2021 RA-IV WMO Workshop on Hurricane Forecasting and Warning

UW-CIMSS Products for TC Centering, Intensity and Structure

Derrick Herndon, Tony Wimmers, Tim Olander, Chris Velden

CIMSS -- Cooperative Institute for Meteorological Satellite Studies
University of Wisconsin- Madison

James Kossin

NOAA National Centers for Environmental Information (NCEI)

Duty Station: Madison, Wisconsin

The Advanced Dvorak Technique Updates- Version 9.0

ARCHER-2 implemtation
Subtropical classifications
Extratropical transition
Wind Radii estimation

AiDT

The Advanced (AI-enhanced) Dvorak Technique

Improving the ADT using Machine Learning

Tim Olander, Tony Wimmers and Chris Velden

Advanced (AI-enhanced) Dvorak Technique (AiDT)

Overview

- **Current Deep Learning (DL) models being developed focus on directly interrogating satellite imagery and deriving objective maximum sustained wind (MSW) speed estimates**

- **These DL models can be time consuming and computationally expensive to derive**
  - Great care must be given to make sure the satellite data is homogeneous

- **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

- **Can a DL model using ADT history file parameters be derived to improve the performance of the algorithm, especially to aid in situations were 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

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)

Data Description

- ADT history file parameters served as model "input" FEATURE DATA
  - ADT-Version 9.0 wind speed estimates for all global TCs from 2005-2018
    - 30-minute temporal resolution; ocean estimates only
    - IR Window image (~10.7μm) from satellite with lowest viewing angle
    - Analysis for all storms with Best Track intensity >= 30 knots
    - **26 different ADT history file parameters utilized**
      - *Cloud and eye temperatures, storm position, scene type, regression values, etc.*

- Final Best Track are used as model "ground truth" LABEL DATA
  - **NHC/JTWC maximum wind speed** values are linearly interpolated to ADT analysis times

- Models derived using combined global dataset but applied to storms in different basins
  - Five ocean basins : North Atlantic, East/Central Pacific, Western North Pacific, North Indian Ocean, and South Pacific/Indian Ocean

Advanced (AI-enhanced) Dvorak Technique (AiDT)

Data Description

- Data from 2005-2016 (minus three years) used as model **TRAINING** data set
  - Machine Learning model derived using this data set
- 2007, 2010, and 2014 data are used at model **VALIDATION** data set
  - Validation data is used to check model performance and help tune/optimize model
  - Years selected to provide a representation of all TC intensities in all five ocean basins
- 2017 and 2018 data are independent **TEST** data set
  - Data not utilized until model is fully derived and tuned with training and validation data
- Total number of ADT records used in each set *(global values)*
  - Training: **146,902** (64.4%)
  - Validation: **43,052** (18.9%)
  - Test: **38,008** (16.7%)

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

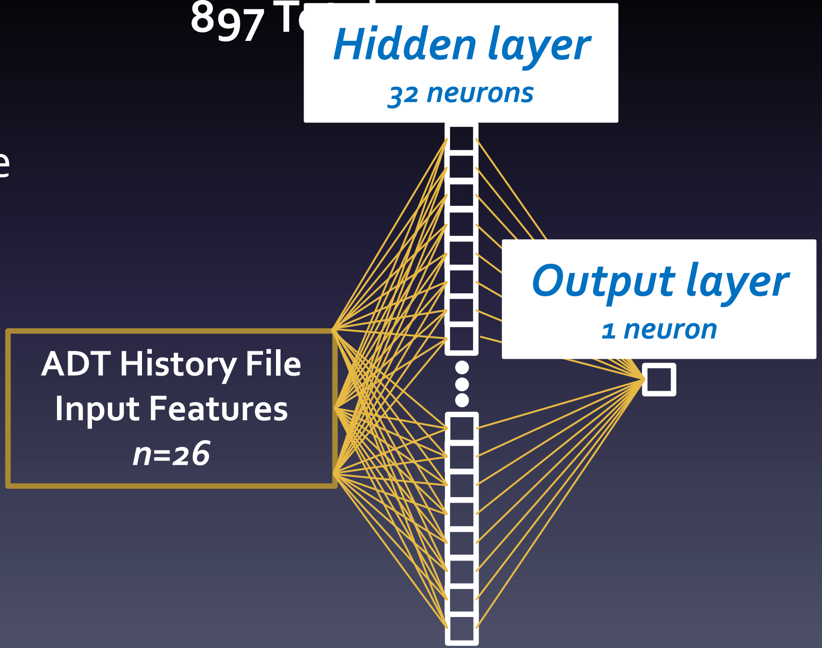
- **A 3-hour time weighted averaging scheme is implemented to dampen out small fluctuations between consecutive intensity estimates**
  - Time averaging reduces error by about 0.3kt

Trainable Parameters

L1: 26 X 32 + 32 = 864

L2: 32 X 1 + 1 = 33

897 T



2017 Statistical Results

- **2017 Regression-base network Independent Test Data Set**
  - Table below shows statistical comparisons using global-derived model maximum sustained wind estimates (MSW) for each specific basin and combined global "All Basins" set
    - **ADT – Advanced Dvorak Technique – Version 9.0**
    - **AiDT-R – AiDT (unaveraged)**
    - **AiDT – AiDT (3-hour time-weighted average)**
    - *+/- Bias equals MSW over/underestimate versus Best Track values (knots)*

	Atlantic			**East Pacific**			**West Pacific**		
Network	Bias	MAE	RMSE	Bias	MAE	RMSE	Bias	MAE	RMSE
ADT	-0.91	9.50	**12.33**	-0.15	7.38	**9.44**	-1.87	8.47	**10.88**
AiDT-R	0.49	6.89	**8.76**	-0.13	5.50	**7.04**	-0.60	6.02	**7.56**
AiDT	0.33	6.59	**8.44**	-0.13	5.30	**6.77**	-0.86	5.89	**7.35**
# records	5188	5188	5188	3677	3677	3677	5475	5475	5475

	South Pacific			**North Indian**			**All Basins**		
Network	Bias	MAE	RMSE	Bias	MAE	RMSE	Bias	MAE	RMSE
ADT	2.71	8.43	**10.70**	5.03	7.51	**9.96**	-0.13	8.50	**10.98**
AiDT-R	0.80	6.52	**8.29**	1.50	5.90	**8.15**	-0.18	6.26	**7.98**
AiDT	-0.98	6.27	**7.99**	1.04	5.33	**7.49**	-0.35	6.03	**7.70**
# records	3766	3766	3766	566	566	566	18672	18672	18672

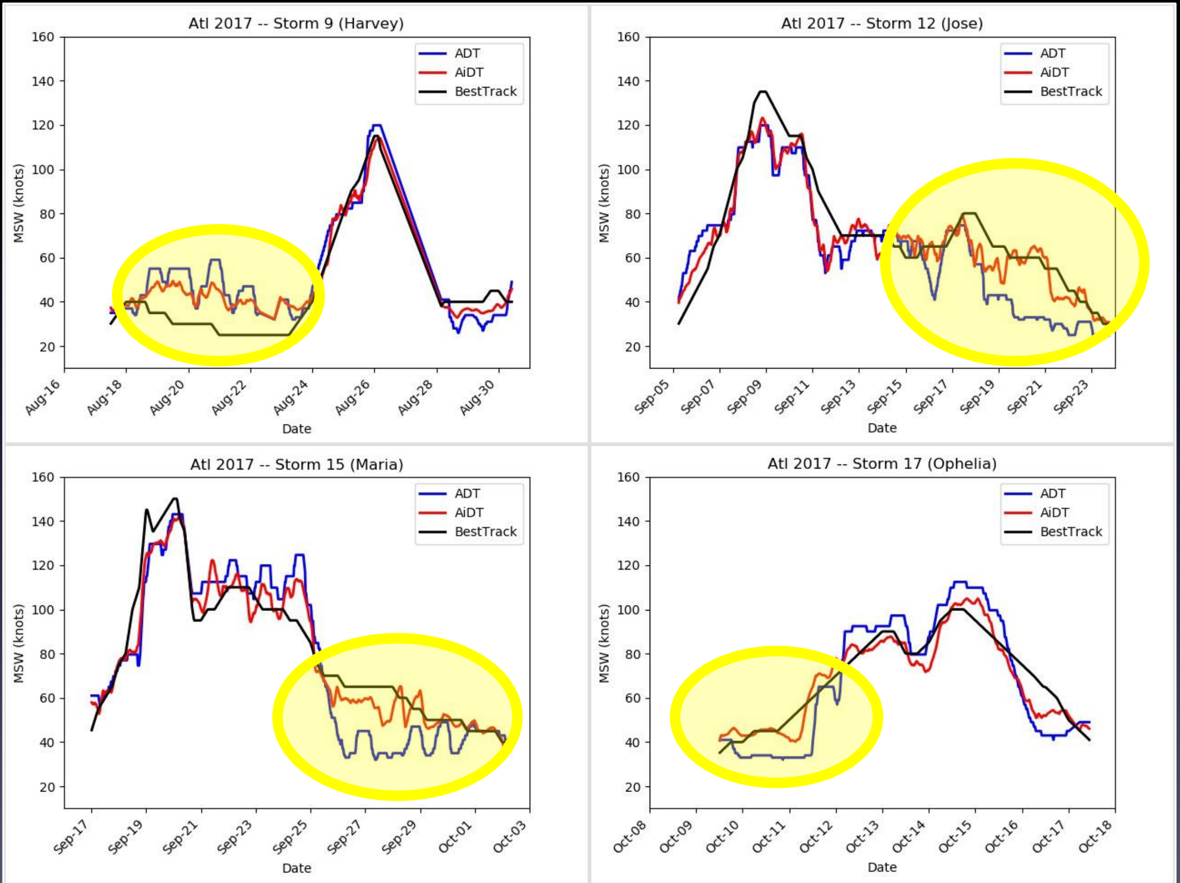
Advanced (AI-enhanced) Dvorak Technique (AiDT)

