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UTILIZING QUANTIFIED UNCERTAINTY IN SYNTHETIC MICROWAVE BRIGHTNESS TEMPERATURES TO REVEAL HIDDEN TROPICAL CYCLONE STRUCTURES

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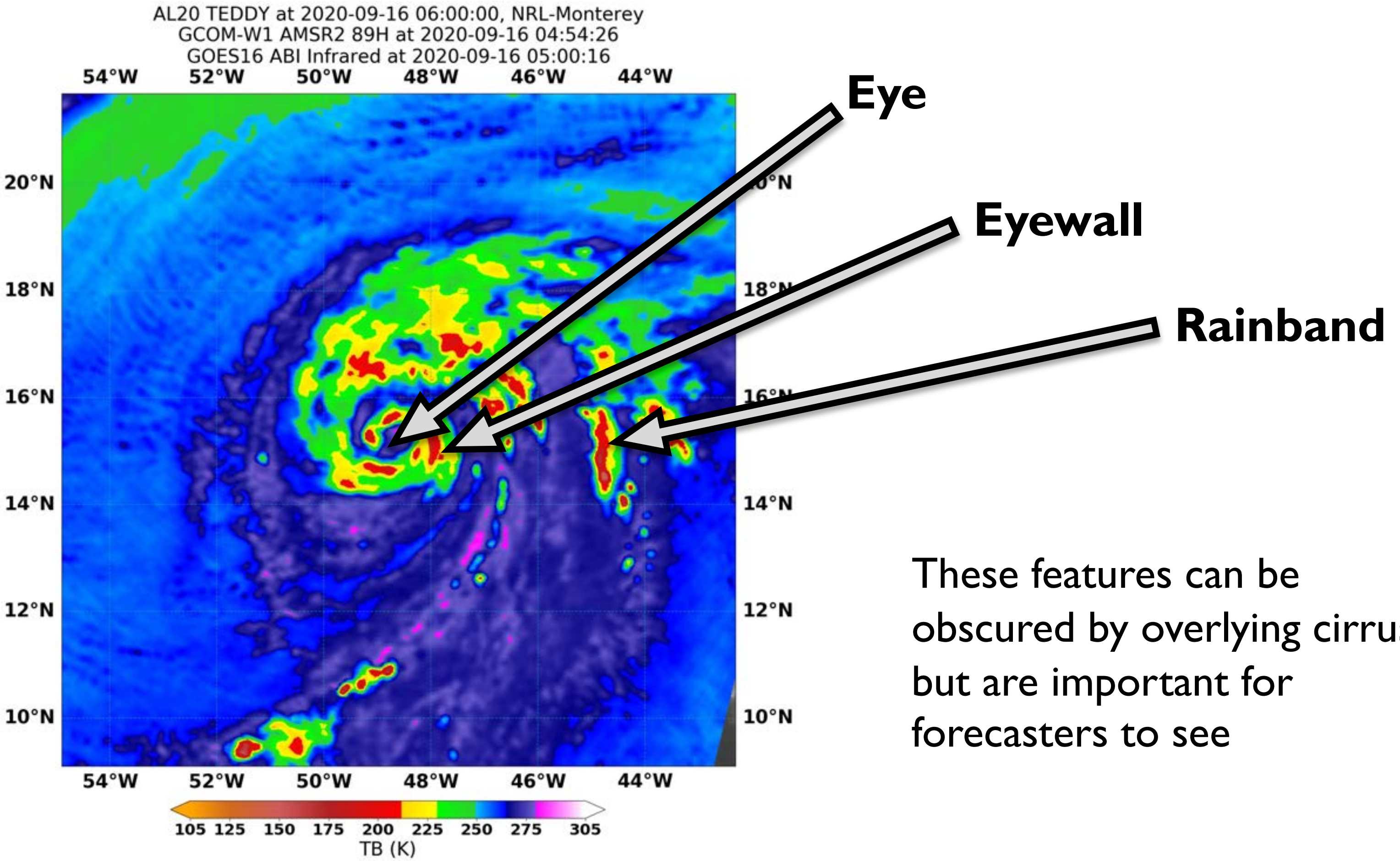
Background: Passive microwave (PMW) is useful for identifying tropical cyclone structures



These features can be obscured by overlying cirrus but are important for forecasters to see

Note: we are focusing on 89 GHz (horizontal polarization) in this presentation, but we are investigating all 13 GMI channels

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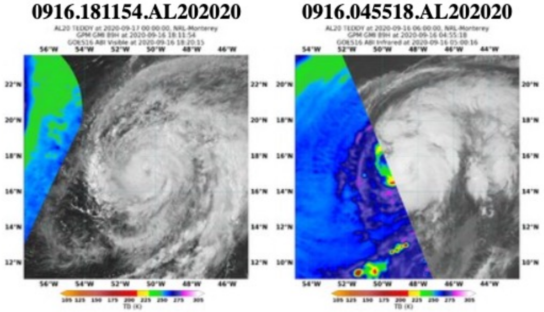
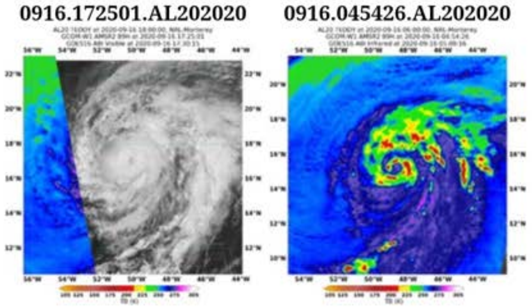
Problem: PMW data temporally and spatially limited for Tropical Cyclones (TCs)

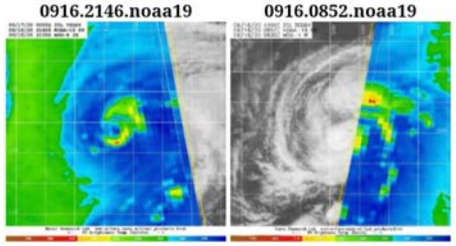
GMI



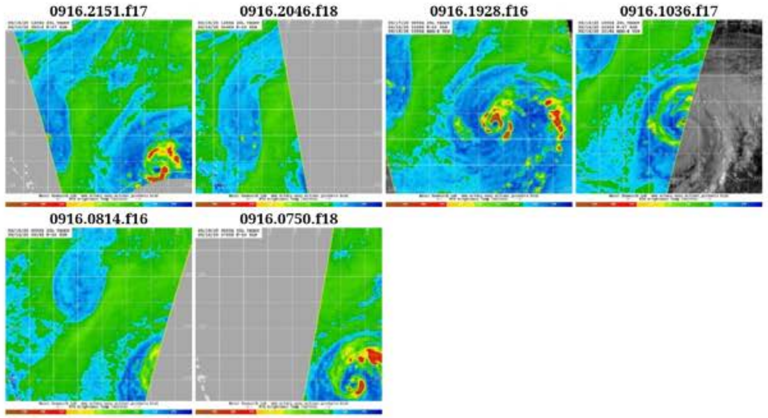
AMSR2



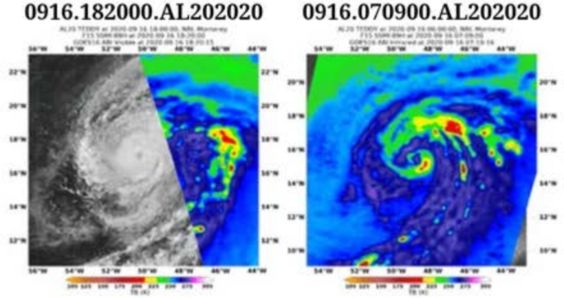
AMSU-B



SSMI/S:



SSMI:



Courtesy of:
https://www.nrlmry.navy.mil/tc-bin/tc_home2.cgi

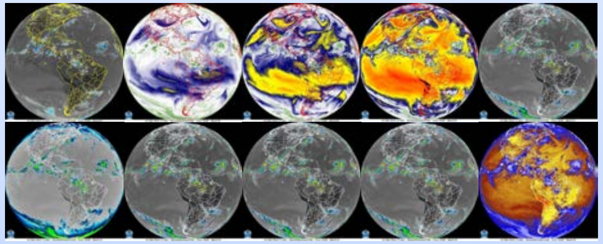
Example: This was a full day of archived real-time 85-89H GHz data coverage that "intersected" Hurricane Teddy on 16 Sep 2020.

