UW-CIMSS Tropical Cyclone Products Updates and New Tools

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UW-CIMSS Tropical Cyclone Products Updates and New Tools

- Advanced Dvorak Technique (ADT) – Version 9.1
- Advanced (AI-enhanced) Dvorak Technique (AiDT)
- DeepMicroIRNet (D-MINT) and DeepIRNet (D-PRINT)
- Satellite Consensus Algorithm (SATCON)
- AI-RI
- ARCHER
- M-PERC

Advanced Dvorak Technique (ADT)

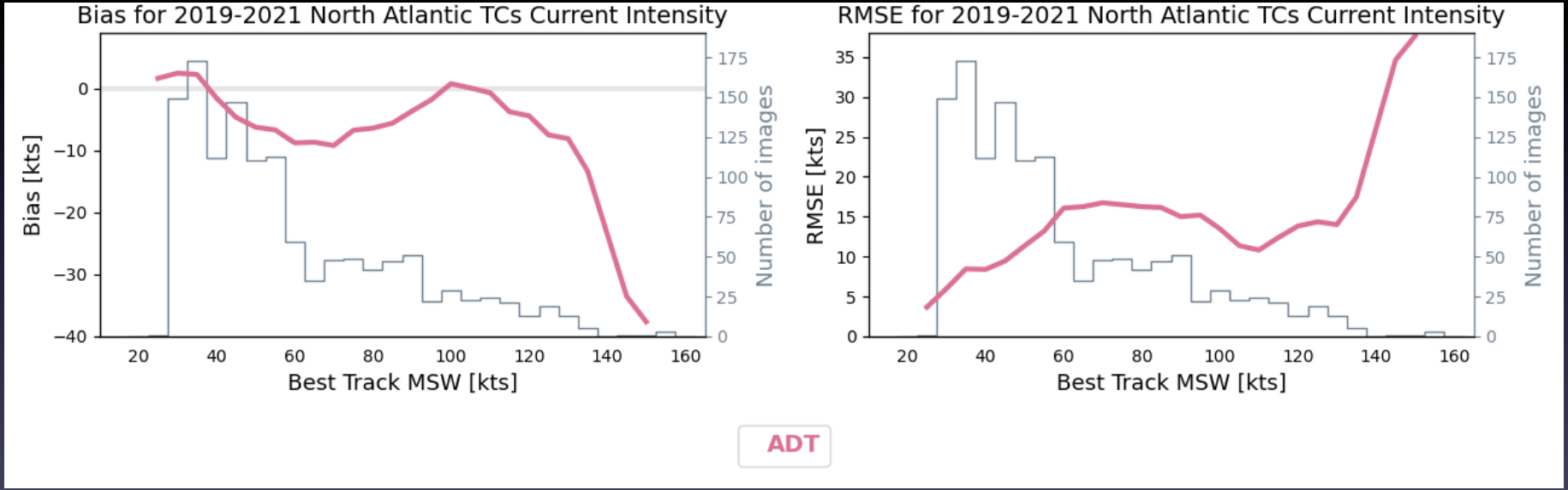
Latest Algorithm Upgrades

Primary ADT-V9.1 upgrades

- Extratropical Transition intensity estimate adjustment
- Analysis of Sub-Tropical systems with modifications to ADT logic
- ARCHER (V2.8) objective algorithm for automated TC center position
- SFC wind radii estimates (4 quadrants analysis, based on Knaff et al)
- Extreme TC (CI=>7.0) intensity adjustments implemented
- Modifications to allow for more frequent temporal image sampling

Advanced Dvorak Technique (ADT)
2019-2021 Performance Statistics

What TC intensity does the ADT underpredict the most?



Category 5 TCs have the most negative Bias in the ADT. The ADT also generally underpredicts Category 1 and 2 TCs.

Advanced (AI-enhanced) Dvorak Technique (AiDT)

- **The Advanced Dvorak Technique (ADT) already objectively interrogates satellite imagery and stores many environmental and analysis parameters in storm history files**
  - ADT accounts for satellite data and ocean basin differences through considerable research efforts developed over 20+ years of operational use

- **We can use a DL model that uses ADT history file parameters to improve the performance of the algorithm, especially to aid in situations where the ADT can struggle?**
  - Many different models could be investigated and would be computationally cheap to derive since we are only dealing with data values and not satellite imagery directly

Advanced (AI-enhanced) Dvorak Technique (AiDT)

AiDT Feature Values

ADT history file parameters used as model input

AiDT Features *(ADT history file parameters)*		
Raw T#	Sin of Longitude	Cloud Symmetry
Adjusted Raw T#	Cos of Longitude	Curved Band Value
Final T#	Viewing Angle	Curved Band Amount
CI#	Eye FFT	C/W Temperature Distance
Eye Temperature	Cloud FFT	PMW Eye Score
Cloud Temperature	Eye Scene ID value	Extratropical Flag
C/W Temperature	Cloud Scene ID value	Subtropical Flag
Latitude	Eye StdDev	Eye Size (2/eye size)
	Shear Distance	CDO Size

C/W: "Coldest-Warmest"
CDO : "Central Dense Overcast"
PMW: "Passive Microwave"
FFT: "Fast Fourier Transform"

Advanced (AI-enhanced) Dvorak Technique (AiDT)

Final AiDT Model

- Final Model
  - Fully-connected Deep Neural Network (DNN)
  - Regression-based loss function
  - 26 input ADT History File Features
  - One Hidden (Dense) layer with 32 neurons
  - One Output layer neuron representing a single continuous wind speed estimate value

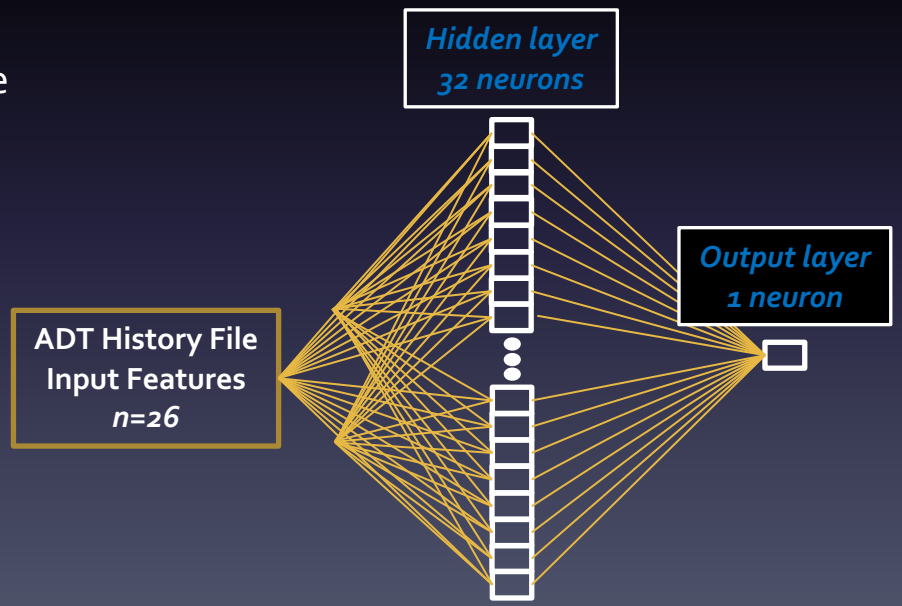
- A 3-hour time weighted averaging scheme is implemented to dampen out small fluctuations between consecutive intensity estimates
  - Time averaging reduces error by about 0.3kt

