: NAVGEM, GFS, ERA5
  - ✓ Major errors in NAVGEM
  - ✓ GFS somewhat better
  - ✓ ERA5 closest to observation

Using temperature from ERA5 right now

Motivation





COAMPS

- Systematic Error
- Forcing mechanisms depend on the physical aspect of the cloudscape

GOES

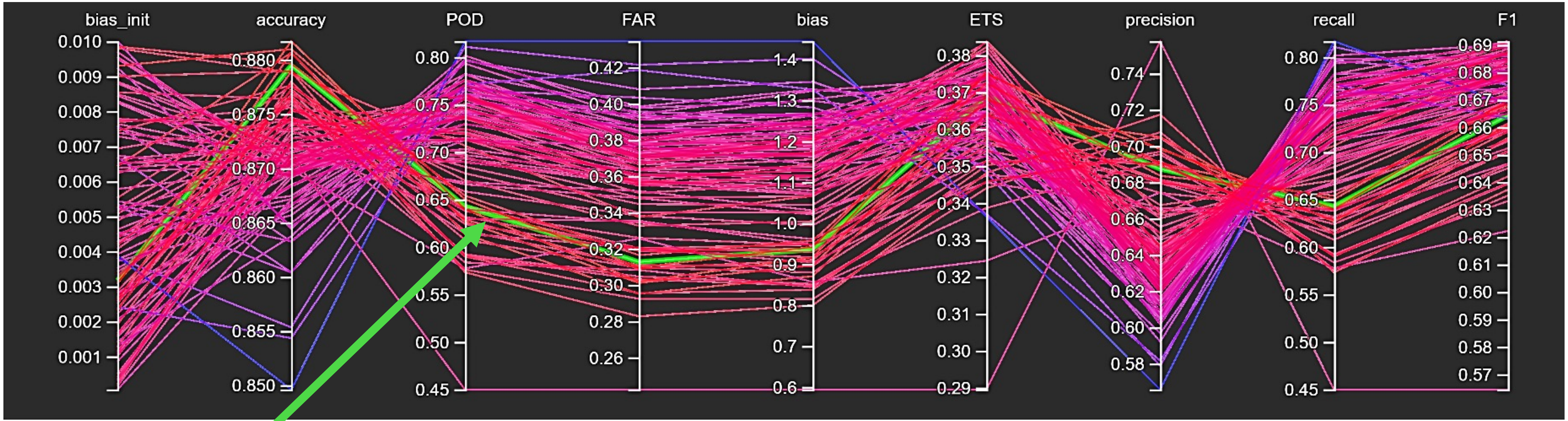
- Top down view limitation
- Multiple clouds types: represented in 1 pixel

- 6-hour forecast accuracy significant reduced
- COAMPS and GOES: different error trends
- Accuracy varies among cloud families

Results and Discussion

Upper tropospheric (6hour forecasts)