This day also occurred during a missed second rapid intensification (RI) forecast, and better microwave coverage could potentially have helped improve forecast accuracy.

Our Solution: We are using Bayesian Deep Learning to "fill in the gaps" of GMI microwave data from GOES-16 IR data

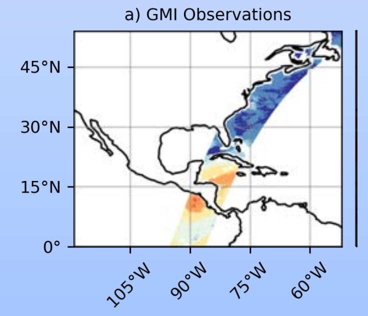
Inputs:

Brightness temperatures (TBs) from all GOES-16 near-IR and IR Bands (3.9 µm – 13.3 µm)



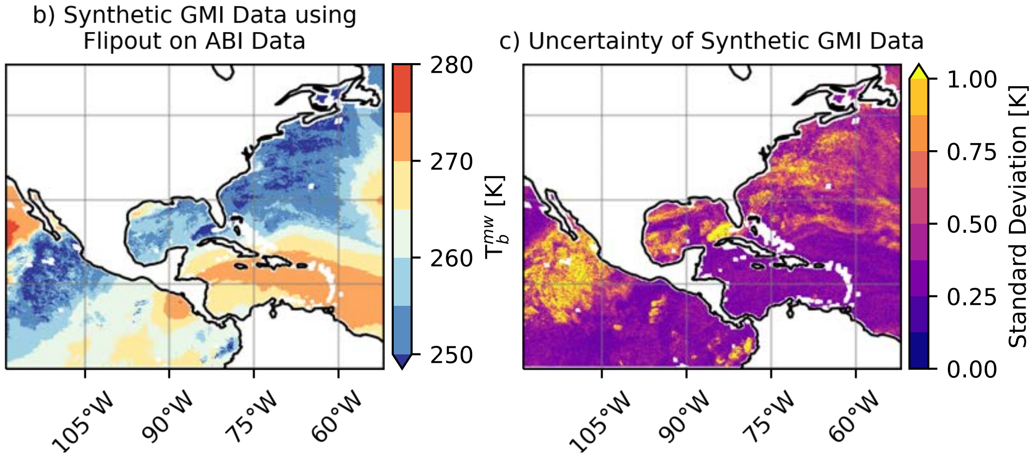
Labels:

Collocated GMI Observations (each channel, 10.6 – 183±3 GHz)



Result:

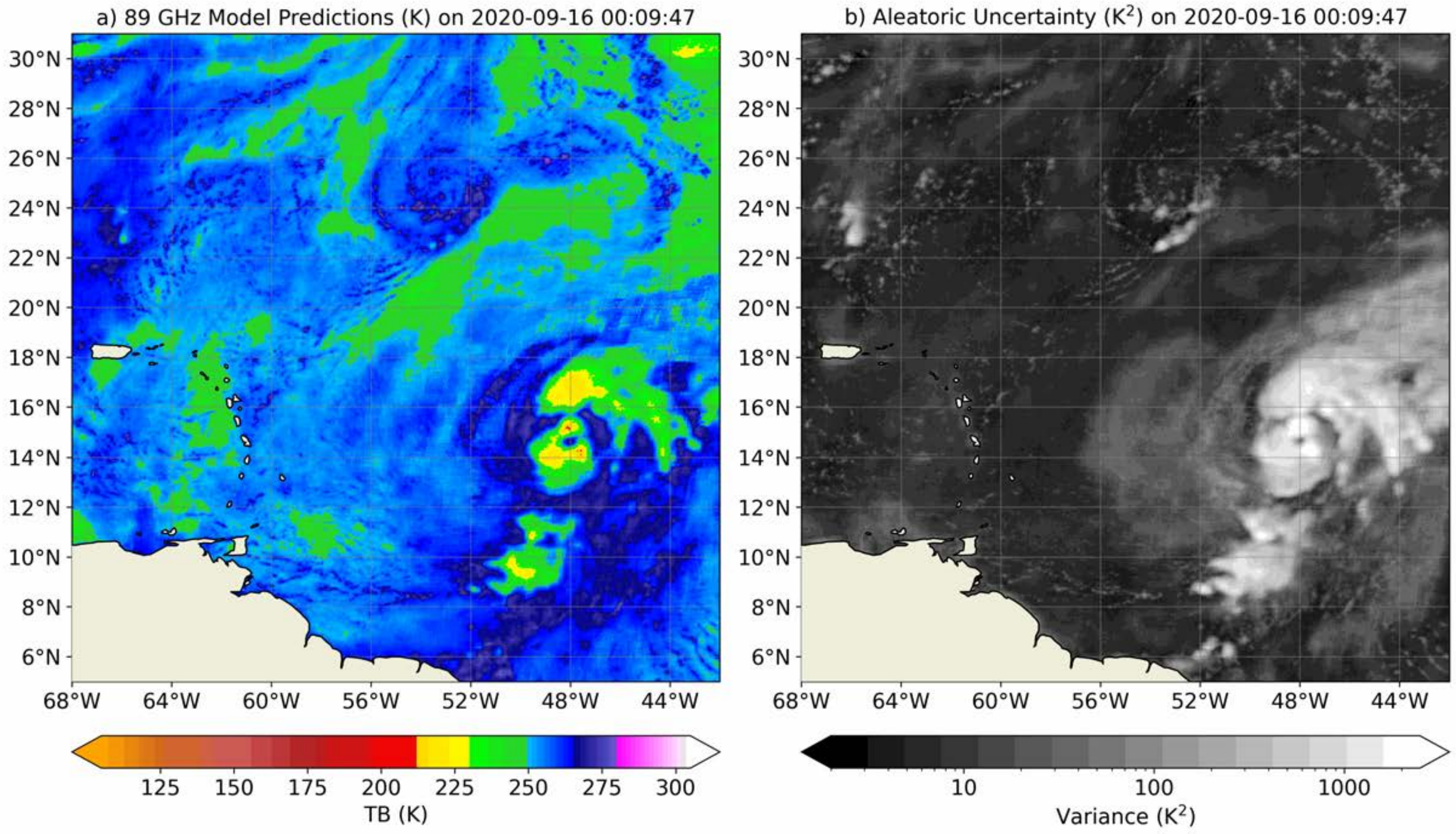
(Ex: 183±3 GHz shown)

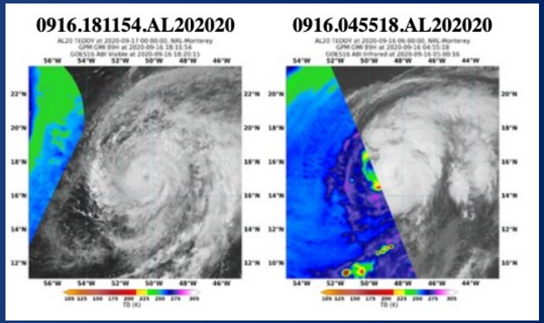


Adapted from:
Ortiz, P., Casas, E., Orescanin, M., Powell, S., Petkovic, V., and Hall, M., (2023): Uncertainty Calibration of Passive Microwave Brightness Temperatures Predicted by Bayesian Deep Learning Models, **(Just accepted in AIES!!)**

We currently have <2 K error in clear sky conditions for all GMI channels, and are currently working on increasing skill in cloudy conditions!