Trainable Parameters

L1: 26 X 32 + 32 = 864

L2: 32 X 1 + 1 = 33

897 Total

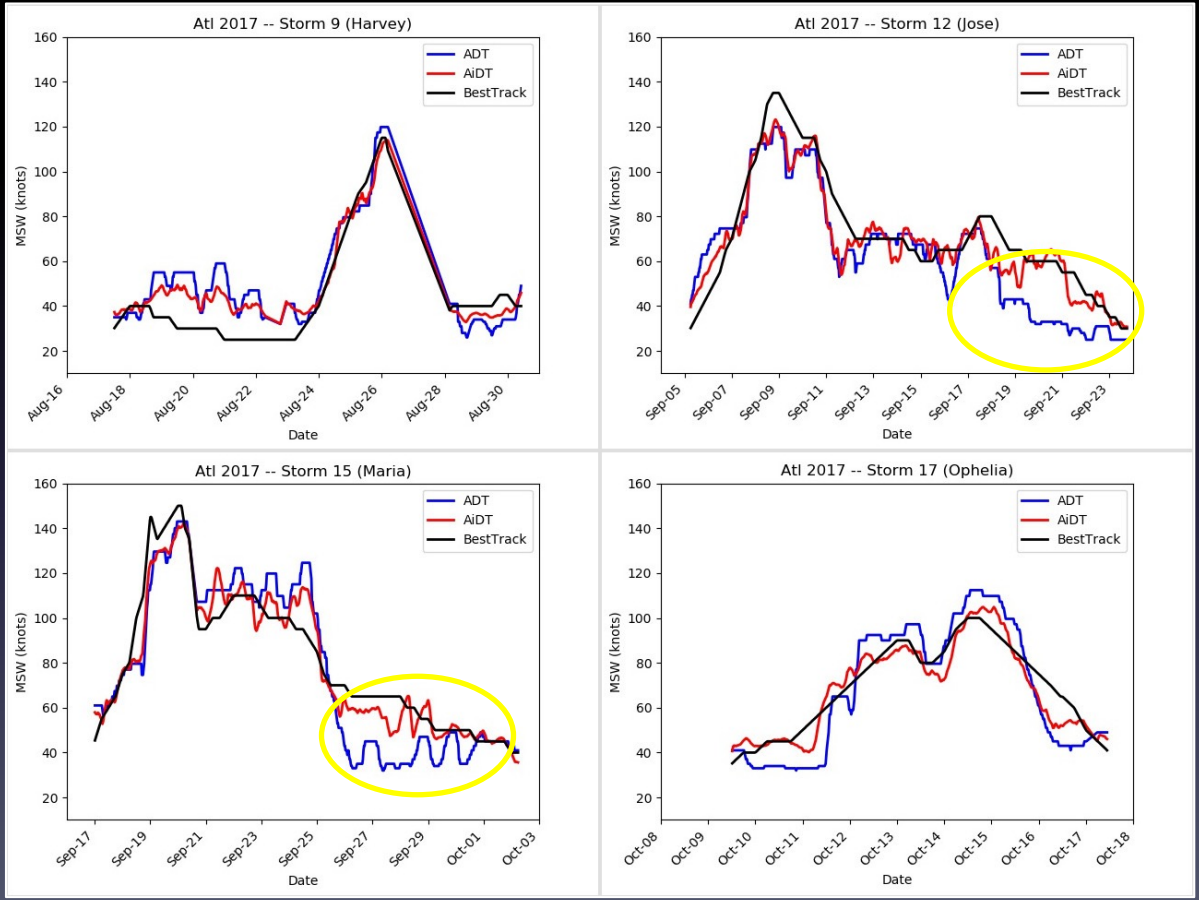


Advanced (AI-enhanced) Dvorak Technique (AiDT)
2017 Storm Examples

- 2017 North Atlantic
  - 09L (Harvey)
  - 12L (Jose)
  - 15L (Maria)
  - 17L (Ophelia)

  - BLUE – ADT
  - RED – AiDT
  - BLACK – NHC Best Track

Note impact of AiDT during formation and dissipation stages



Advanced (AI-enhanced) Dvorak Technique (AiDT)

ADT Scene Type Analysis

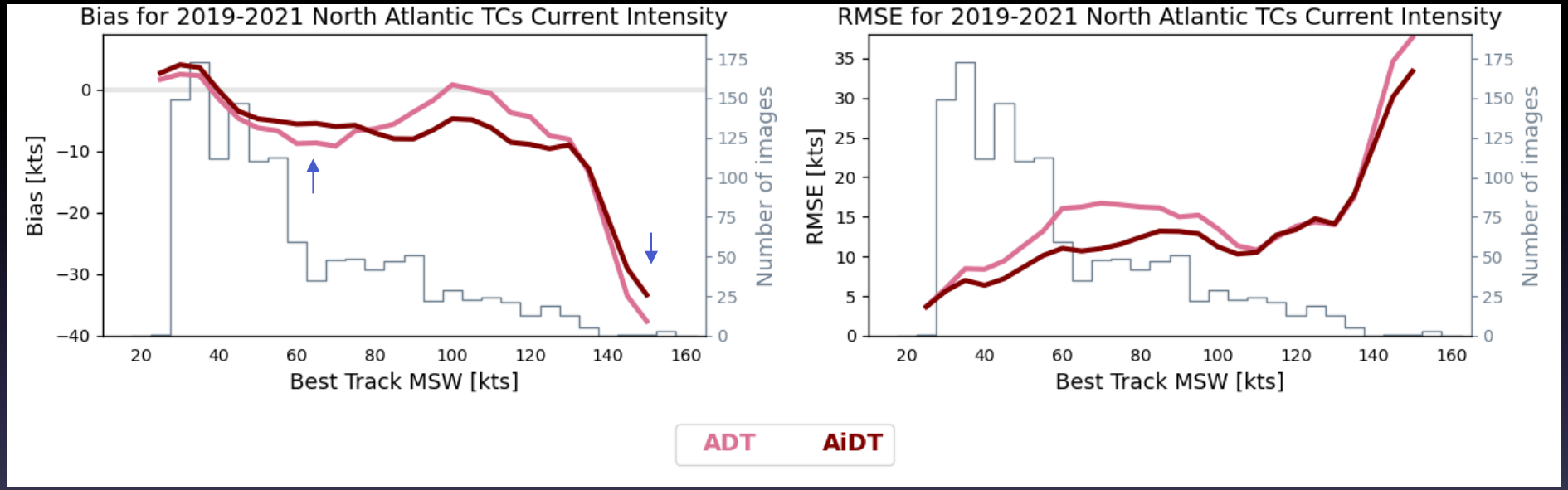
AiDT impacts on ADT performance by Scene Type

- 2017 Independent data set
- Using AiDT Regression-based global model
- AiDT reduces error most for ADT estimates using Curved Band and Shear scene types as well as also significantly reducing biases, especially for Shear estimates
- Curved Band and Shear scenes are least studied scene types in ADT algorithm
- +/- Bias equals MSW over/underestimate versus Best Track values (knots)

ADT Scene Type	Sample Size	ADT			AiDT		
		Bias	MAE	RMSE	Bias	MAE	RMSE
Eye	2590	0.10	8.66	11.03	-1.43	6.55	8.30
CDO	7246	2.20	8.92	11.18	-0.67	6.53	8.30
Curved Band	5670	-1.50	8.54	11.17	0.57	5.75	7.27
Shear	3166	-3.21	7.36	10.12	-0.41	4.95	6.35

Advanced (AI-enhanced) Dvorak Technique (AiDT)

2019-2021 Performance Statistics



Primary improvements in bias for strong TS to CAT 1 and also at Cat 5

D-MINT and D-PRINT

(Formally DMN and OPEN-AIR)

- Can we use another method of machine learning, called convolutional neural networks, to estimate current TC intensity

- Why 2 models?
  - D-MINT which uses MW imagery in addition to IR imagery
    - MW imagery is not always available
    - MW imagery has a lag, it can take 1-3 hours for it to be available.

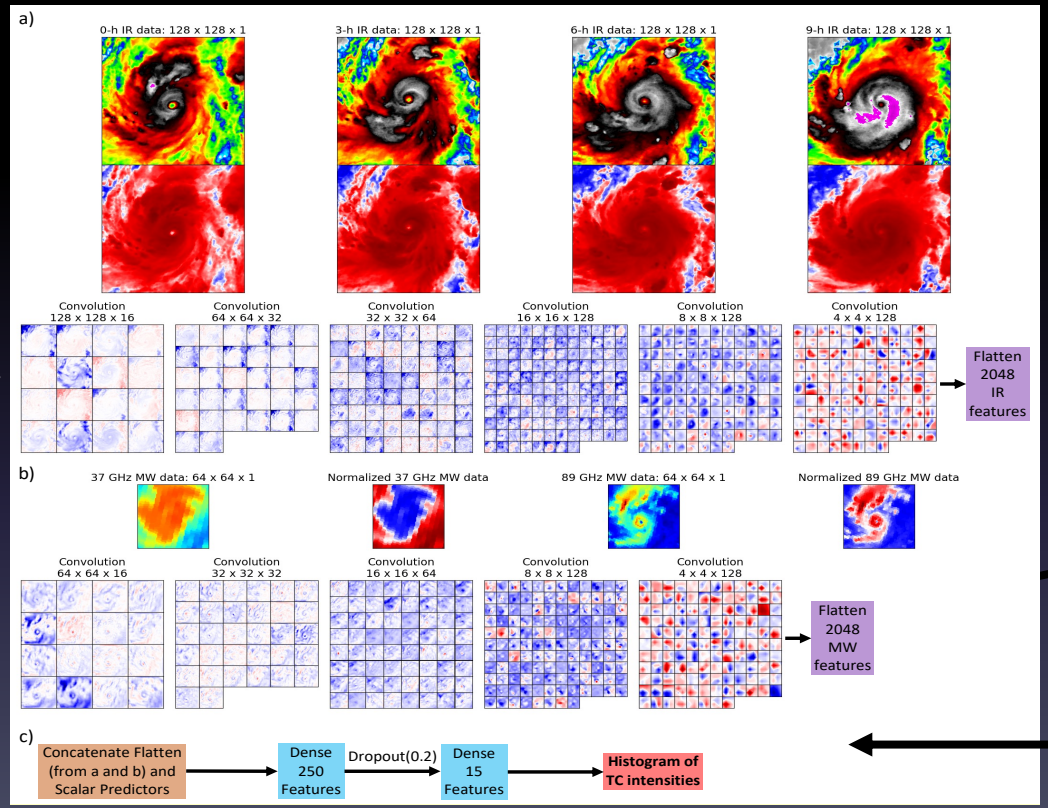
  - D-PRINT is constantly available since it only uses IR imagery and only has a 30 minute lag.

D-MINT and D-PRINT

Input Features:
IR data: 128x128 grid over ~6 X 6° area centered on TC, normalized.

6 convolution layers where the scale gradually increases and more feature maps are added.

Input Features:
Add normalized scalar location and time features.



D-MINT
Steps a), b) and c)

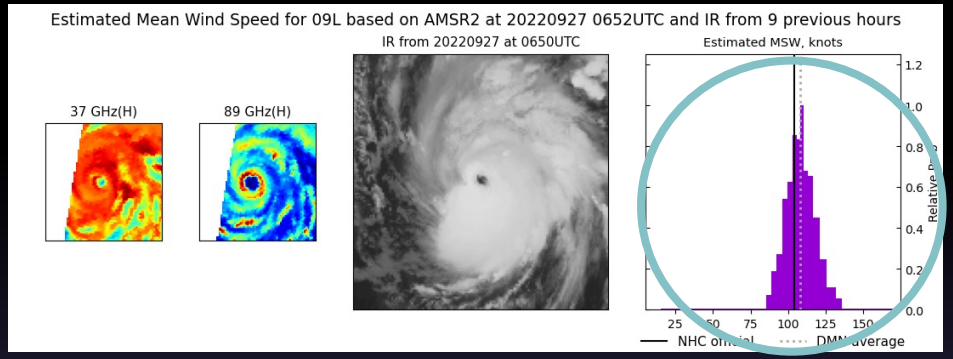
D-PRINT
Steps a) and c) only

Input Features
MW data: 64 x 64 grid over ~3.2 X 3.2° area centered on TC, normalized.