2017 Storm Examples

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

  - *Note impact of AiDT during formation and dissipation stages*

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



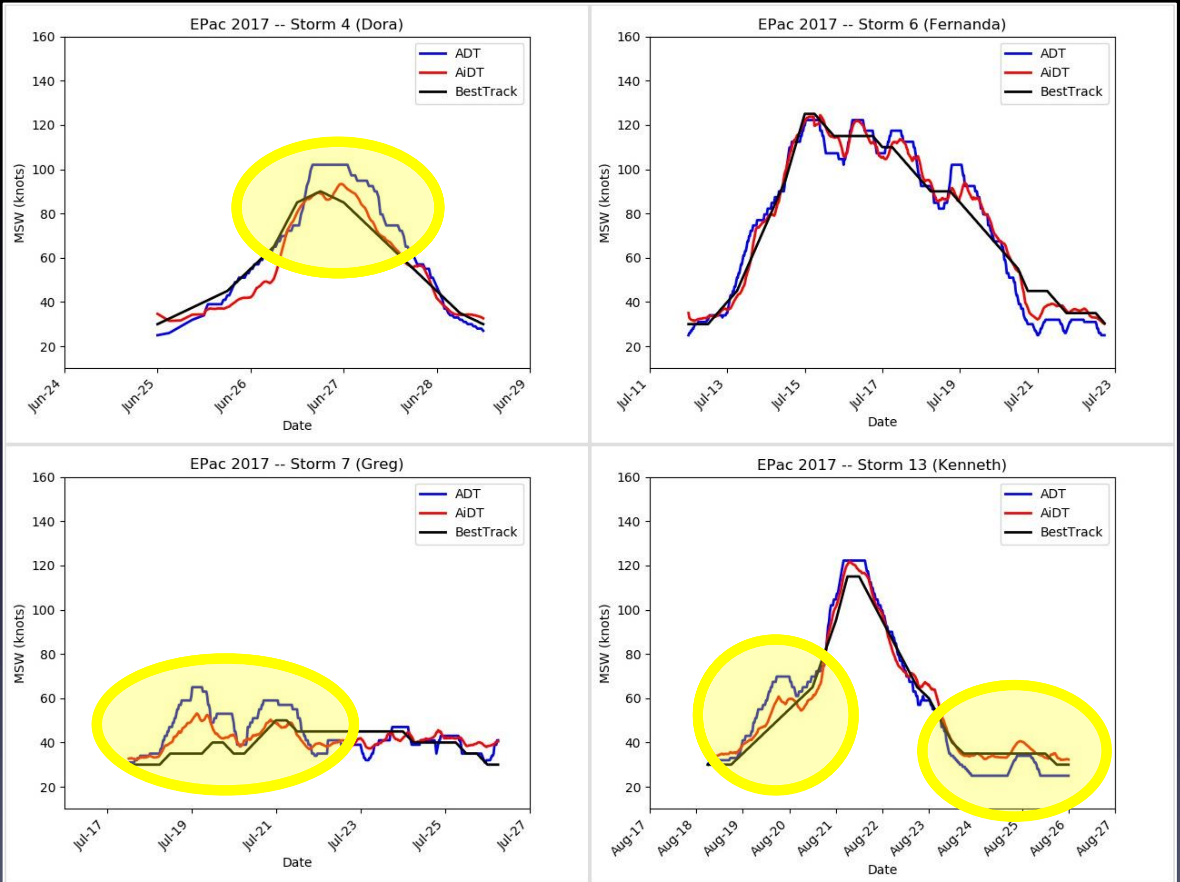
Advanced (AI-enhanced) Dvorak Technique (AiDT)

2017 Storm Examples

- **2017 East Pacific**
  - *04E (Dora)*
  - *06E (Fernanda)*
  - *07E (Greg)*
  - *13E (Kenneth)*

  - *Note: ADT used in derivation of NHC Best Track. Also note impact of AiDT in various stages*

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



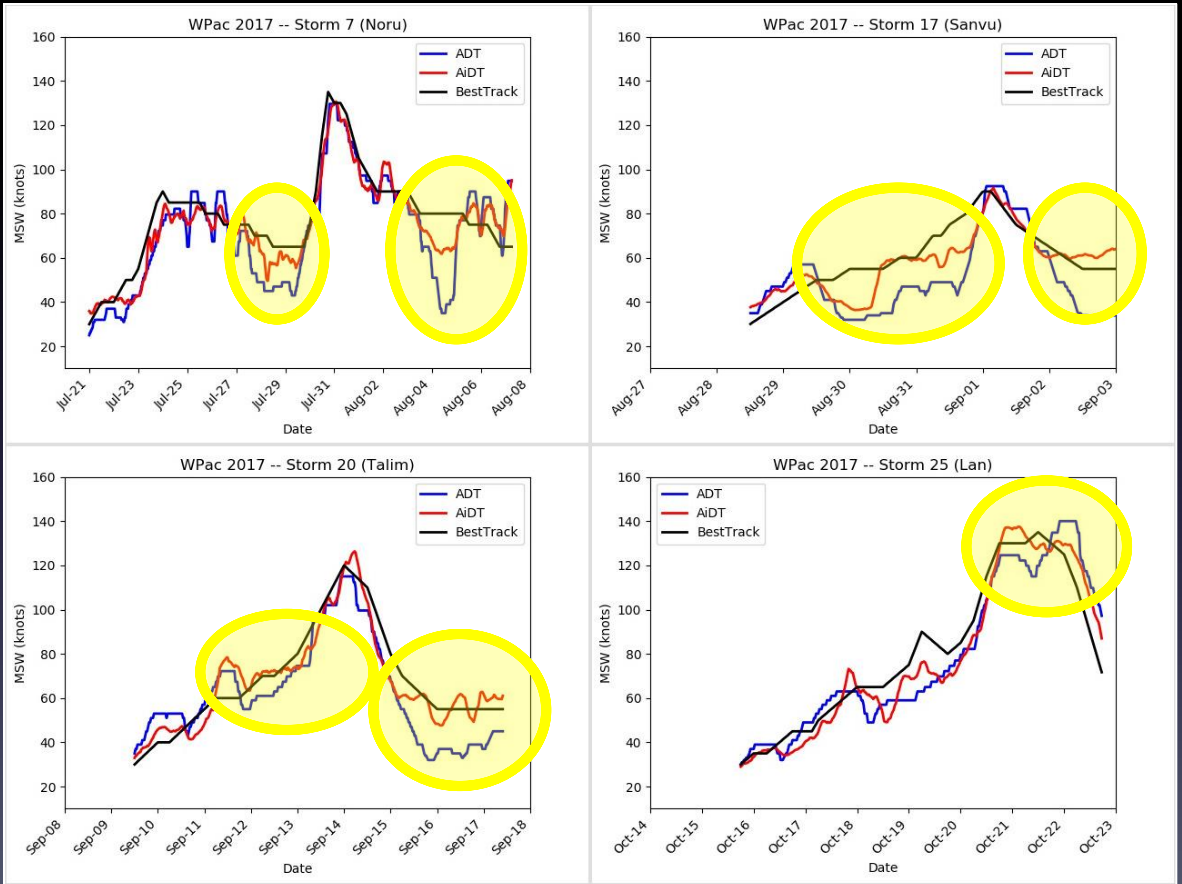
Advanced (AI-enhanced) Dvorak Technique (AiDT)