Our Solution: We are using Bayesian Deep Learning to "fill in the gaps" of GMI microwave data from GOES-16 IR data





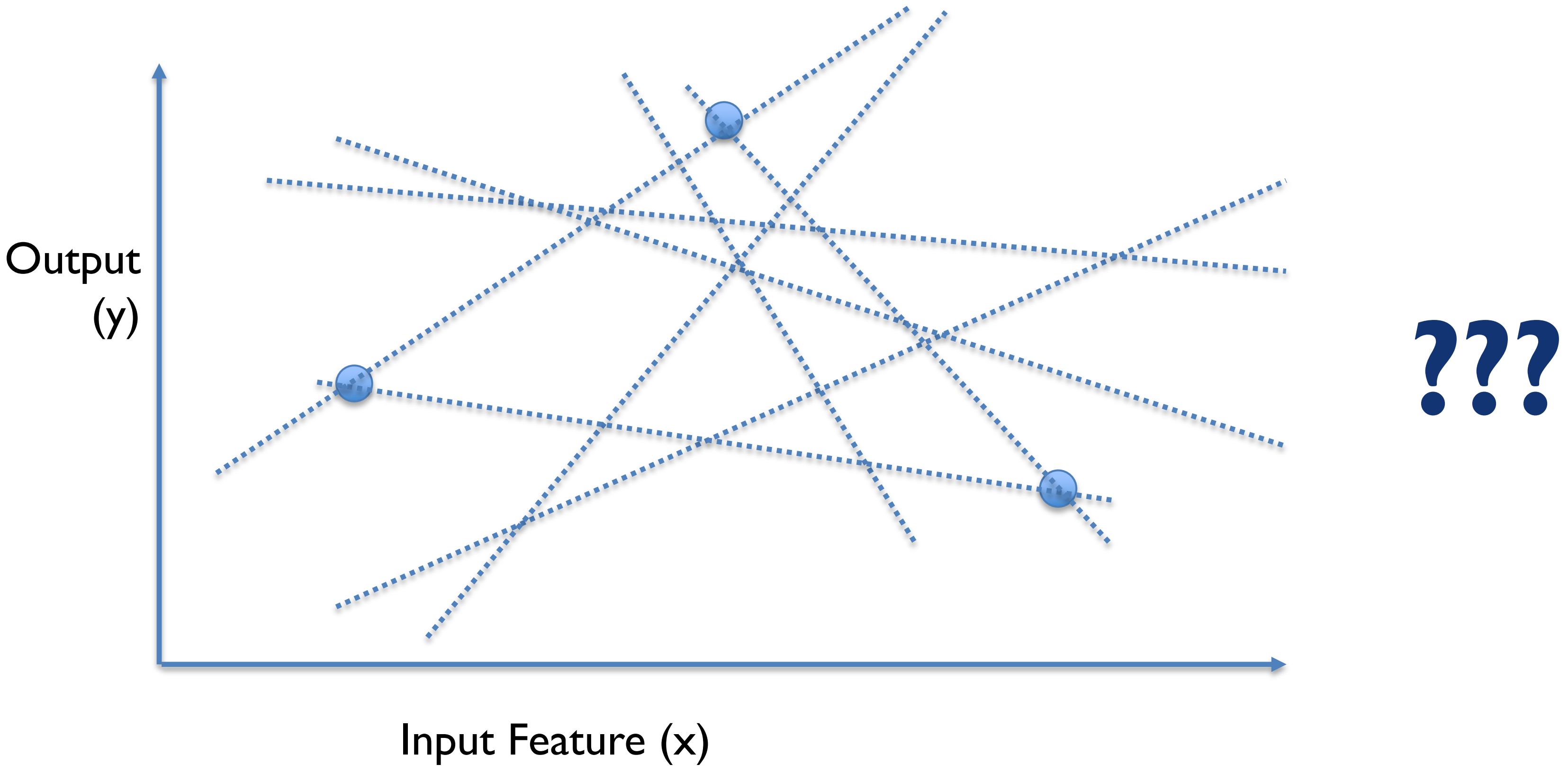
(Full day of GMI swaths for comparison)

We can go one step further! Decompose the uncertainty!

$$\hat{\sigma}_n^2 = \frac{1}{T}\sum_{t=1}^{T} \underbrace{\hat{\sigma}_t^2(x_n, \mathbf{w}_t)}_{\text{Aleatoric Uncertainty}} + \boxed{\underbrace{\hat{\mu}_t^2(x_n, \mathbf{w}_t) - \hat{\mu}_n^2}_{\text{Epistemic Uncertainty}}}$$

Mean of predicted variance
Represents inherent stochasticity of data
Cannot be predicted from the given input features; **"irreducible" uncertainty**

High Epistemic Uncertainty



Model:

Y = mx + b

Are the learned values of "m" and "b" predicting consistent values of Y?

We can collect more data to improve the fit and reduce epistemic uncertainty

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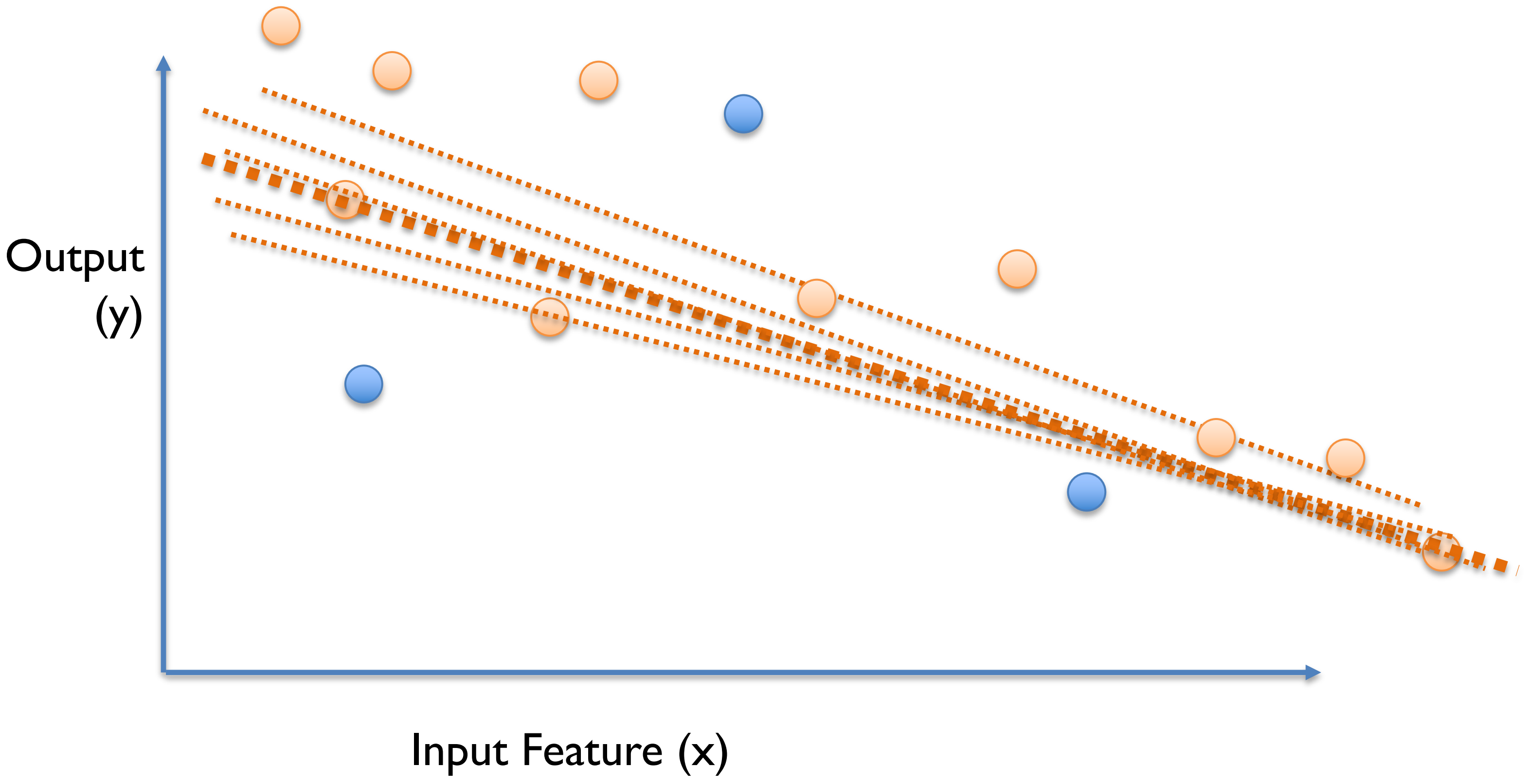
Low Epistemic Uncertainty



Model:

Y = mx + b

Are the learned values of "m" and "b" predicting consistent values of Y?