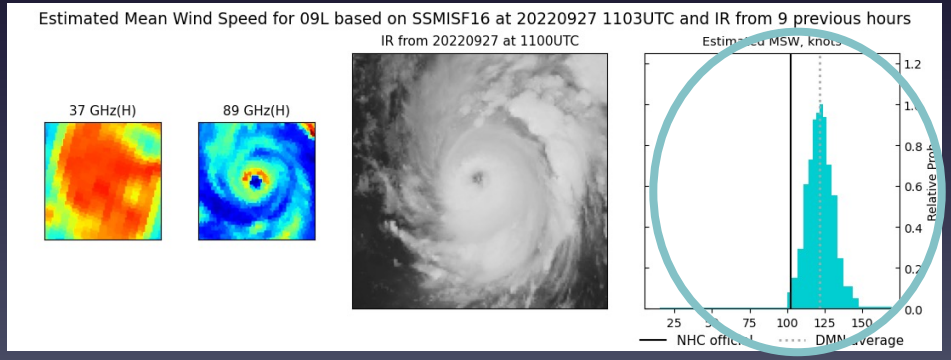
5 convolution layers (not included in D-PRINT)

Output: 15 quantiles of TC intensity probabilities

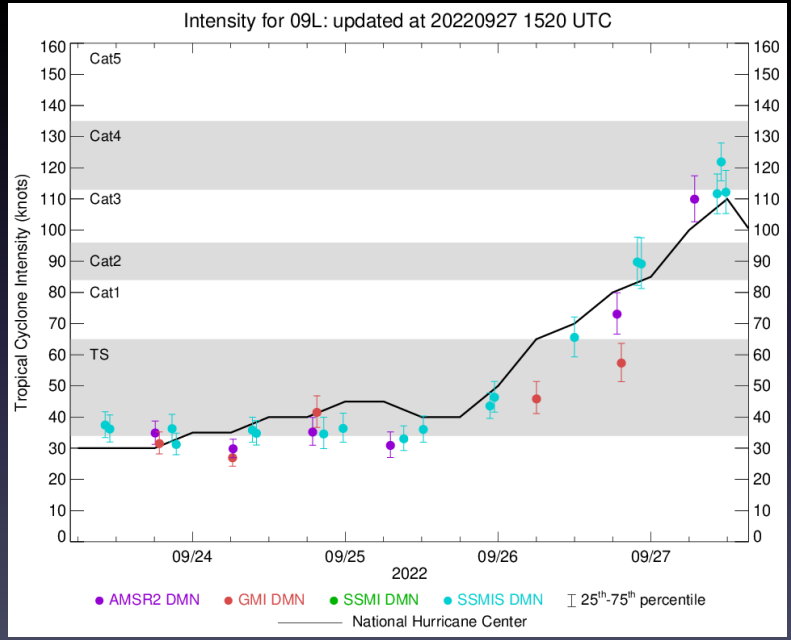
D-MINT and D-PRINT



Good agreement with BT

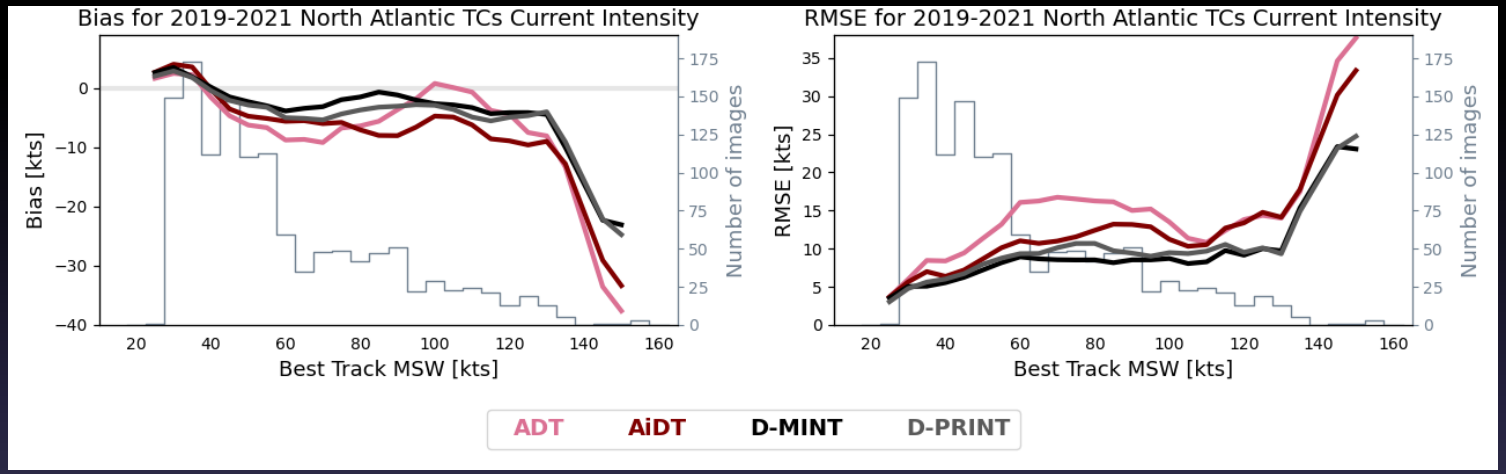


Beginning ERC process



D-MINT and D-PRINT

2019-2021 Statistical Results



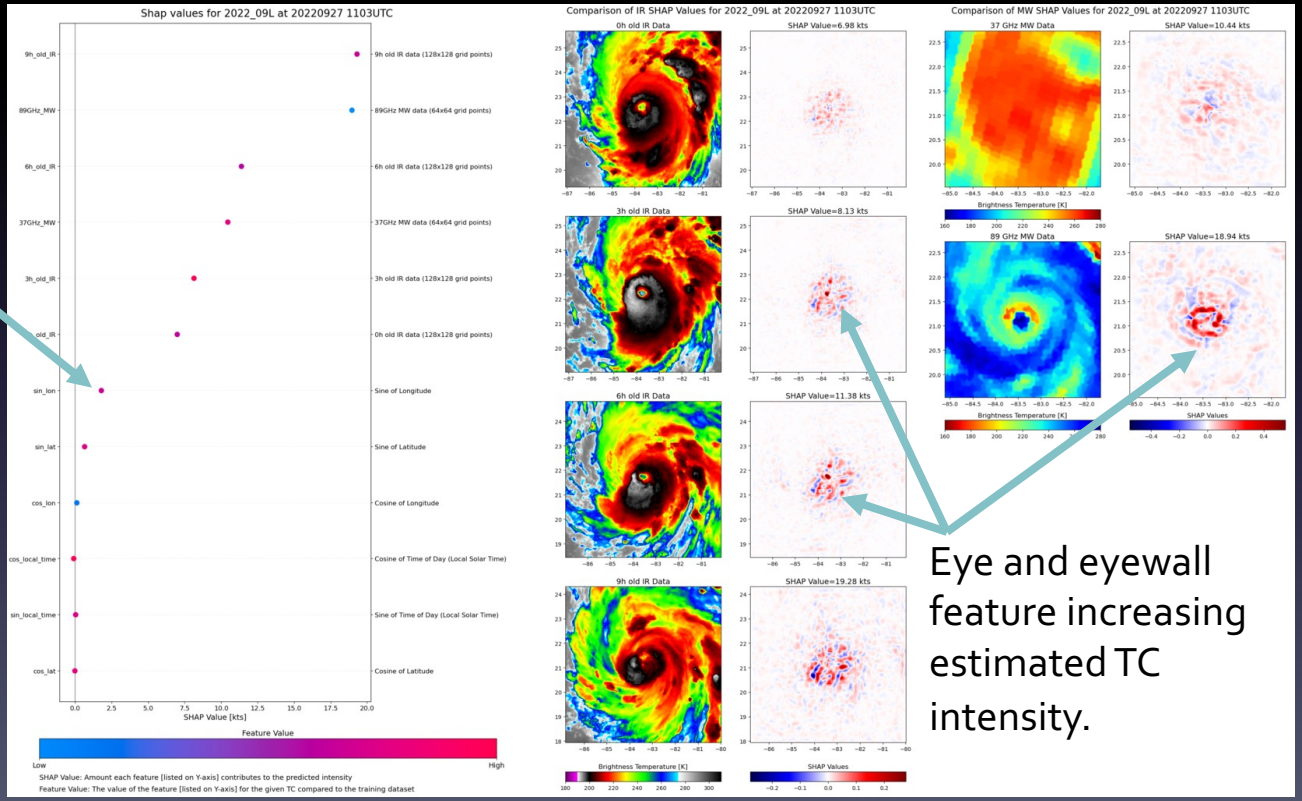
D-MINT is more skillful than D-PRINT, but has a lower temporal resolution.
D-MINT and D-PRINT are more skillful than ADT or AiDT.
They have a less negative bias and lower RMSE.*

* Largest errors at highest intensity may be influenced by SFMR inputs to BT which are still being evaluated.

D-MINT and D-PRINT

What features in satellite imagery indicate a strong TC? SHAP values indicate what AI identifies.