2017 Storm Examples

- **2017 Northwest Pacific**
  - *07W (Noru)*
  - *17W (Sanvu)*
  - *20W (Talim)*
  - *25W (Lan)*

  - *AiDT helps alleviate some of the TC periods where the ADT has historically struggled*

  - BLUE – ADT
  - RED – AiDT
  - BLACK – JTWC



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)

TC intensity Analysis

- **AiDT impacts on TC intensity categories**
  - 2017 Independent data set
  - Using AiDT Regression-based global model
  - **Largest AiDT impact on TS and H1 categories** (typically Curved Band and Shear scene types, along with CDO)
  - *+/- Bias equals MSW over/underestimate versus Best Track values (knots)*

Saffir-Simpson Intensity Category	Sample Size	ADT			AiDT		
		Bias	MAE	RMSE	Bias	MAE	RMSE
TD *<35.0 kt*	3519	5.34	6.58	9.27	5.96	6.28	7.83
TS *35.0-63.9kt*	9016	-0.37	8.54	**10.72**	-1.19	5.30	**6.79**
H1 *64.0-82.9kt*	3001	-3.99	9.90	**12.87**	-2.09	6.45	**8.15**
H2 *83.0-95.9kt*	1445	-2.03	10.02	12.43	-3.50	8.01	9.92
H3 *96.0-112.9kt*	845	2.44	8.35	10.22	-0.44	6.21	7.86
H4 *113.0-136.9kt*	607	-4.18	7.83	10.15	-4.14	6.35	8.24
H5 *>137.0kt*	239	-10.34	10.84	13.44	-10.02	11.00	12.82
H1-H2 *64.0-95.9kt*	4446	-3.35	9.94	**12.73**	-2.55	6.96	**8.77**
H3-H5 *>96.0kt*	1691	-2.95	8.52	10.71	-3.41	6.94	8.88

Advanced (AI-enhanced) Dvorak Technique (AiDT)

Method Comparisons

- Comparison of AiDT with various TC intensity estimation models/algorithms
  - AiDT is on-par or superior to many more complex and time-consuming DL methods or historical objective techniques currently utilized in TC operations

Technique	Method	Data Type	Inputs	Region	Dataset Years	MSW RMSE (kt)
Dvorak *(Dvorak, 1975, 1984)*	Empirical	Geo	IR, VIS	Global	1970s-80s	**10-15**
DAV-T *(Ritchie, et al., 2014)*	Statistical	Geo	IR (10.7um)	North East/West Pacific	2007-2011	**12.9-13.4**
SATCON *(Velden and Herndon, 2020)*	Statistical Ensemble	Geo Leo	IR (10.7um) PMW (various, based on method)	Global	2006-2014	**9.0**
ADT *(Olander and Velden, 2019)*	Statistical Empirical	Geo Leo	IR (10.7um) PMW (eye score)	Global	2017	**10.98**
DeepMicroNet *(Wimmers et al., 2019)*	2D-CNN	Leo	PMW (37GHz, 85-92GHz)	Global	2007, 2012	**9.6-14.3**
CNN-TC *(Chen et al,, 2019)*	2D-CNN	Geo Leo	IR (10.7um) WV (6.7um) PMW (Rain Rate)	Global	2017	**8.39**
Pradhan model *(Pradhan et al., 2018)*	2D-CNN	Geo	IR	Global	1999-2014	**10.18**
2D3 *(Lee et al., 2019)*	2D-CNN	Geo	IR1 (10.7um) IR2 (12.0um) WV (6.7um) SWIR (3.9um)	NorthWest Pacific	2011-2016, 2017	**8.32**
AiDT	1D-DNN	Geo Leo	IR (10.7um) PMW (eye score)	Global	2017, 2018	**7.70-8.23**

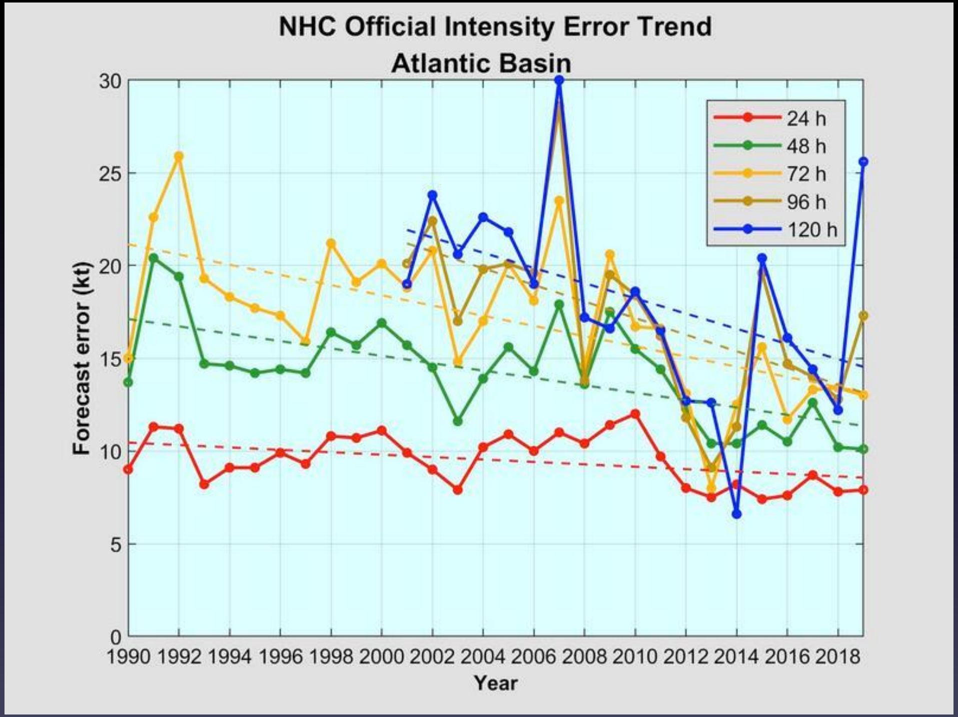
Advanced (AI-enhanced) Dvorak Technique (AiDT)

Conclusions

- The AiDT improves ADT estimates overall, especially in certain TC stages where the ADT has historically struggled or not been fully investigated
- An AiDT article has been submitted to the AMS journal *Weather and Forecasting* and is currently undergoing peer review
- We are running the AiDT experimentally at UW-CIMSS in parallel with our real-time ADT processing
    - The AiDT analysis will be made public once the article has been accepted and published, hopefully in the second half of 2021
- Integration of the AiDT estimates within the UW-CIMSS SATellite CONsensus (SATCON) algorithm is planned

SATCON: Motivation

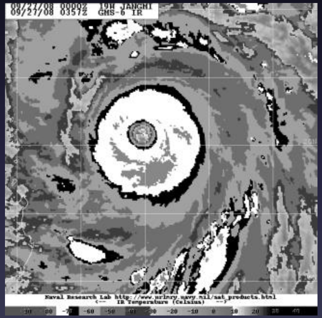
- Estimation of Tropical Cyclone current intensity is the first step in the TC intensity forecast.
- Current intensity information is used in several statistical and diagnostic intensity models: SHIPS, SHIPS-RI, PERC, M-PERC, RIPA, AHI
- TC parameters which include current intensity are used to initialize the TC vortex in dynamic models



SATCON: A Multi-Spectral Approach

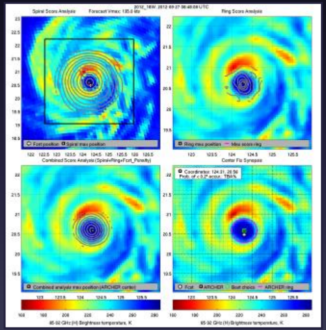
- In order to account for storms with different structures an “all the above” approach is needed.
- Multiple satellite scanning strategies (Geo/LEO)
- Multiple channels to measure the various TC features that are related to intensity. (IR, imager channels, temp/moisture sounders)