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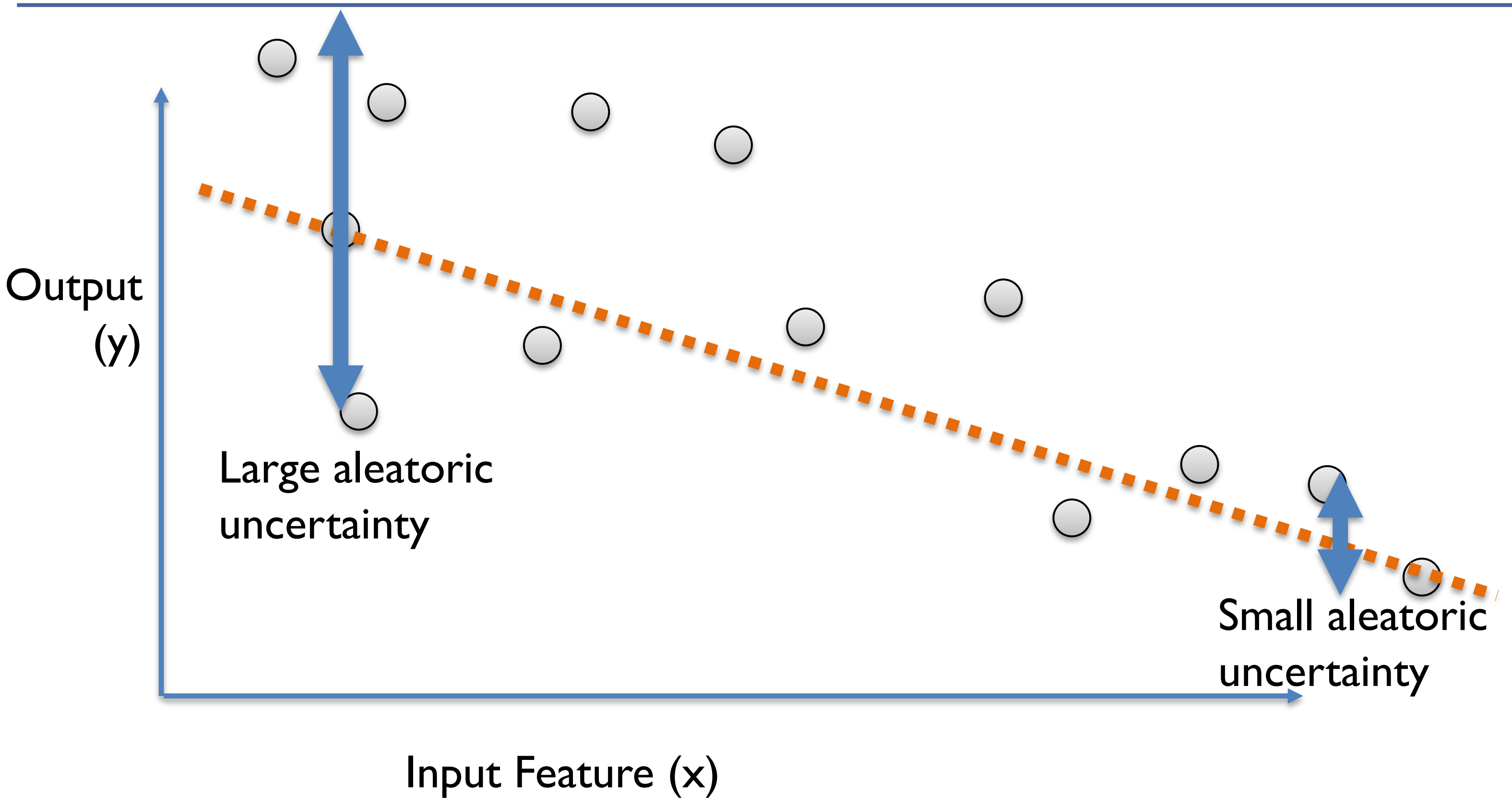
Aleatoric Uncertainty



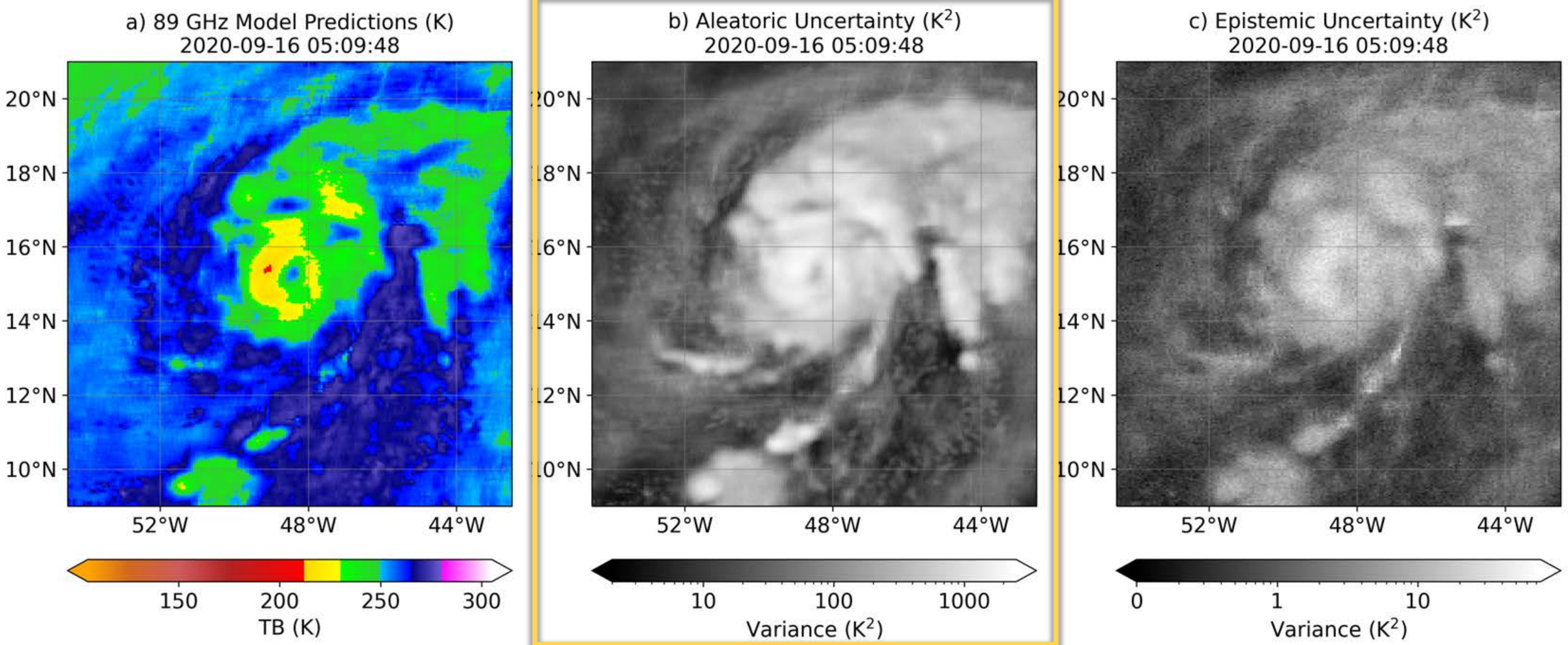
Model:

Y = mx + b

Given a good model fit, what is the remaining uncertainty that the model can't capture?

Uncertainty

Mean PMW Brightness Temps.



Uncertainty due to microphysics, etc.