Ian is in a good location to be more intense.

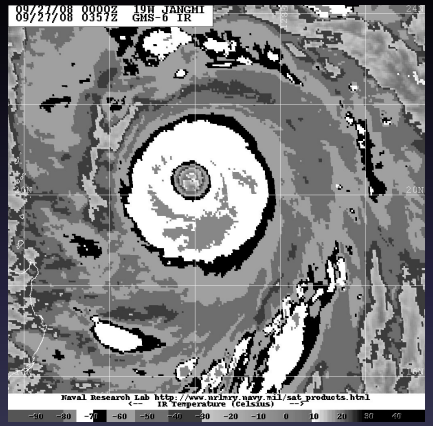


Eye and eyewall feature increasing estimated TC intensity.

D-MINT and D-PRINT can compare current and older imagery, which is why older image has more impact on TC intensity.

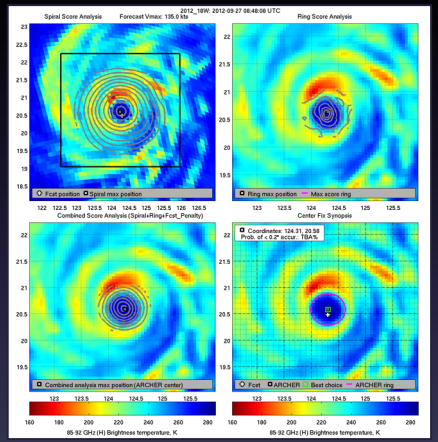
SATellite CONsensus (SATCON)

- In order to account for storms with different structures an "all the above" approach is needed.
- Multiple satellite scanning strategies (Geo/LEO)
- Multiple channels to measure the various TC features that are related to intensity. (subjective/objective)



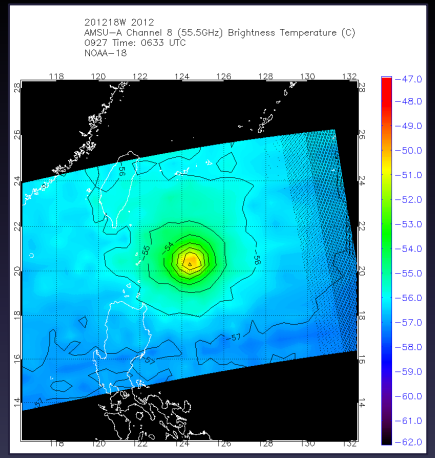
Geostationary
(G-16/G-18/H9)

- Intensity
- Position
- Structure



MW Imager
(AMSR2, GMI, SSMIS)

- Position
- Structure



MW Sounder
(AMSU, SSMIS, ATMS)

- Intensity
- Structure

SATCON

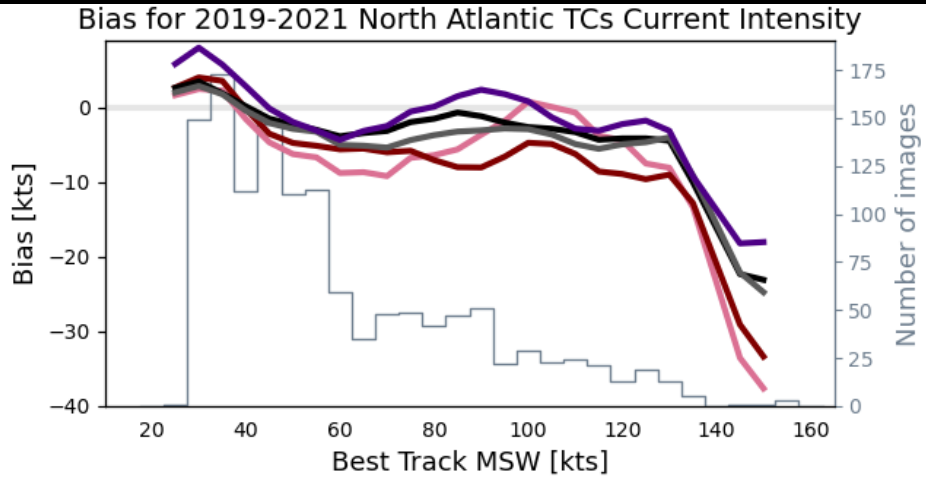
- Current SATCON members
  - LEO microwave sounder based
    - AMSU (Channels 6-8 and 16)
      - NOAA-15,-16,-18,-19 (N16 AMSU-A failure 2014)
      - Metop A-C (Metop-A Channel 7 failure 2008)
    - SSMIS (Channels 3-5 and 17)
      - F16-F19 (F18 failure 2015, F19 failure 2016)
    - CIMSS ATMS (Channels 7-9)
      - SNPP/N-20
    - CIRA ATMS (Channels 1-22)
      - Used when eye > 40km
  - GEO IR imager based
    - ADT

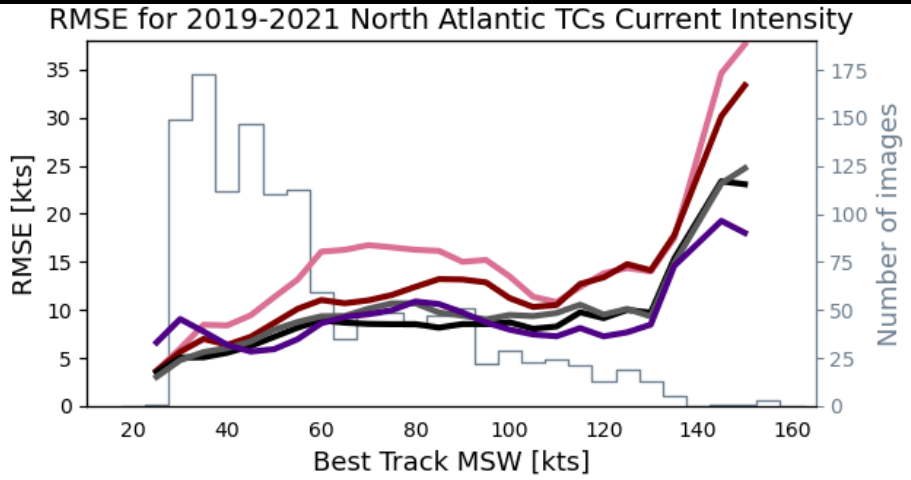
Also Displayed

- Warning agency BT
- SMAP
- SAR
- D-MINT (previously DMN)

SATCON

2019-2021 Statistical Results





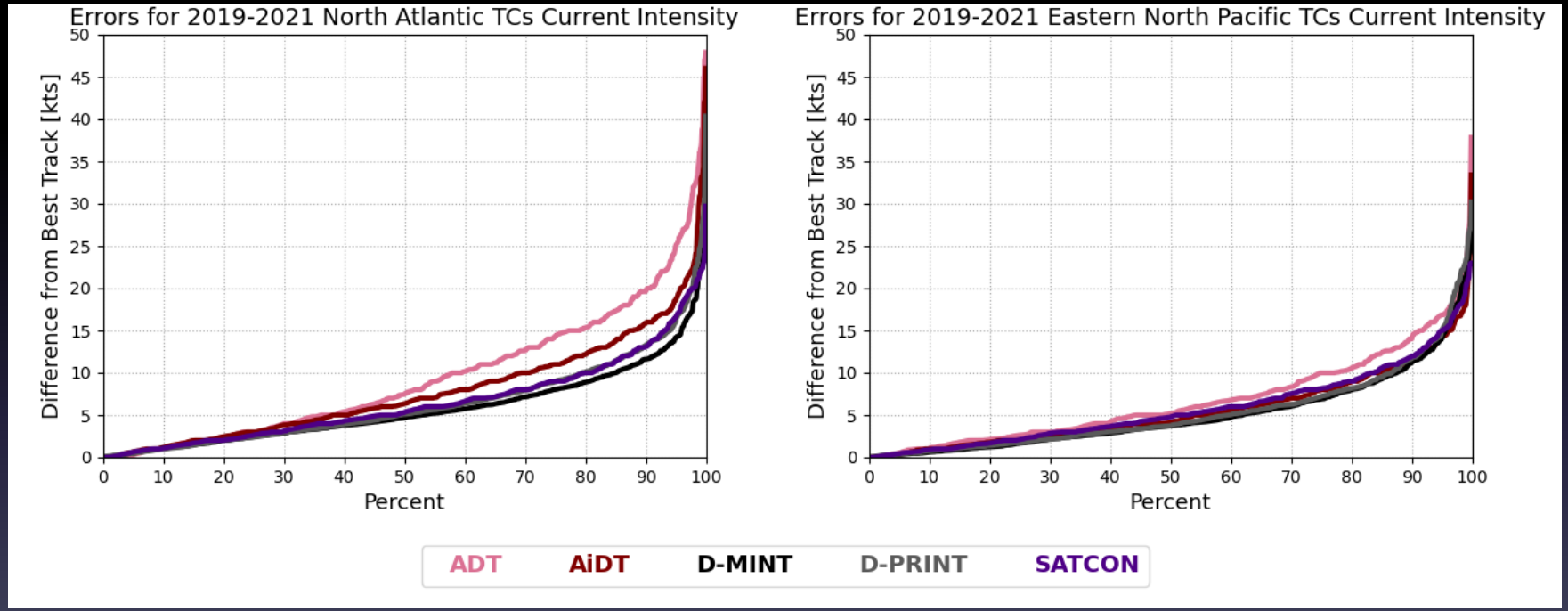
ADT AiDT D-MINT D-PRINT SATCON

SATCON is the most skillful for TC intensity > 95 kts. It underestimates strong TCs the least.