ADT



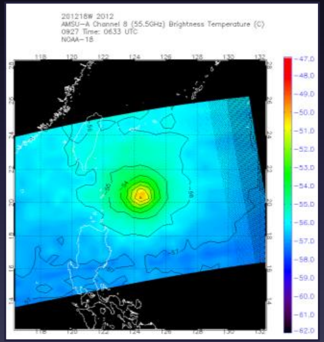
Geostationary
- Intensity
- Position
- Structure

ARCHER



MW Imager
- Position
- Structure
- ~Intensity

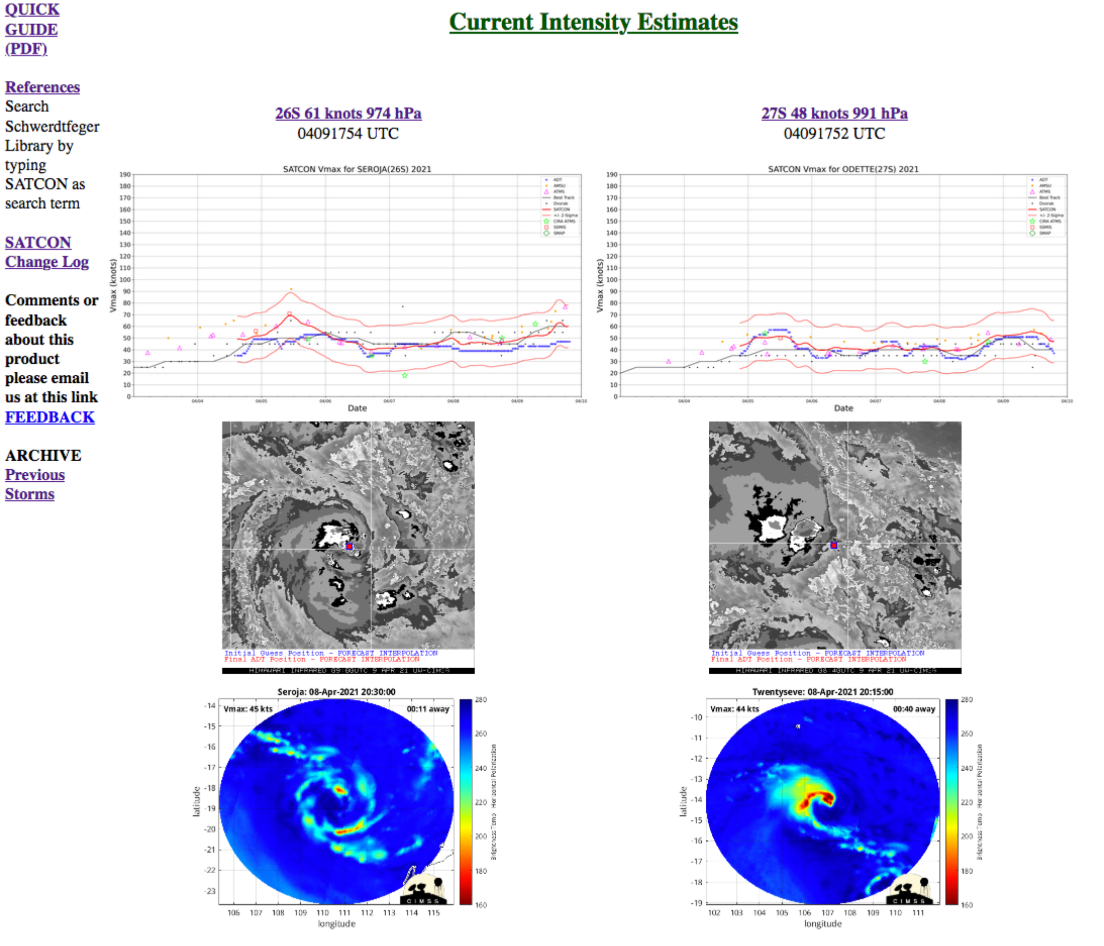
CIMSS AMSU, SSMIS and CIMSS/CIRA ATMS



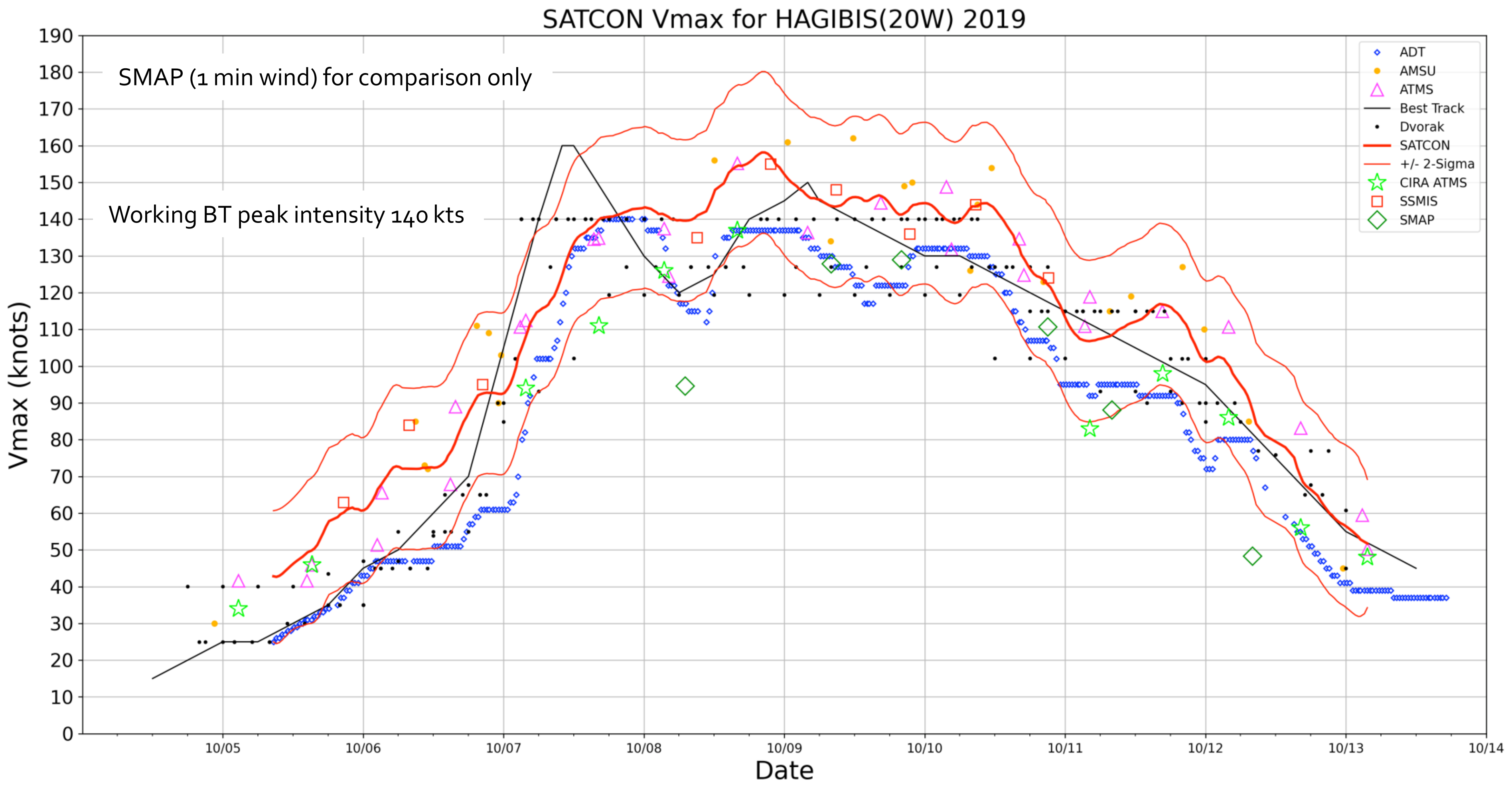
MW Sounder (esp. ATMS)
- Intensity
- Structure

SATCON Quick Look Page

- Current and past intensity
- Short current IR animation
- Recent MIMIC-TC microwave



http://tropic.ssec.wisc.edu/real-time/satcon/PG/satcon_pg.html


SATCON Vmax for HAGIBIS(20W) 2019
SMAP (1 min wind) for comparison only
Working BT peak intensity 140 kts
Vmax (knots)
Date
ADT
AMSU
ATMS
Best Track
Dvorak
SATCON
+/- 2-Sigma
CIRA ATMS
SSMIS
SMAP
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
190
10/05
10/06
10/07
10/08
10/09
10/10
10/11
10/12
10/13
10/14