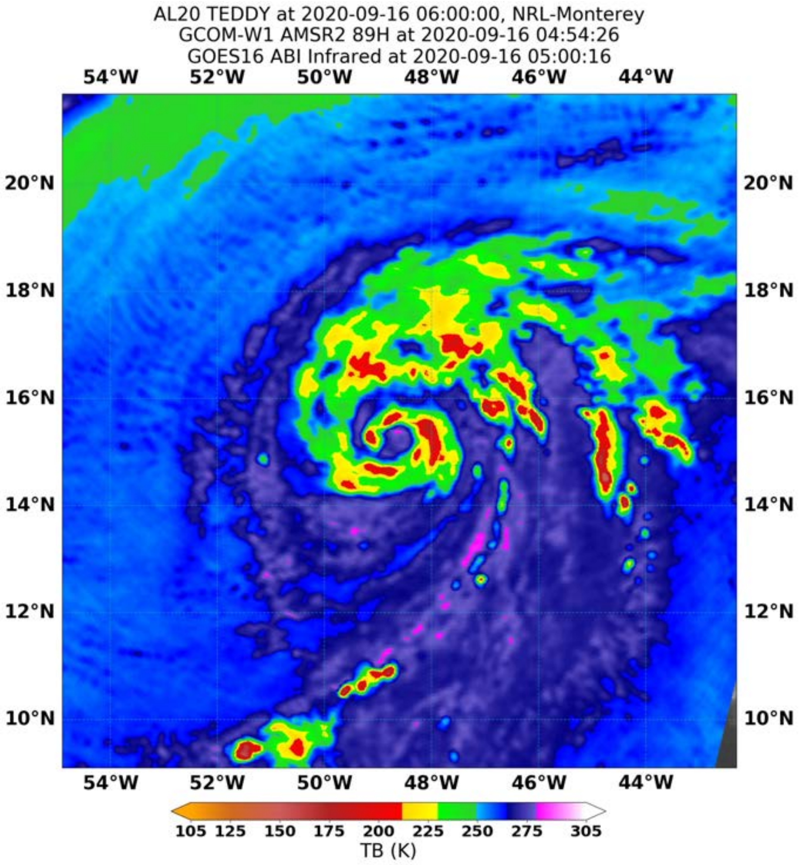
Uncertainty due to not enough training data

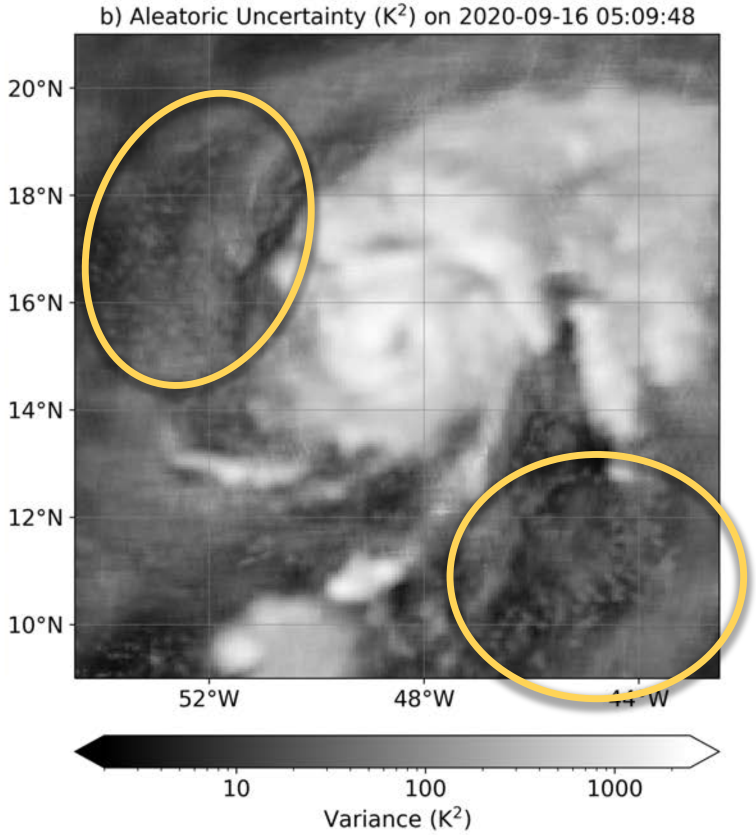
Stay tuned for better skill in the near future!

This is the uncertainty that meteorologists want to quantify

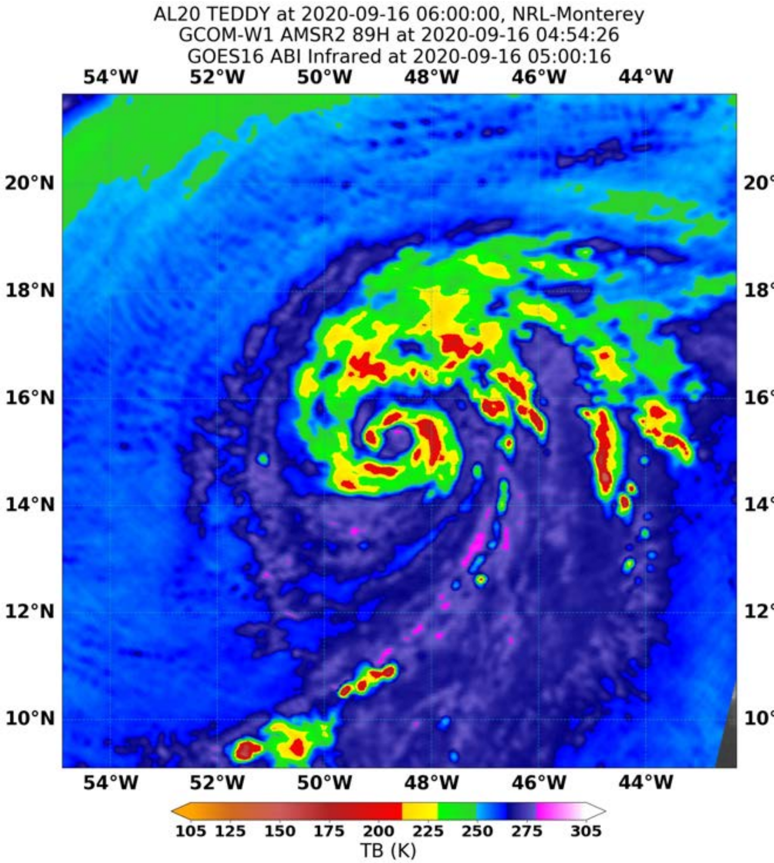
The model is telling us that it really needs more examples of TCs!!

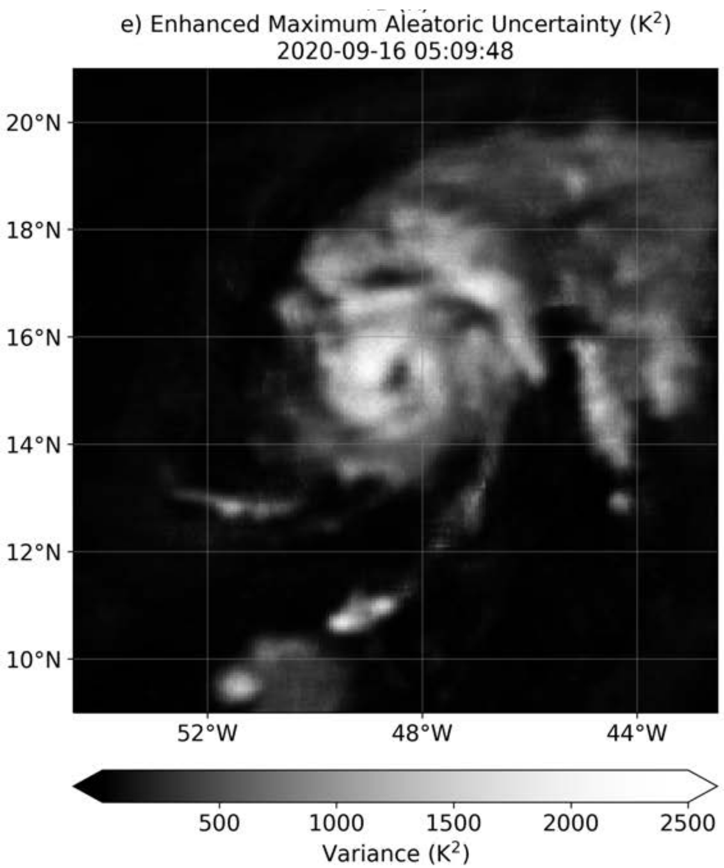
Aleatoric uncertainty is great for revealing low clouds outside of deep convection