SATCON tends to overestimate weak TCs (< 45 kts) some due to sounder members

SATCON

2019-2021 Statistical Results

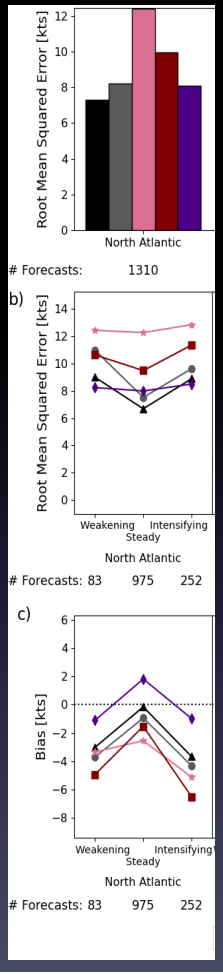


Skill as a function of percentage within BT. 90% of SATCON estimates within 12 knots of BT.
SATCON DOES influence BT, especially when recon is not available

SATCON

Future Directions

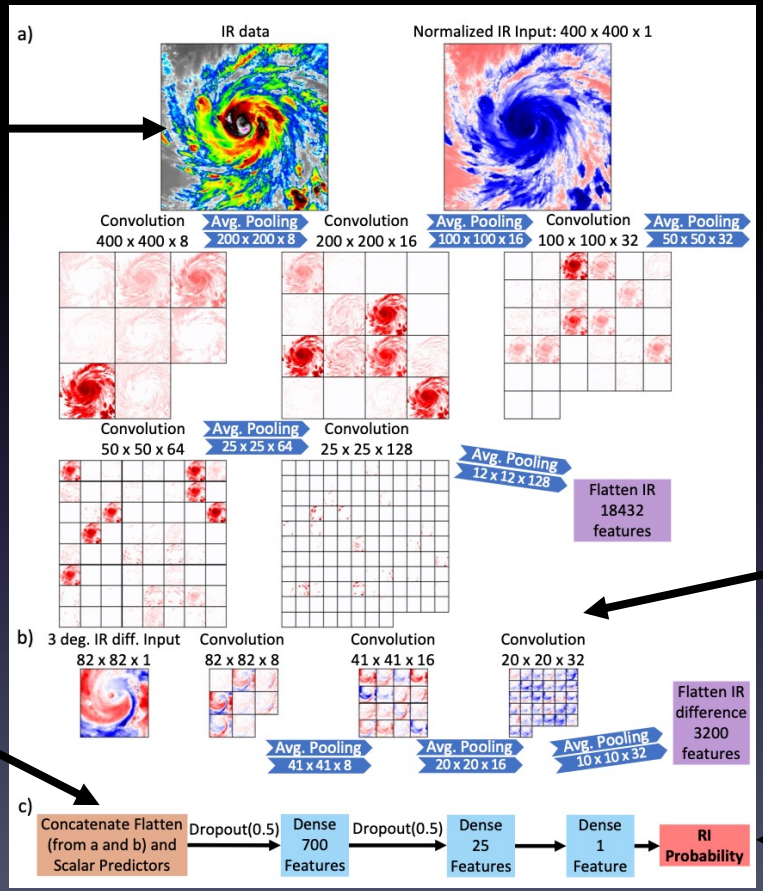
- Future members of the CIMSS SATCON
  - New Members
    - "D-MINT" Deep Learning Model
      - Lower RMSE overall
      - More Skillful for steady TCs (-10kt < 12h intensity change < 10 kts) but less skillful for weakening and intensifying TCs.
    - CIMSS AiDT Deep Learning Model
      - Could balance overestimation of steady TCs?
      - Blended with ADT as an ensemble member
    - TROPICS
      - Microwave sounder intensity (TCIE) similar to AMSU/ATMS but better temporal frequency



AI-RI

IR data: 400x400 grid at 4km resolution, normalized.

5 convolution and pooling layers where the scale gradually increases and more feature maps are added.



AI-RI is an ensemble of output from 5 different CNNs with the same configuration

IR differencing data: 82 x 82 grid at 4km resolution, normalized.

3 convolution and pooling layers.

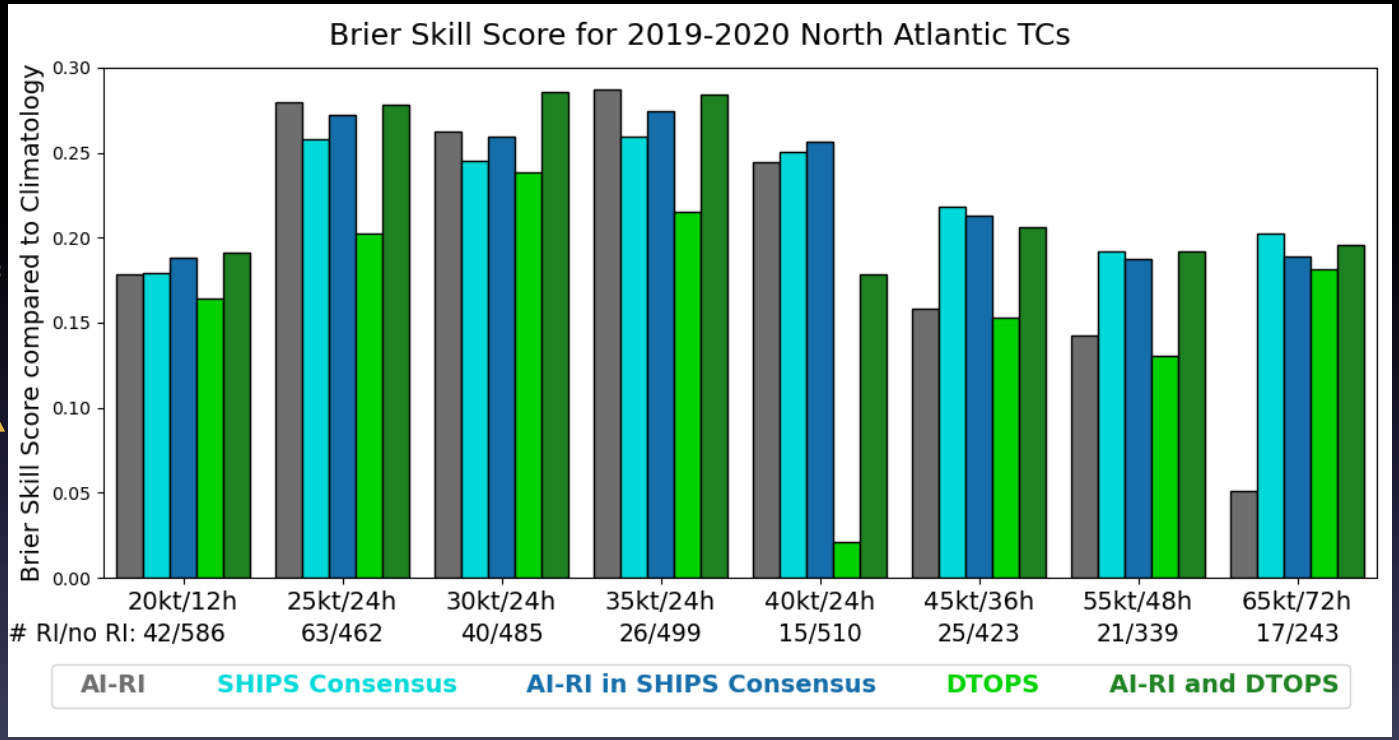
Add normalized scalar features from SHIPS lsdiag file.

Probability of RI from 0-1

AI-RI

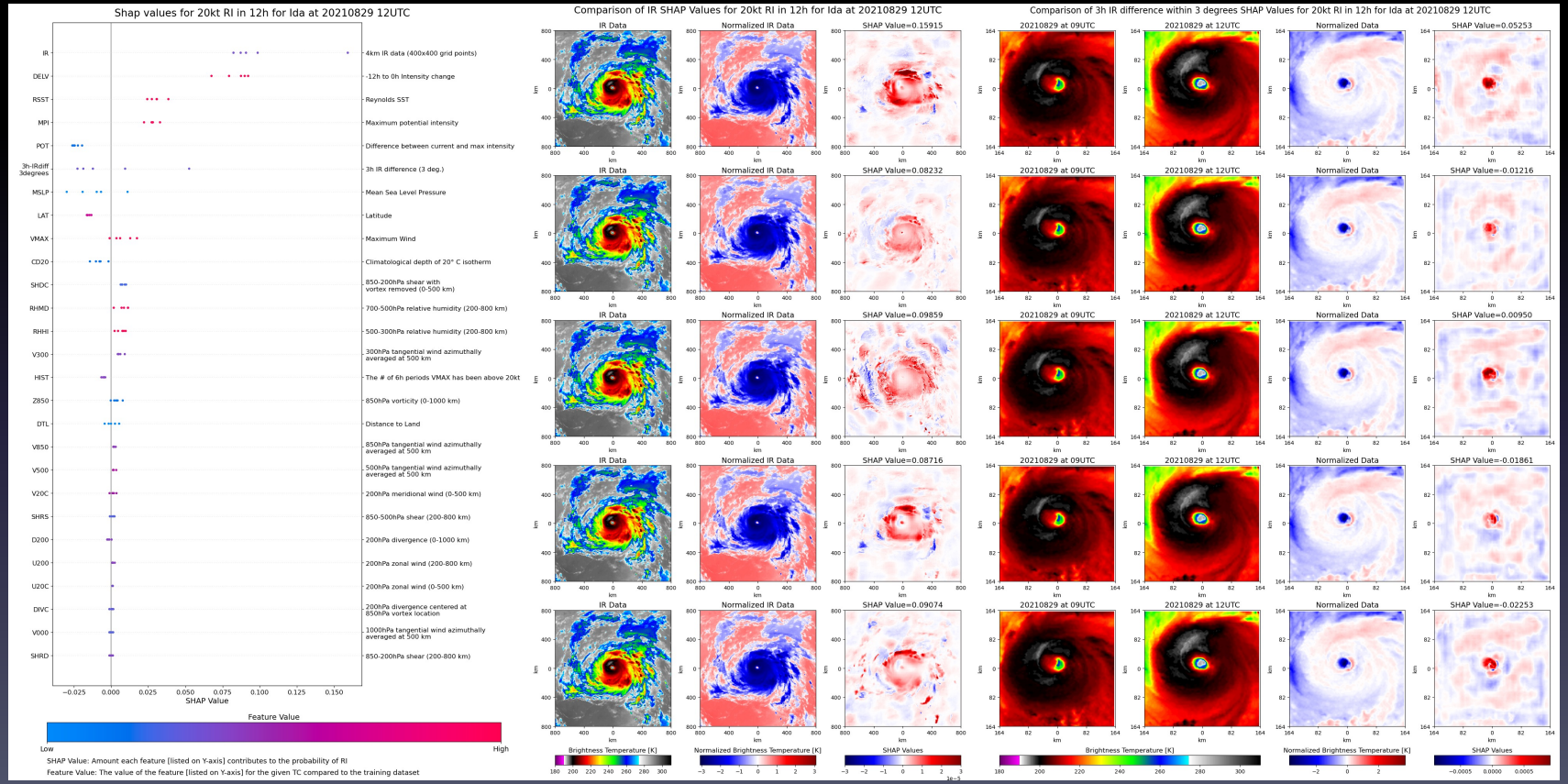
Brier Skill Score: higher = more skillful