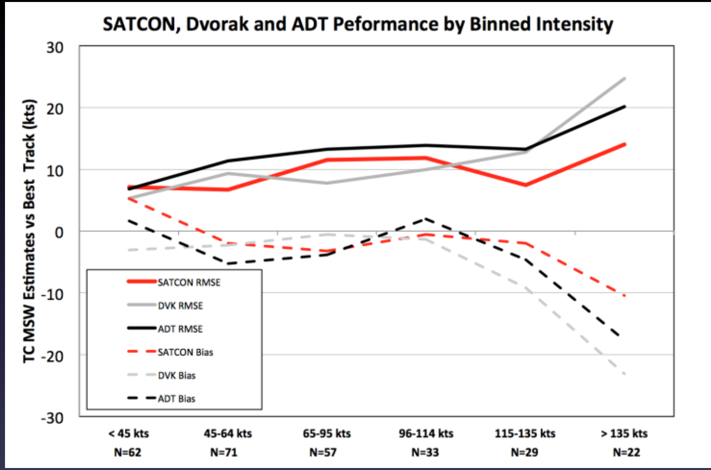
SATCON Performance

Comparison with SATCON members and Dvorak. Independent verification MSW 2015-2019 using aircraft-aided best track

N =400	SATCON	ADT	SSMIS/ ATMS	Simple Average
Bias (knots)	-0.9	-3.0	-0.7	-1.8
Abs Error (kt)	7.5	10.1	10.0	9.1
RMSE (kt)	9.5	12.9	12.3	11.2

N =568	SATCON	ADT	AMSU	Simple Average
Bias (knots)	-1.5	-3.2	-4.2	-3.7
Abs Error (kt)	7.6	9.5	10.8	8.6
RMSE (kt)	9.8	12.3	12.9	11.0

Comparison to Dvorak

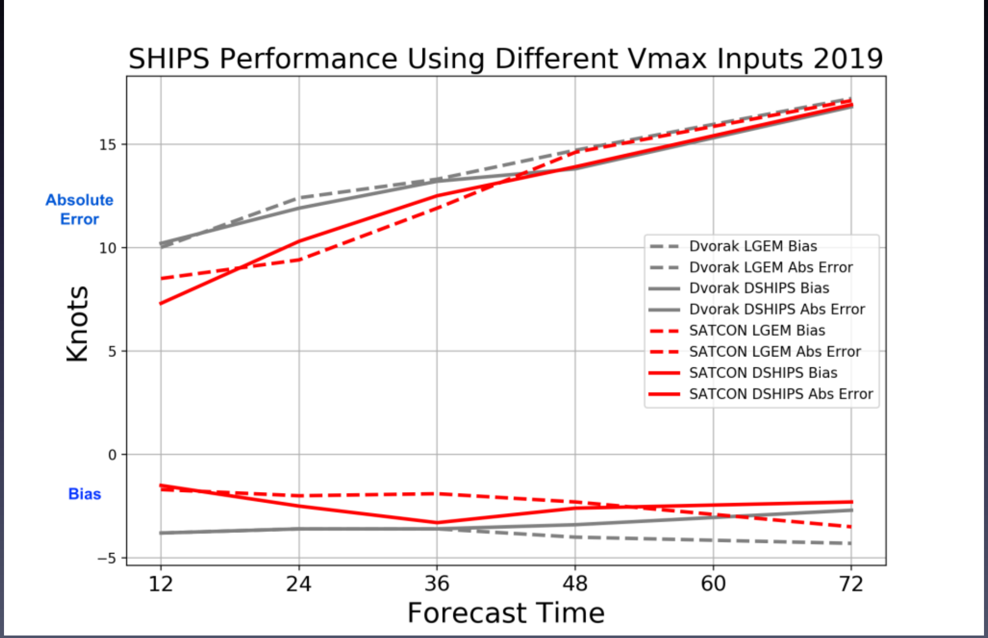


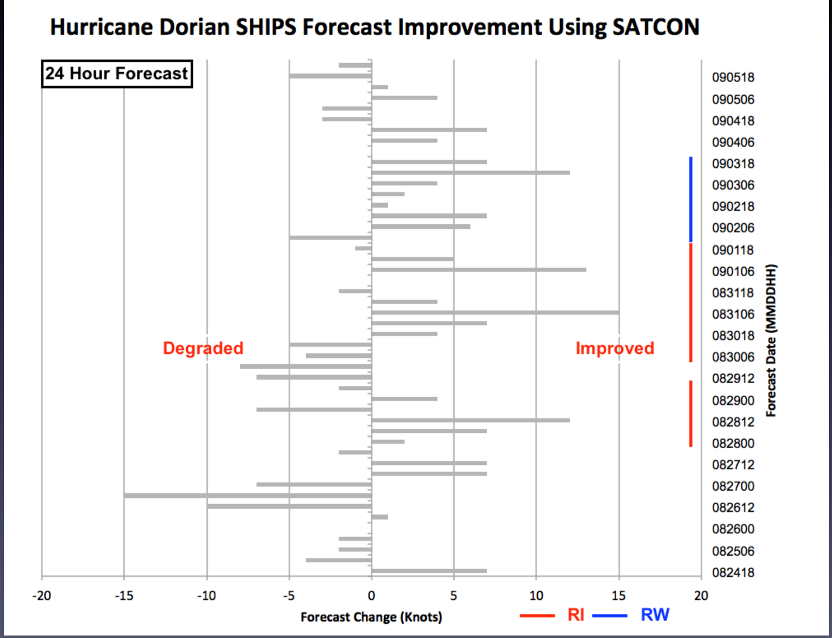
Velden, C. S., and D. Herndon, 2020: A Consensus Approach for Estimating Tropical Cyclone Intensity from Meteorological Satellites : SATCON in Weather and Forecasting

Dvorak (average of available agencies) RMSE ~ 10.9 knots

SATCON Impacts on Forecast

- Test SHIPS performance using SATCON intensity inputs. Replace “best track” with SATCON current and previous 12 hour Vmax values (2019 Atlantic storms)
- Repeat using Dvorak (average of two centers)
- RI/RW forecast errors are historically double that of non-RI/RW storms. Potential for modest improvements to intensity forecasts