Maximum values of Aleatoric uncertainty show good agreement with locations of deep convection

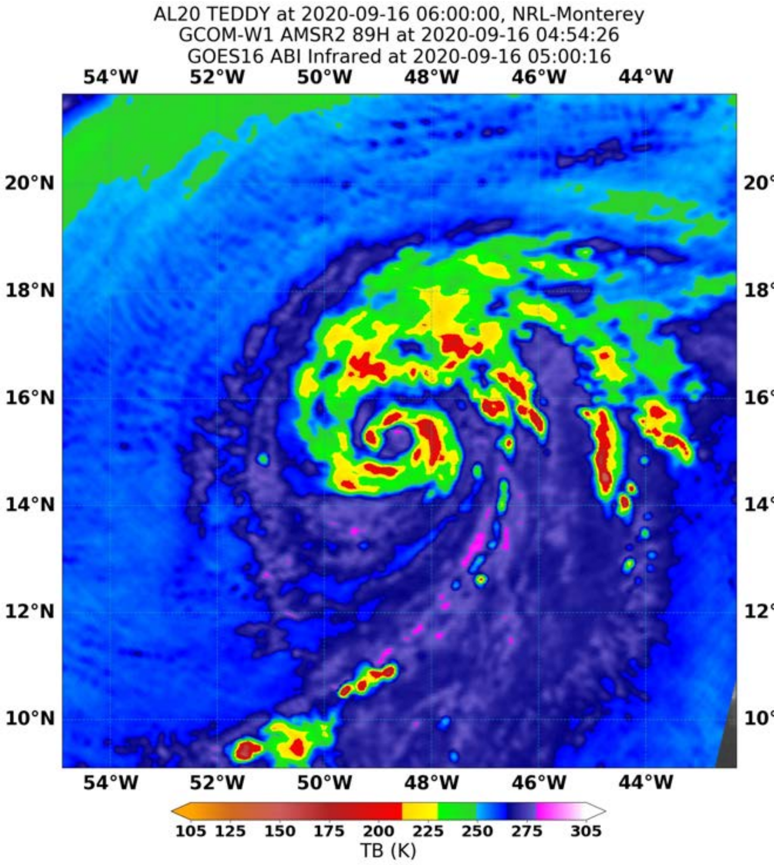


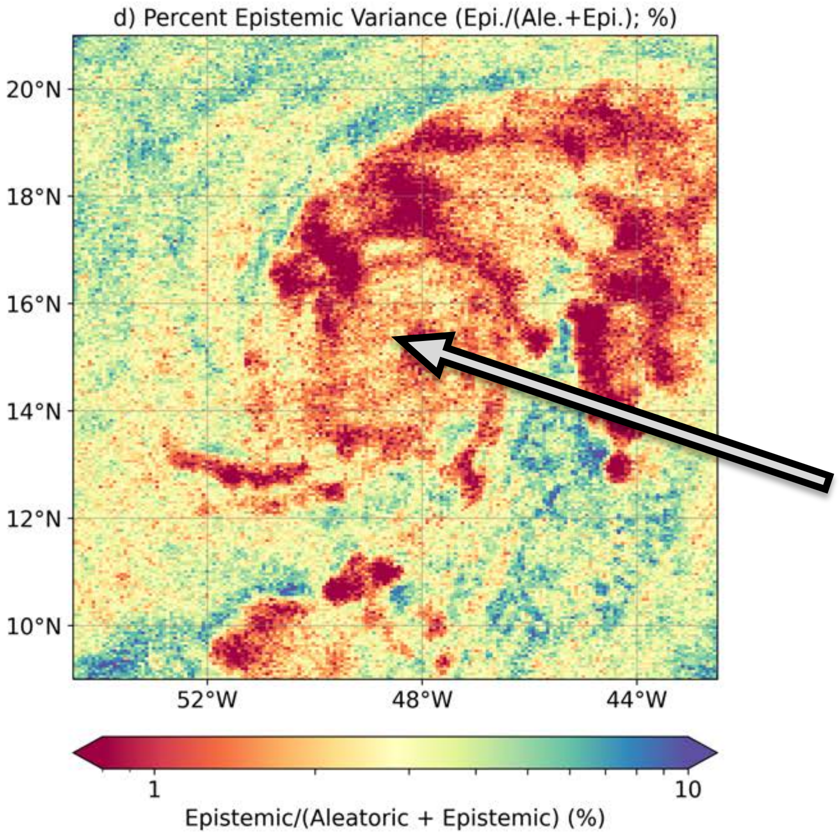


Same data; different grayscale normalization

This color scheme is also great for enhanced eye detection

"Percent" Epistemic enhances visibility of deep convection (reds)





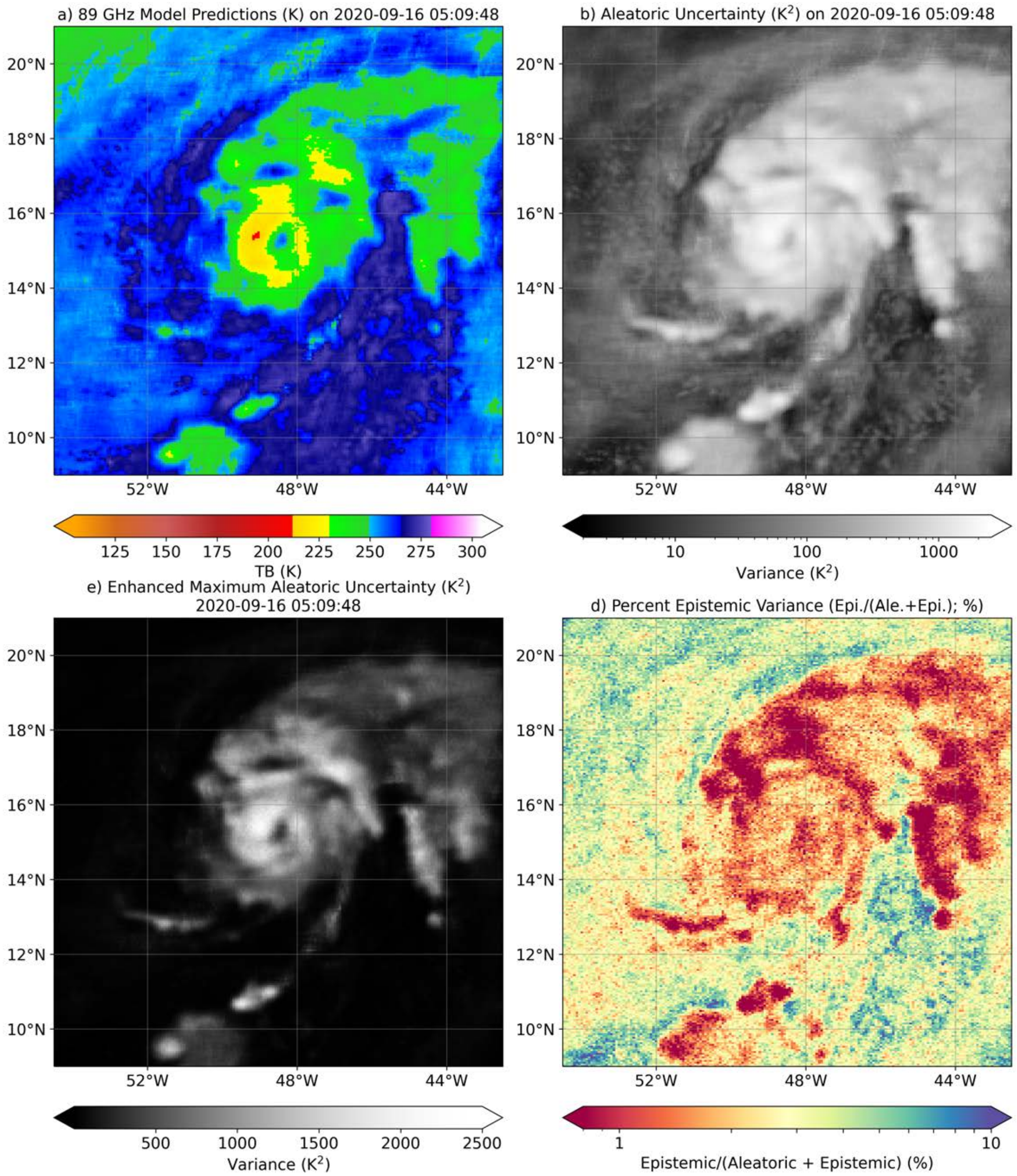
"Percent Epistemic"

$$\frac{Epistemic}{Epistemic+Aleatoric} * 100$$

Lack of red in inner core suggests that our model can improve representation of TC structure with more training data