better



AI-RI is more skillful than SHIPS Consensus for 25-, 30-, and 35-kt RI thresholds.
Including AI-RI in the SHIPS Consensus average is more skillful than SHIPS Consensus for all 12h and 24h RI.
AI-RI is more skillful than DTOPS for 7 RI thresholds.

AI-RI

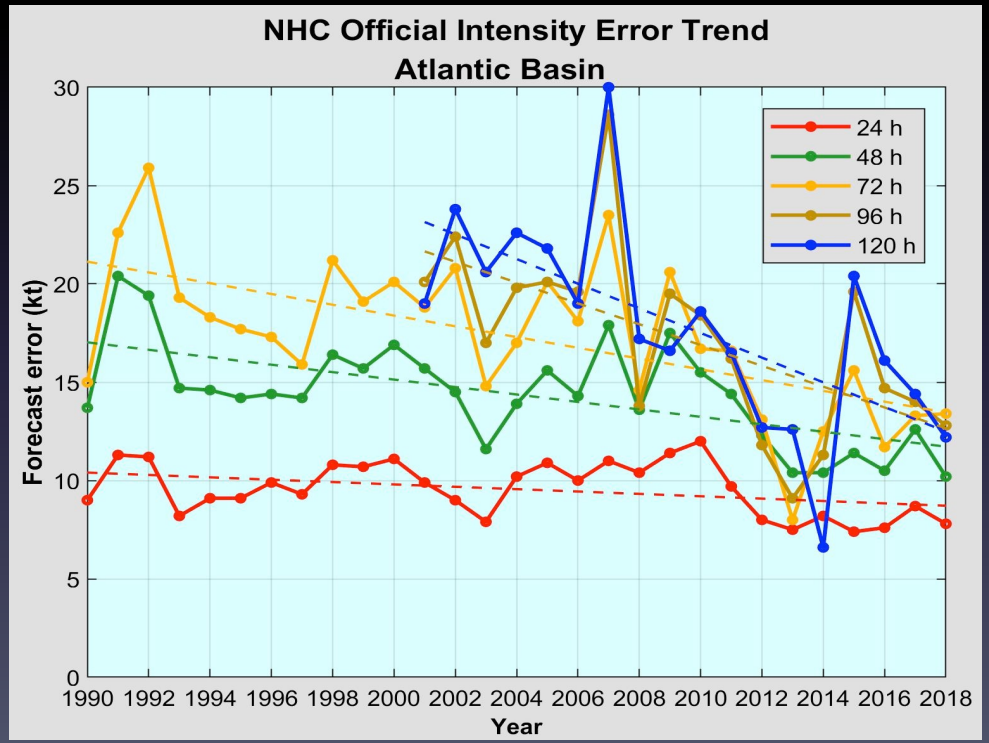

Shap values for 20kt RI in 12h for Ida at 20210829 12UTC
IR
DELV
RSST
MPI
POT
3h-IRdiff_3degrees
MSLP
LAT
VMAX
CD20
SHDC
RHMD
RHHI
V300
HIST
Z850
DTL
VB50
V500
V20C
SHRS
D200
U200
U20C
DIVC
V000
SHRD
4km IR data (400x400 grid points)
-12h to 0h Intensity change
Reynolds SST
Maximum potential intensity
Difference between current and max intensity
3h IR difference (3 deg.)
Mean Sea Level Pressure
Latitude
Maximum Wind
Climatological depth of 20° C isotherm
850-200hPa shear with vortex removed (0-500 km)
700-500hPa relative humidity (200-800 km)
500-300hPa relative humidity (200-800 km)
300hPa tangential wind azimuthally averaged at 500 km
The # of 6h periods VMAX has been above 20kt
850hPa vorticity (0-1000 km)
Distance to Land
850hPa tangential wind azimuthally averaged at 500 km
500hPa tangential wind azimuthally averaged at 500 km
200hPa meridional wind (0-500 km)
850-500hPa shear (200-800 km)
200hPa divergence (0-1000 km)
200hPa zonal wind (200-800 km)
200hPa zonal wind (0-500 km)
200hPa divergence centered at 850hPa vortex location
1000hPa tangential wind azimuthally averaged at 500 km
850-200hPa shear (200-800 km)
SHAP Value
Feature Value
Low
High
SHAP Value: Amount each feature [listed on Y-axis] contributes to the probability of RI
Feature Value: The value of the feature [listed on Y-axis] for the given TC compared to the training dataset
Comparison of IR SHAP Values for 20kt RI in 12h for Ida at 20210829 12UTC
IR Data
Normalized IR Data
SHAP Value=0.15915
SHAP Value=0.08232
SHAP Value=0.09859
SHAP Value=0.08716
SHAP Value=0.09074
Brightness Temperature [K]
Normalized Brightness Temperature [K]
SHAP Values
Comparison of 3h IR difference within 3 degrees SHAP Values for 20kt RI in 12h for Ida at 20210829 12UTC
20210829 at 09UTC
20210829 at 12UTC
Normalized Data
SHAP Value=0.05253
SHAP Value=-0.01216
SHAP Value=0.00950
SHAP Value=-0.01861
SHAP Value=-0.02253
km

M-PERC

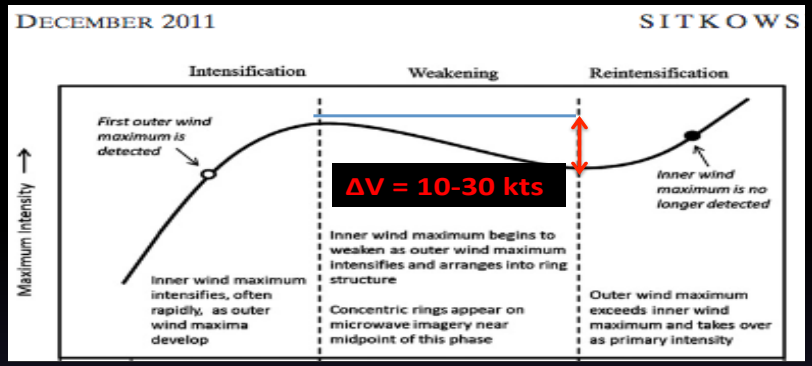
Goal – Make incremental improvements to short range forecasts by giving forecasters a tool that objectively identifies Eyewall Replacement Cycle (ERC) onset.

Microwave Probability of Eyewall Replacement (M-PERC) model

M-PERC was developed using Atlantic data but runs in all basins



M-PERC

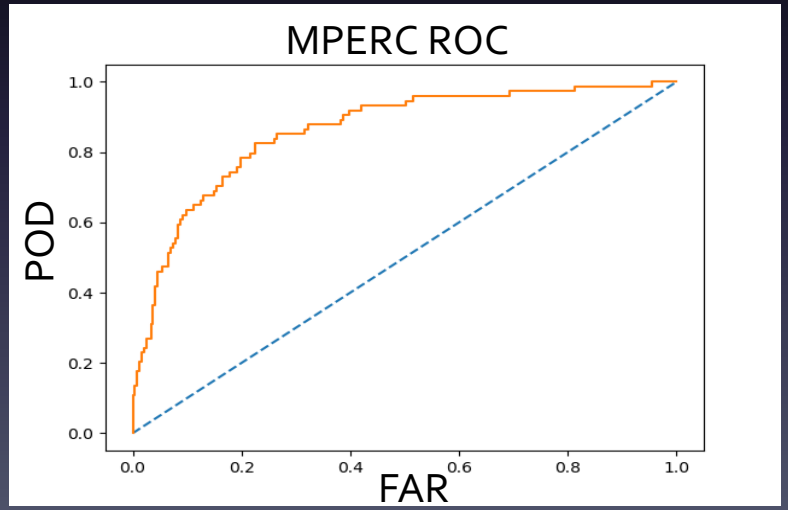


Guidance to forecasters:

- Increase attention when probabilities exceed 25%.
- Probabilities > 70% likely will result in weakening

Model is sensitive to Vmax.