Bias_initializer tuning



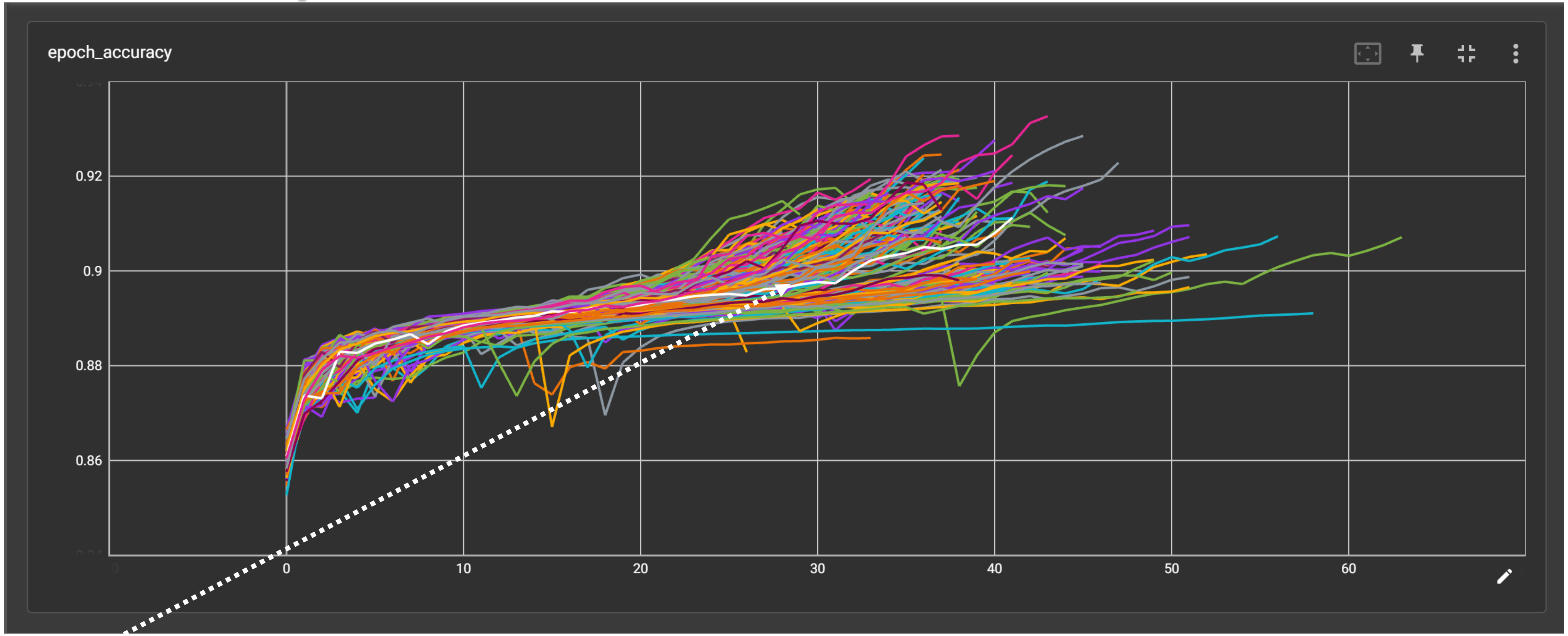
Model with optimal bias initial value

	Accuracy	POD	FAR	Bias	ETS	Precision	Recall	F1
COAMPS	79%	0.61	0.34	0.75	0.32	0.75	0.70	0.65
UNET -CNN	86%	0.65	0.31	0.98	0.43	0.85	0.80	0.75

Results and Discussion

Upper tropospheric (6hour forecasts)

Epoch accuracies of different bias initial values



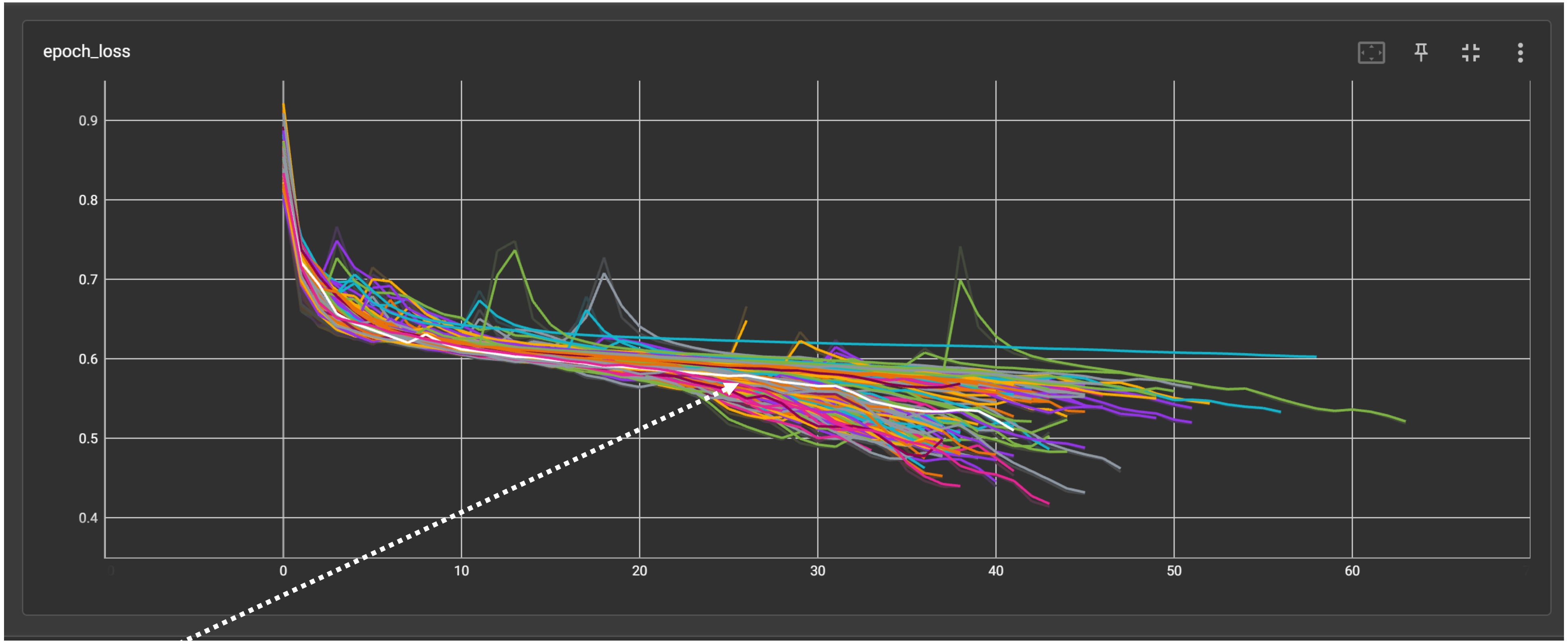
Training accuracy of the selected optimal bias initial value

Run number 63, Initial Bias value =0.0048 , Number of epoch =43

Results and Discussion

Upper tropospheric (6hour forecasts)

Epoch loses of different bias initial values



Training loss of the selected optimal bias initial value

Run number 63, Initial Bias value =0.0048 , Number of epoch =43