Mean 89H GHz TBs
Currently good for low-level circulations

Aleatoric Uncertainty
Currently good for low cloud detection



High Contrast Aleatoric Uncertainty
Currently good for identifying TC centers and deep convection

"Percent Epistemic"
Currently good for enhancing deep convection (reds) and spurious features (purples)

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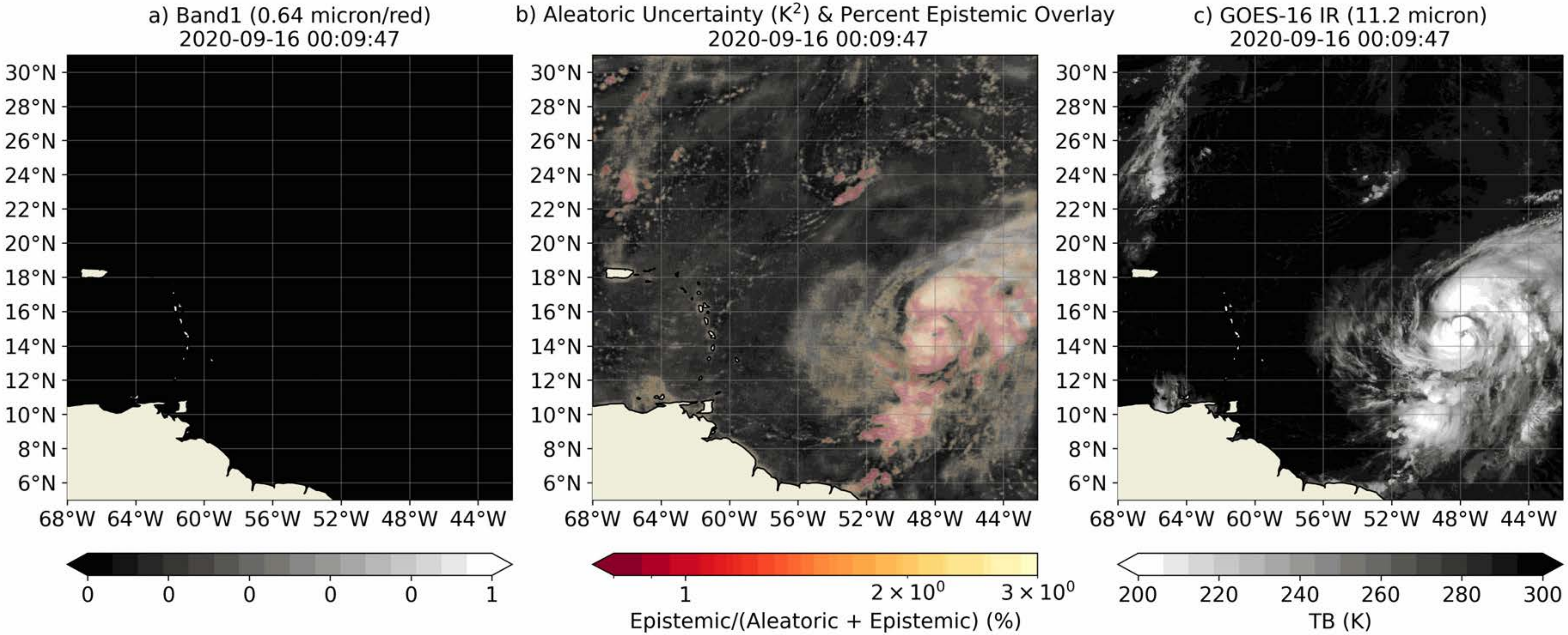
VIS (nighttime)

Experimental ML Uncertainty Product

IR



Shows promise for enhancing visibility of rainbands and low-level circulations in improved models

Conclusions

- **We have developed a large-scale Bayesian Deep Learning regression model with uncertainty decomposition to predict PMW TBs and uncertainties from IR data**
- **Decomposing total uncertainty into its aleatoric and epistemic uncertainty components shows promise for enhancing visibility of structures of interest to TC forecasters**
  - Low-level circulations
  - Enhanced visibility of eye location compared to IR
  - Shows promise for enhancing convective structures
    - Rainband convection
    - Eyewall replacement cycles in future improved models?

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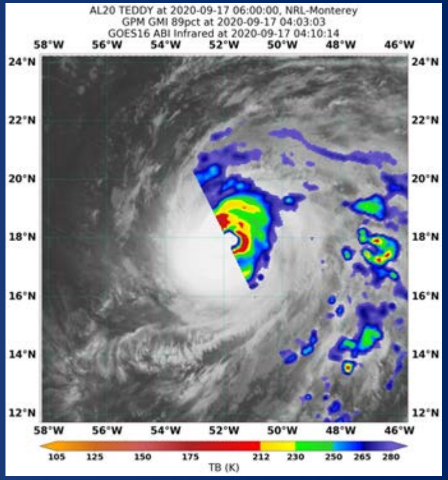
Future Work

- **Continue increasing synthetic microwave product skill**
  - Curate bigger and TC-optimized training dataset
  - Refine collocation techniques
  - Incorporate visible data into model development
  - Newer, faster, and possibly more capable machine learning architectures

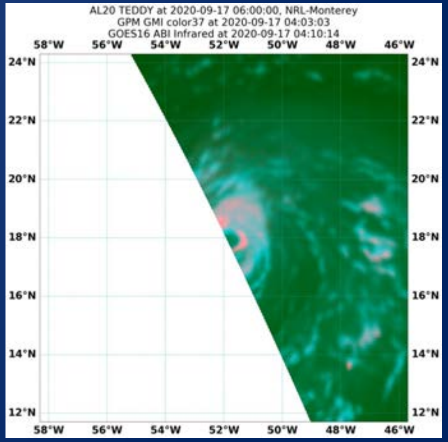
- **Extend methodology to additional satellites**

Eventual goals:
Create synthetic 89PCT & 37color products with uncertainties

89PCT example



37color example



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Millersville University

I am now the newest tenure-track meteorology professor at Millersville University!

(Exciting MU news: MU has a brand-new X-Band radar!)

Questions? Comments?