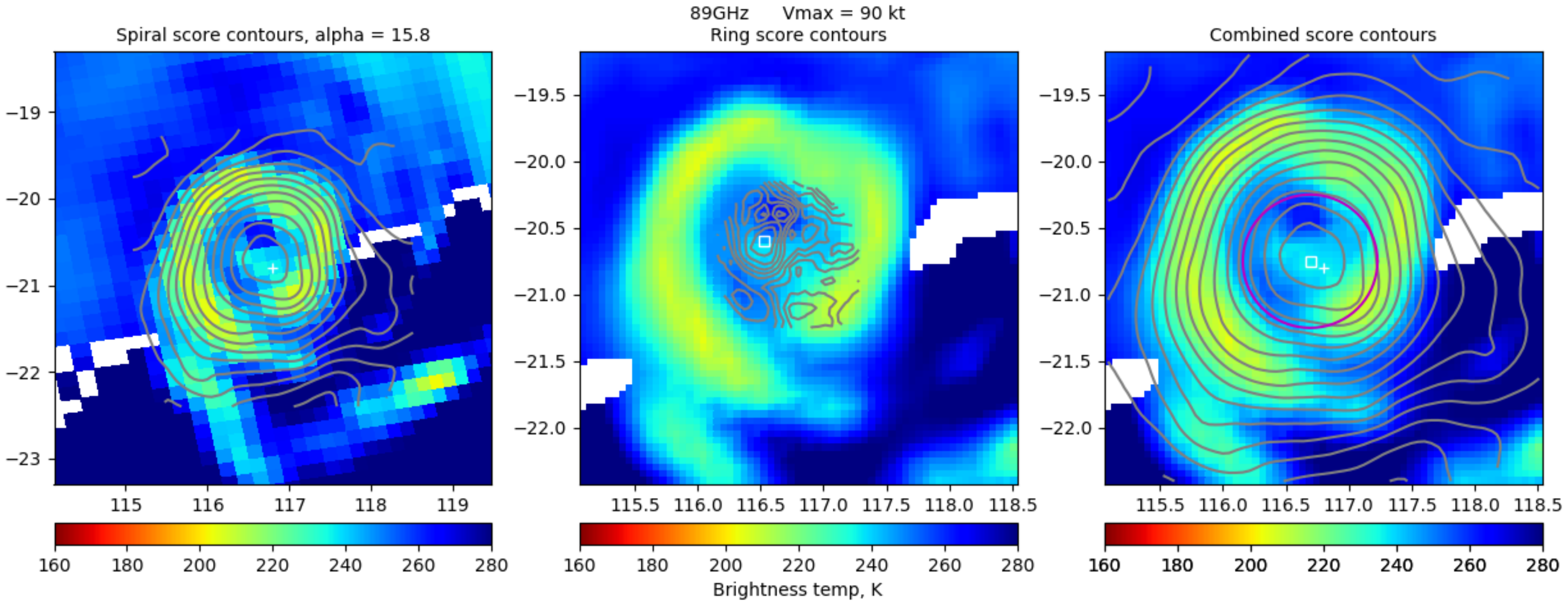




SATCON: Next steps

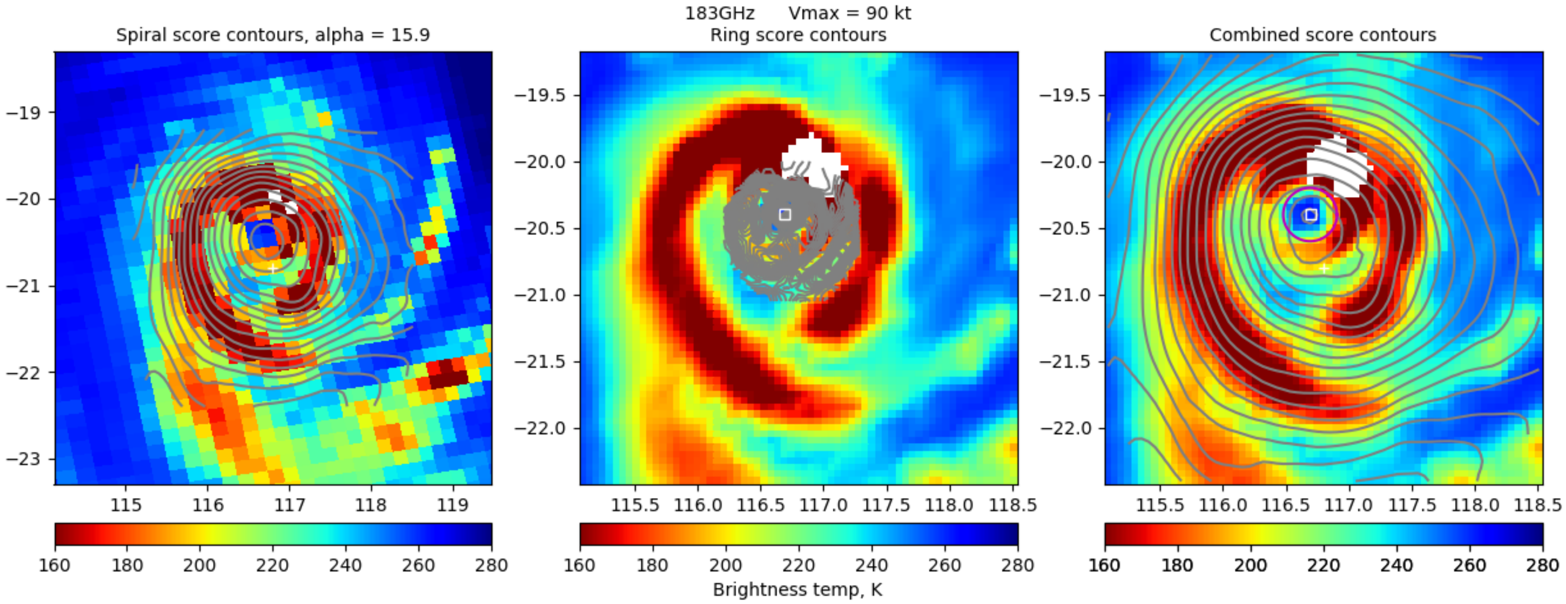
- SATCON currently “delivered” to JTWC via ATCF fixes. Fixes are performed when new microwave sounder estimates are available. However the living nature of SATCON means it is always updating with new information. Replace one-time data push with continual ATCF updates (hourly)
- Adapt the algorithm to work with the GeoIPS system. IDL dependencies replaced with Python. Continue integration work including Direct Broadcast production
- *SMAP integration including eye size corrections*
- *DeepMicroNet, AiDT and DAV potential members*
- *Explore real-time import of SAR fixes*
- Explore adding an ATMS 89 GHz –based intensity estimate derived from deep learning *(Time permitting).*
- *SATCON uses ARCHER structure inputs. Addition of ATMS?AMSU ARCHER production will fill gaps from current MI*