- Probabilities only output for Vmax > 65 knots.
- Uncertainty of 10 knots in Vmax results in ~ 10% change in M-PERC



Performance

Use a probability of 13% for ERC (Kossin and Sitkowski 2009)
2016-2019 Atlantic
BSS for Atl-trained model 0.40 compared to 0.27 using only Vmax

2012-2021 East/Central Pacific. (11% for climo)
BSS for Epac/Cpac model 0.41 (using subset of Atl predictors)

M-PERC

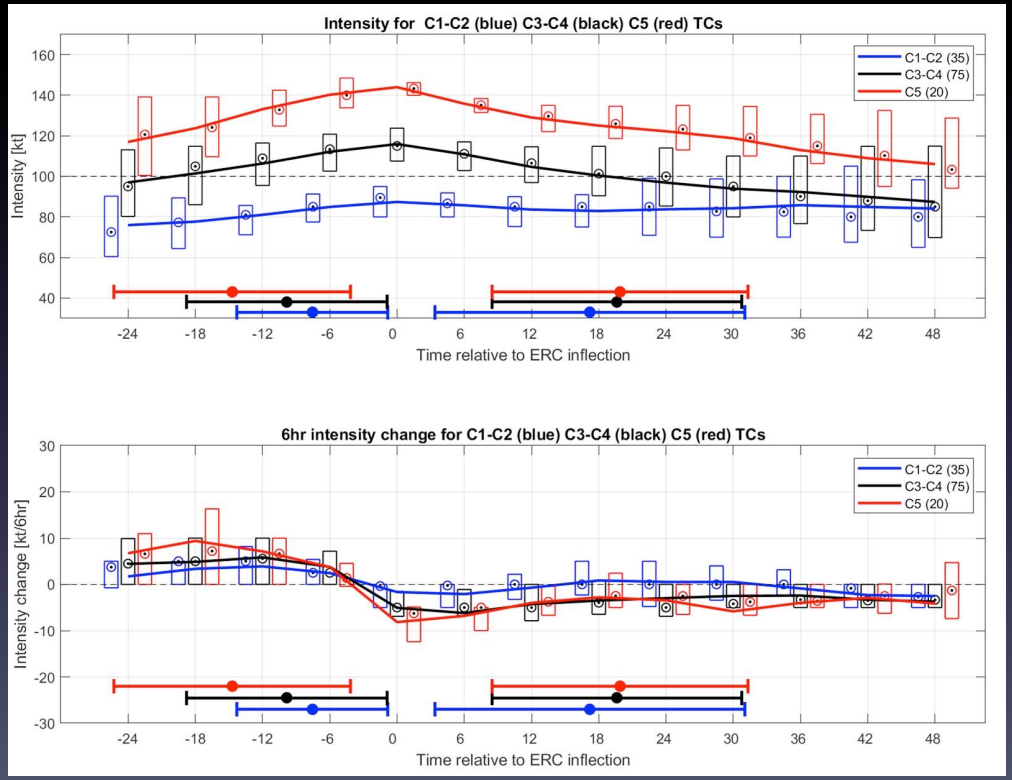
TC intensity change/ERC length for ERC events binned by intensity category- ATL
Moving beyond the ERC "weakening" paradigm

How can forecasters adjust intensity forecasts based on M-PERC?

Cat 1-2 ERCs are faster and result in less weakening or none at all (a pause in RI)

Cat 4-5 ERCs take longer and result in more weakening. TCs may not return to previous intensity (LMI occurs prior to ERC)

M-PERC peaks at different values based on storm intensity and phase. Smaller peaks = fast ERCs
Larger values tend to result in storm weakening.

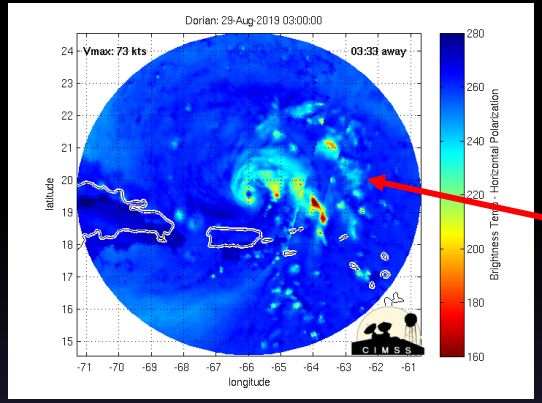


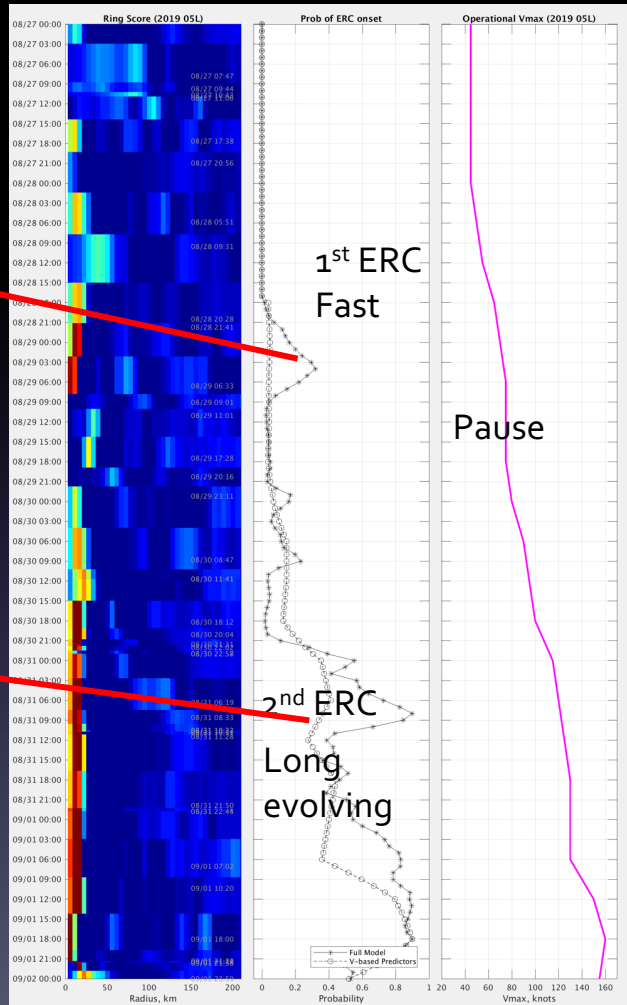
M-PERC

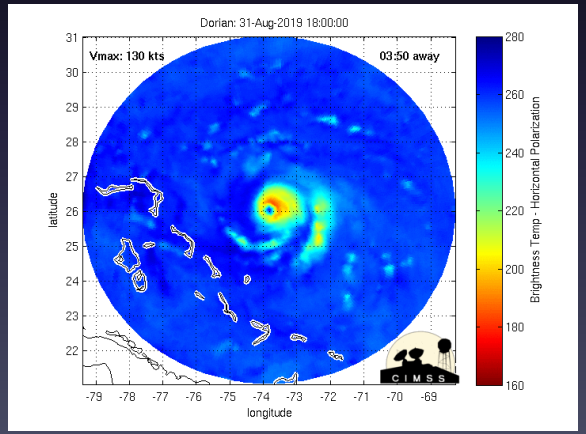
Hurricane Dorian 2019

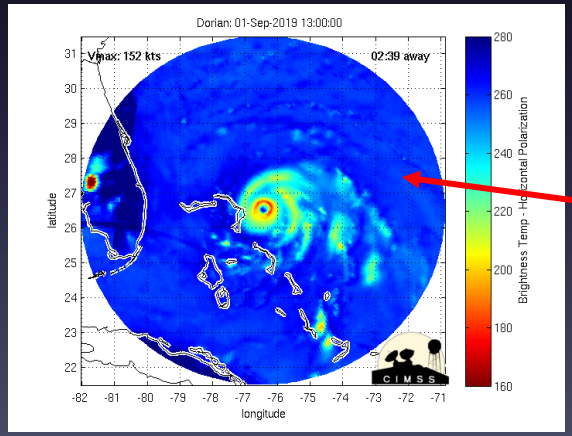
Types of ERC Events
Fast Evolving: early events with lower probability that has less impact on Vmax.

Higher Probability: Larger impact on Vmax. More likely to cause weakening.