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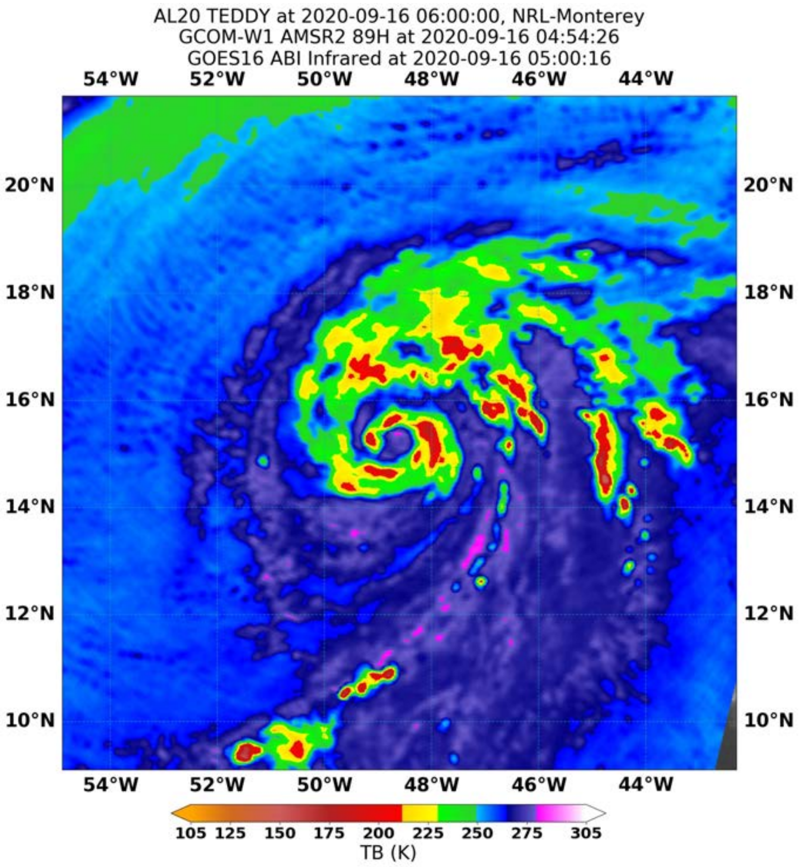
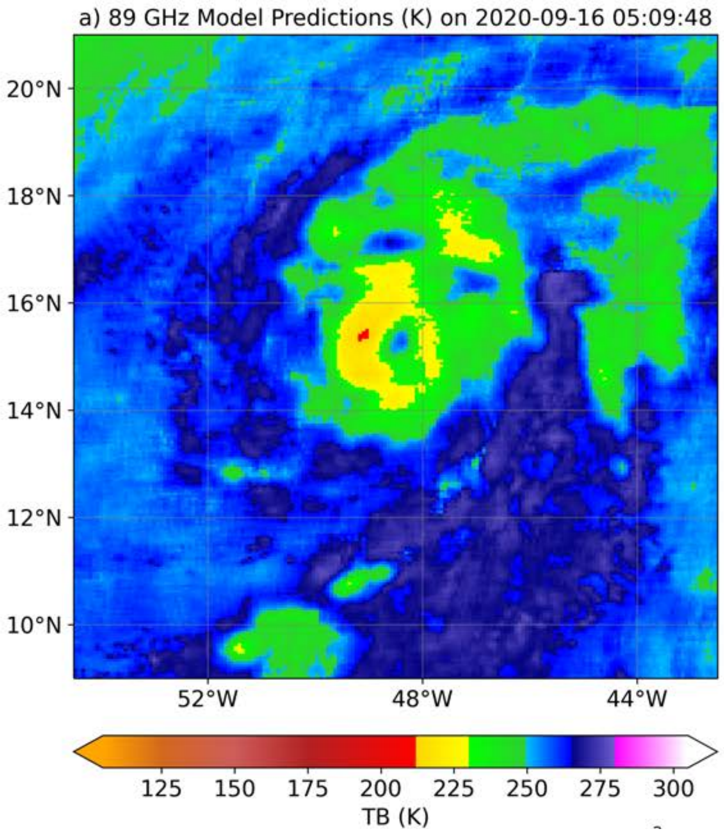
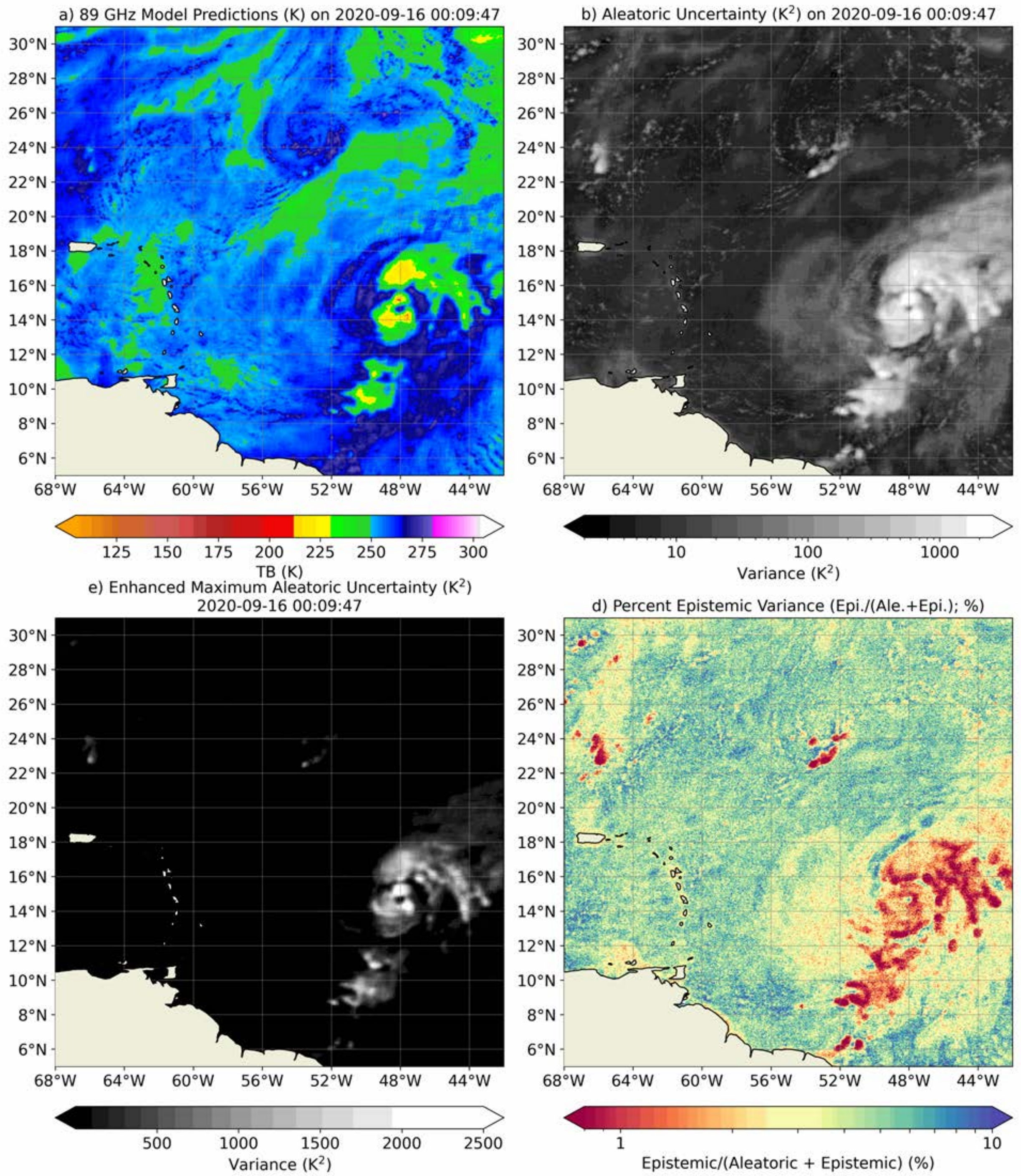
Extra Slides

Mean TBs need more training data before being useful for mature TC structure






a) 89 GHz Model Predictions (K) on 2020-09-16 00:09:47
b) Aleatoric Uncertainty (K^2) on 2020-09-16 00:09:47
e) Enhanced Maximum Aleatoric Uncertainty (K^2)
2020-09-16 00:09:47
d) Percent Epistemic Variance (Epi./(Ale.+Epi.); %)
30°N 28°N 26°N 24°N 22°N 20°N 18°N 16°N 14°N 12°N 10°N 8°N 6°N
68°W 64°W 60°W 56°W 52°W 48°W 44°W
125 150 175 200 225 250 275 300
TB (K)
10 100 1000
Variance (K^2)
500 1000 1500 2000 2500
Variance (K^2)
1 10
Epistemic/(Aleatoric + Epistemic) (%)