Adapting ARCHER to JPSS: **ATMS 89 GHz (H)**



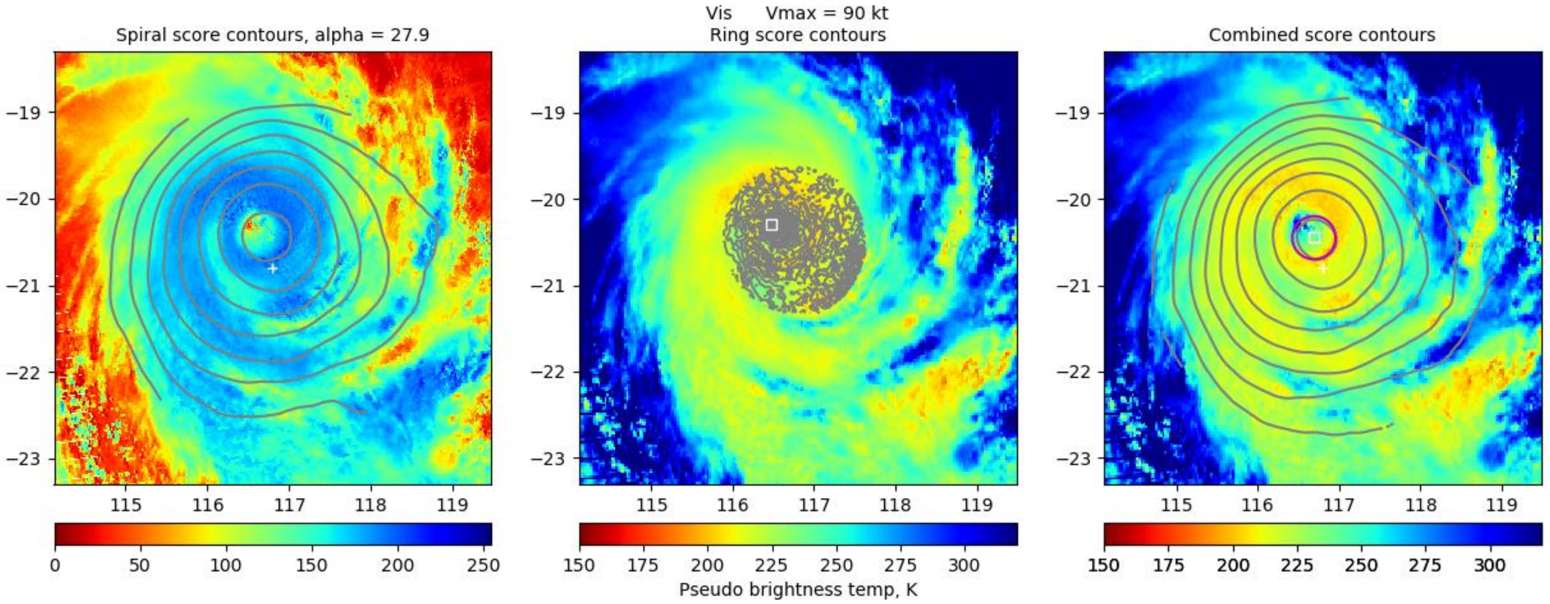
Cyclone Damien, 8 Feb 2020

Adapting ARCHER to JPSS: **ATMS 183 GHz (H)**



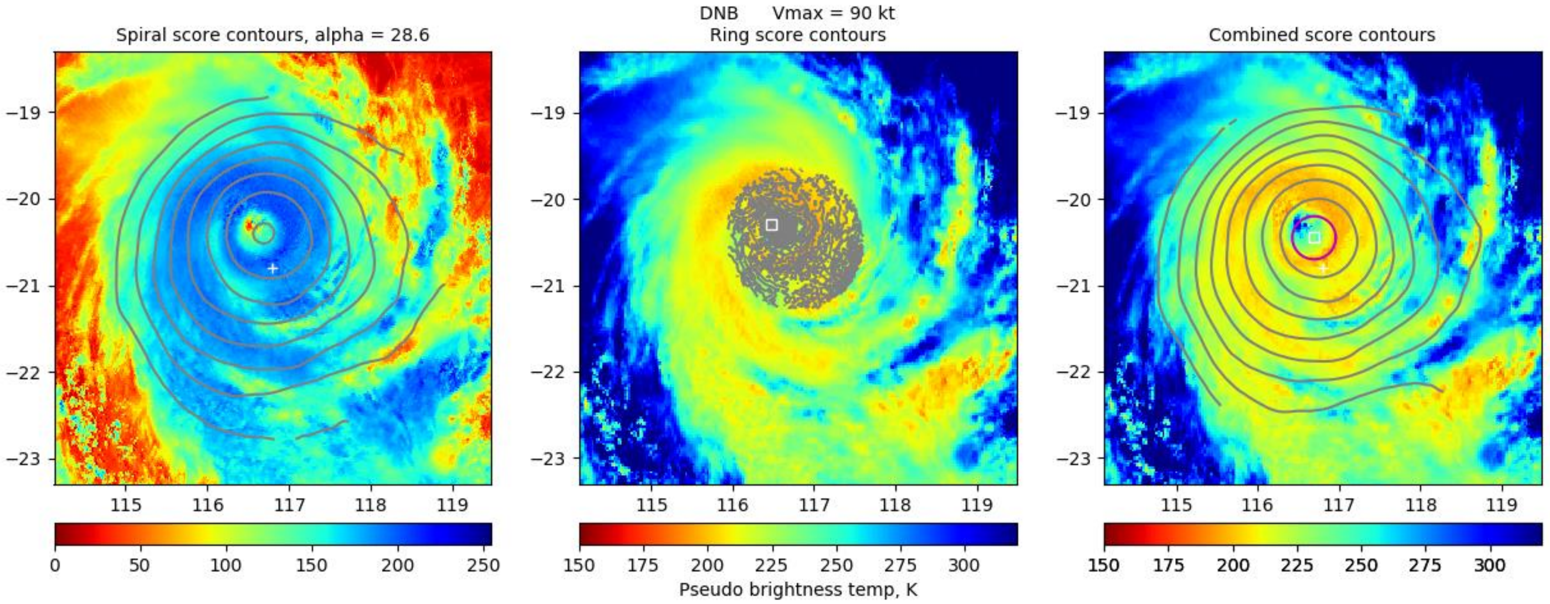
Cyclone Damien, 8 Feb 2020

Adapting ARCHER to JPSS: **VIISR (Visible channel)**



Cyclone Damien, 8 Feb 2020

Adapting ARCHER to JPSS: **VIISR (Day/Night Band)**



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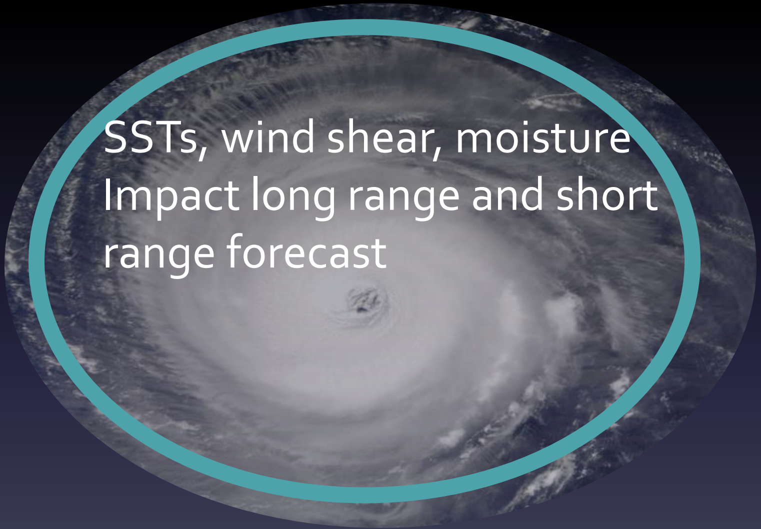
ERC Onset Guidance: M-PERC

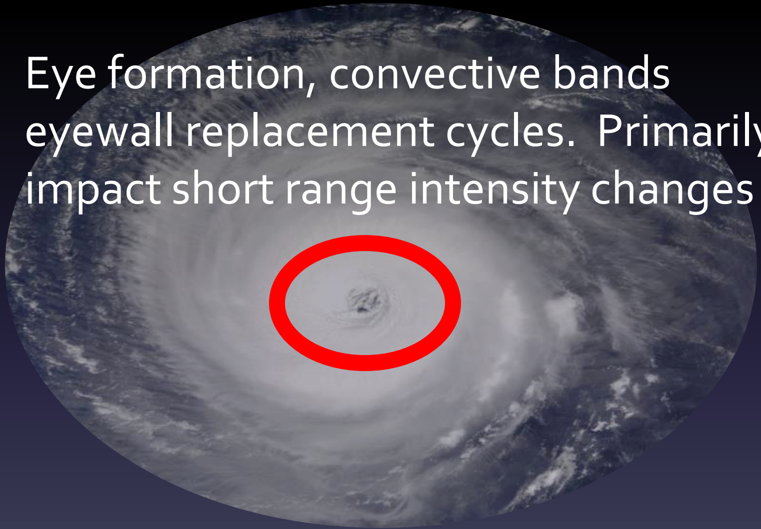
TC Intensification

Environmental Controls



SSTs, wind shear, moisture
Impact long range and short range forecast

Internal Controls



Eye formation, convective bands eyewall replacement cycles. Primarily impact short range intensity changes

"The disparity between SHIPS forecasts and the observed intensity changes during ERCs is strongly suggestive that the typical environmental controls of intensity change, on which SHIPS is largely based, are temporarily **countermanded** while dynamic processes internal to the storm dominate the intensity evolution."- Kossin

ERC Onset Guidance: M-PERC

ERC forecast tools available to forecasters currently

E-SHIPS – ERC adjustments to SHIPS forecast when ERC onset is known

- Our work with M-PERC is helping to inform meaningful updates to E-SHIPS

PERC – Probability of ERC (based on environment, Vmax and infrared satellite information)

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** PROBLTY OF AT LEAST 1 SCNDRY EYEWL FORMTN EVENT AL142016 MATTHEW    10/01/2016   00 UTC **
TIME(HR)    0-12   12-24(0-24)  24-36(0-36)  36-48(0-48)
CLIMO(%)     48      43( 70)      28( 79)      23( 84)     <-- PROB BASED ON INTENSITY ONLY
PROB(%)      47      51( 74)      92( 98)      97(100)     PC4 UNAVAIL...MODEL SKILL DEGRADED