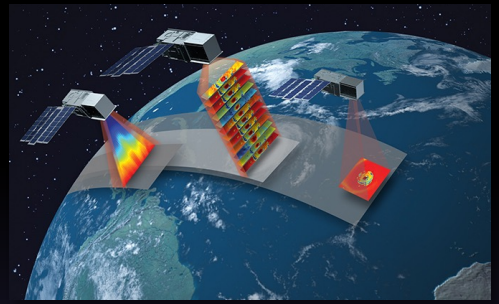






Kossin, J. P., D. C. Herndon, A. J. Wimmers, X. Guo, and E. S. Blake, 2022: M-PERC pub: *Wea. Forecasting*, in review

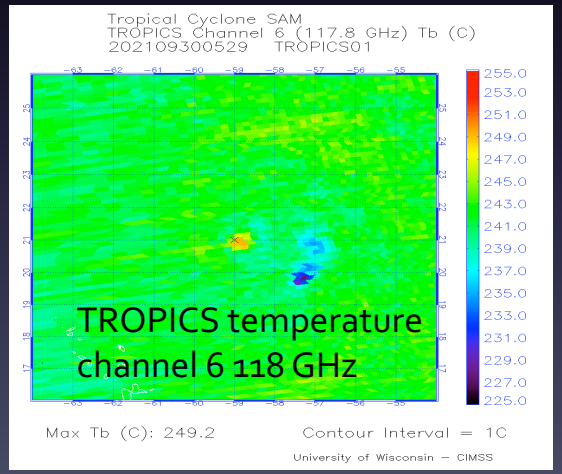
TROPICS



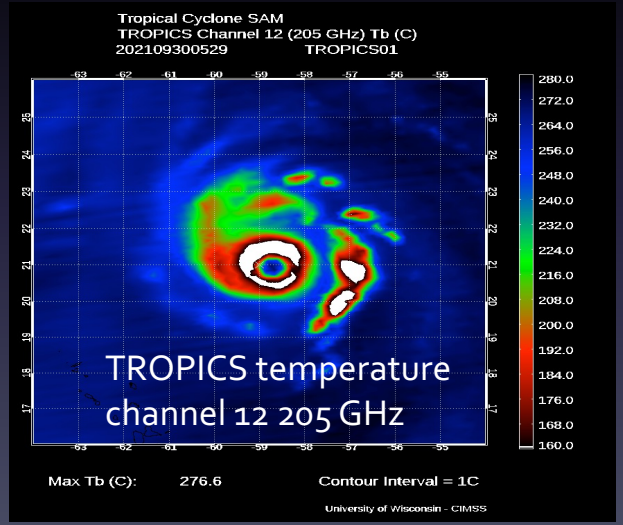
The Time-Resolved Observations of Precipitation structure and storm Intensity with a Constellation of Smallsats (TROPICS). NASA Earth Venture class mission that began with the launch of a single-unit TROPICS Pathfinder satellite on June 30th, 2021

4 Satellites launched in two phases this spring

Temperature, moisture, TC intensity, structure and precipitation products.



Warm anomaly used to estimate TC intensity similar to AMSU/ATMS

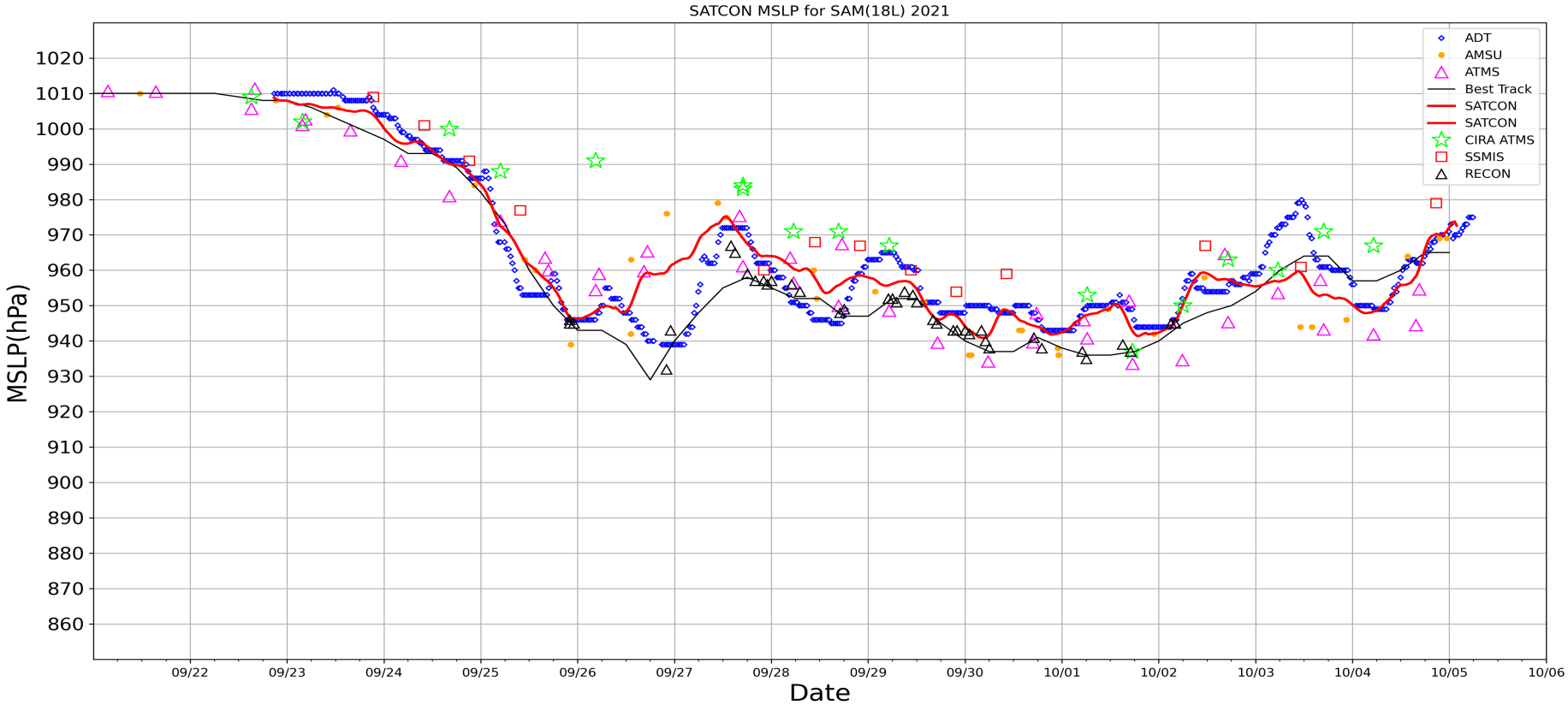


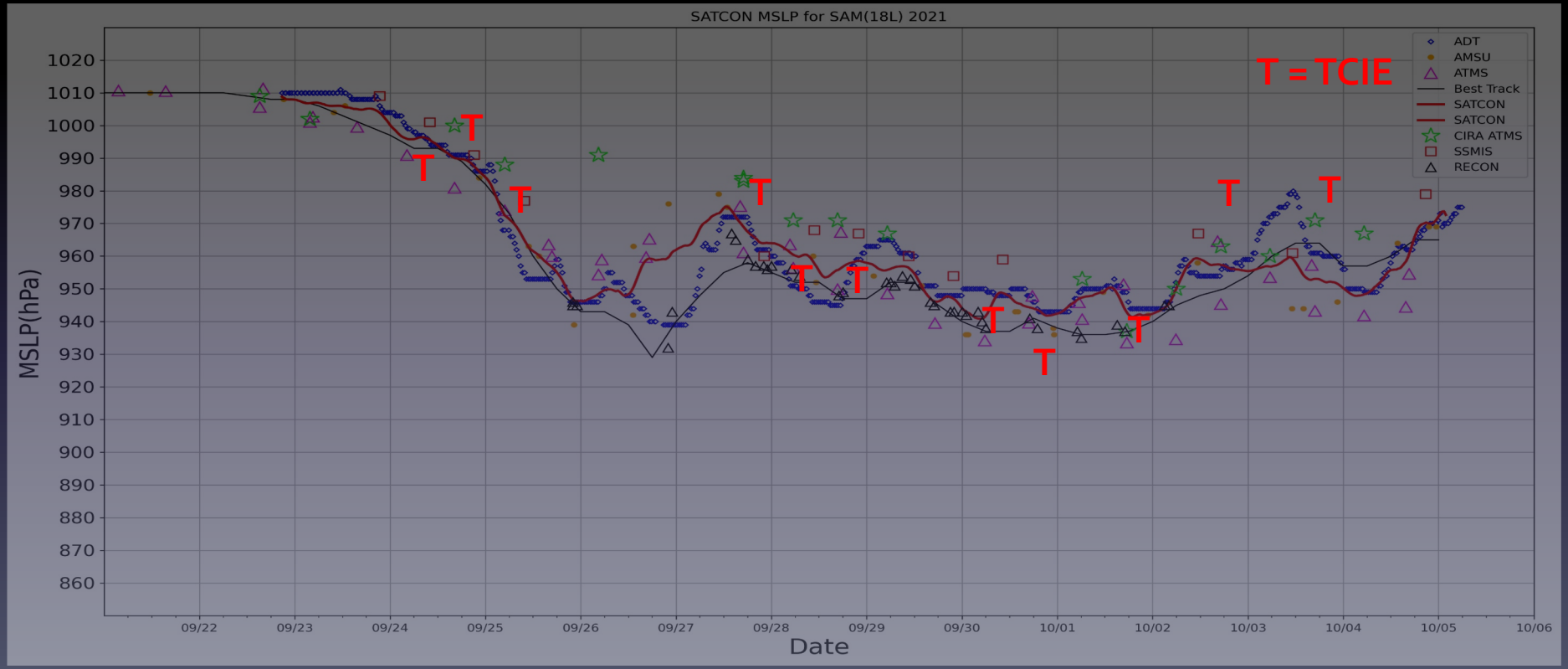
183 -205 GHz provides information about storm structure and inner core organization.

CIMSS TROPICS TC Intensity Estimation:
2021 EIGHTEEN (SAM) 2021 0930 0529Z
Latitude: 20.987 Longitude: -58.746
Storm position corresponds to TROPICS CH7 FOV 60 [1<--->96]
---------- SAT is TROPICS Path ----------
| Estimated MSLP: 961.0 hPa
| Estimated Maximum Sustained Wind: 90.0 kts
Channel 7 Tb Anomaly: 6.2
Channel 6 Tb Anomaly: 7.4
EYE: 46.0301 km
Environmental Pressure: 1011
ARCHER score used is: 77.5

TROPICS

SATCON plot for Hurricane Sam 2021



TROPICS

TROPICS TCIE compared to SATCON plot for Hurricane Sam 2021