** DSHIPS INTENSITY FORECAST ADJUSTED RELATIVE TO ONSET OF ERC WEAKENING PHASE **
      TIME (HR)       0     6    12    18    24    36    48    60    72    84    96   108   120
>24HR AGO (DSHIPS)  135   136   128   117   108   101   102   107   104    67    71    69    72
 18HR AGO           135   134   126   115   106    99   100   105   102    65    69    67    70
 12HR AGO           135   132   131   120   111   104   105   110   107    70    74    72    75
  6HR AGO           135   129   126   125   116   109   110   115   112    75    79    77    80
      NOW           135   126   120   117   116   109   110   115   112    75    79    77    80
  IN  6HR           135   136   127   121   118   115   116   121   118    81    85    83    86
  IN 12HR           135   136   128   119   113   109   110   115   112    75    79    77    80
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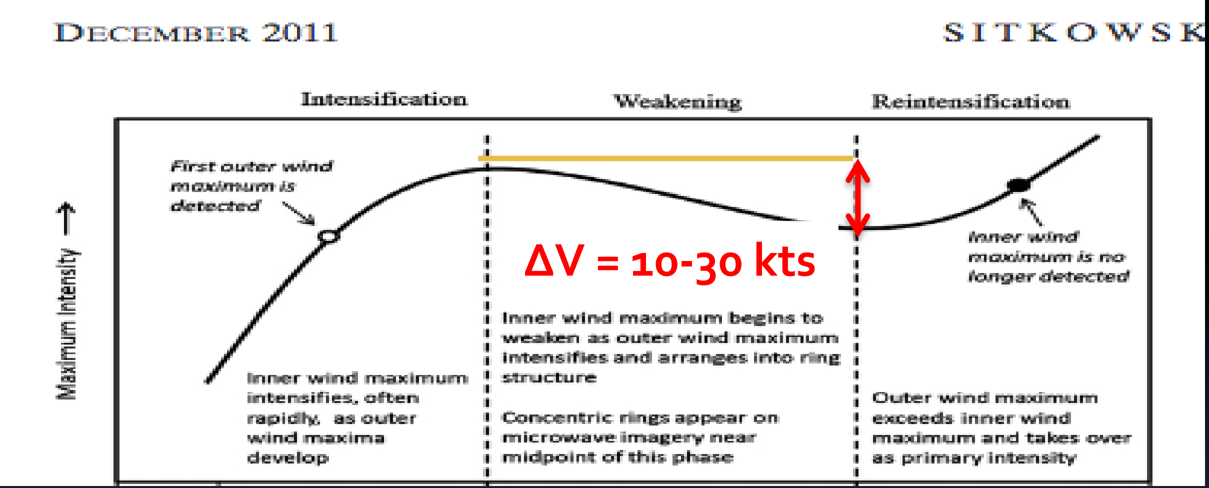
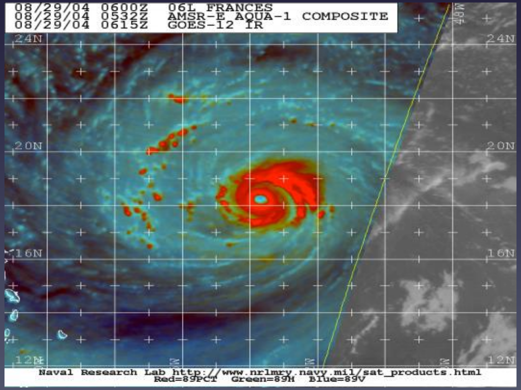
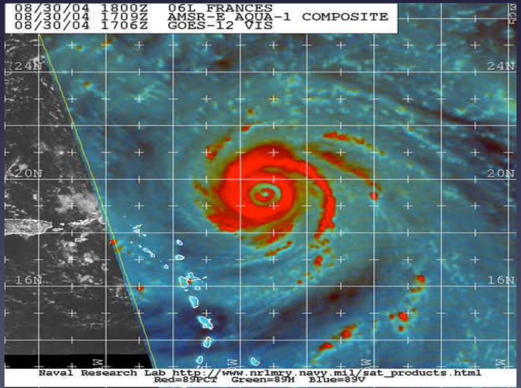
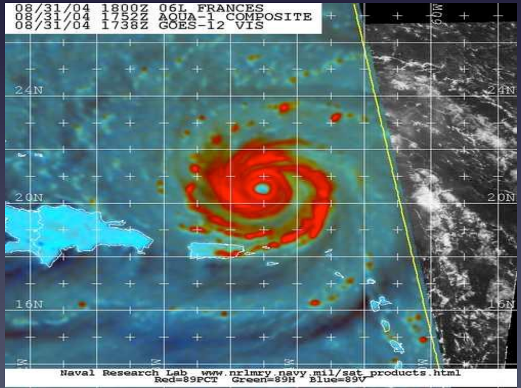
ERC Onset Guidance: M-PERC



Sitkowski, M., J. P. Kossin, and C. M. Rozoff, 2011: Intensity and structure changes during hurricane eyewall replacement cycles. *Mon. Wea. Rev.*, **139**, 3829-3847.

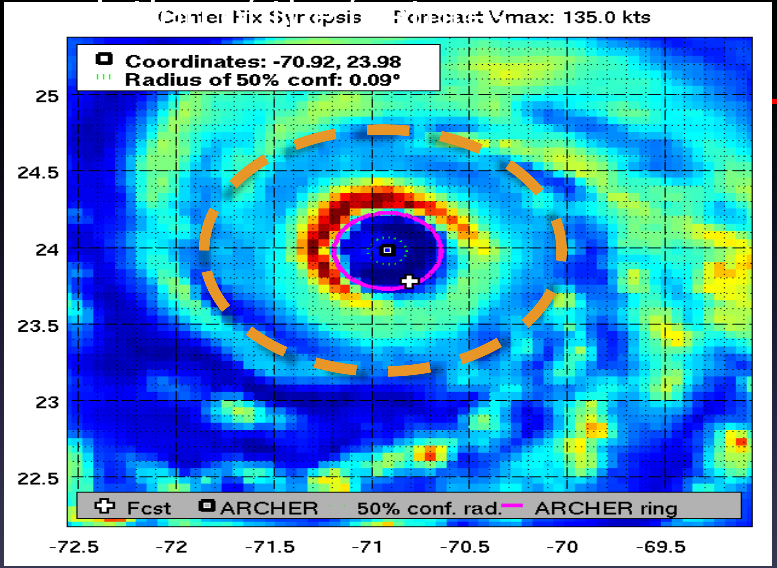






ERC Onset Guidance: M-PERC

89 GHz ring scores can be displayed in hovemuller form to show time and space



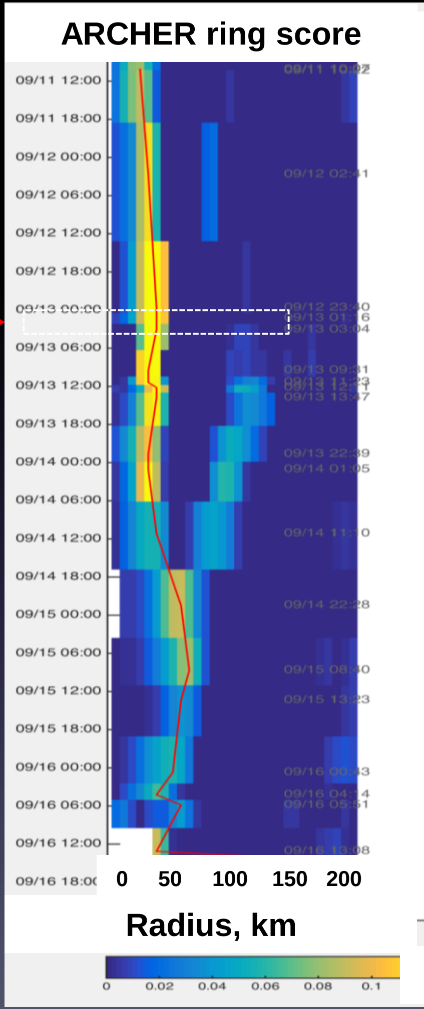
9/12

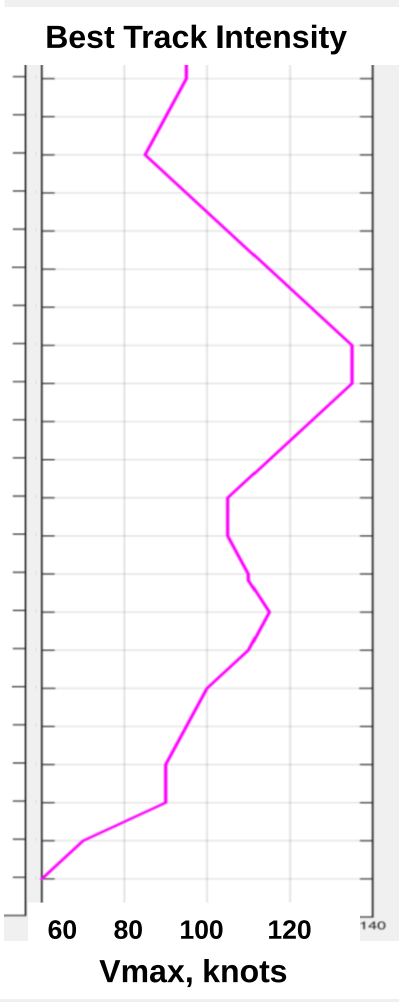
9/13

9/14

9/15

9/16





*ARCHER ring score plotted versus time shows a branching/merging pattern during ERCs

ERC Onset Guidance: M-PERC

Web page output for M-PERC
On CIMSS ARCHER page

Training Data 1999-2011 -> 41 storms with 84 ERC events (1787 profiles)

Completed Work to Date

Developed baseline validation of Atlantic data

Baseline validation of Eastern Pacific cases

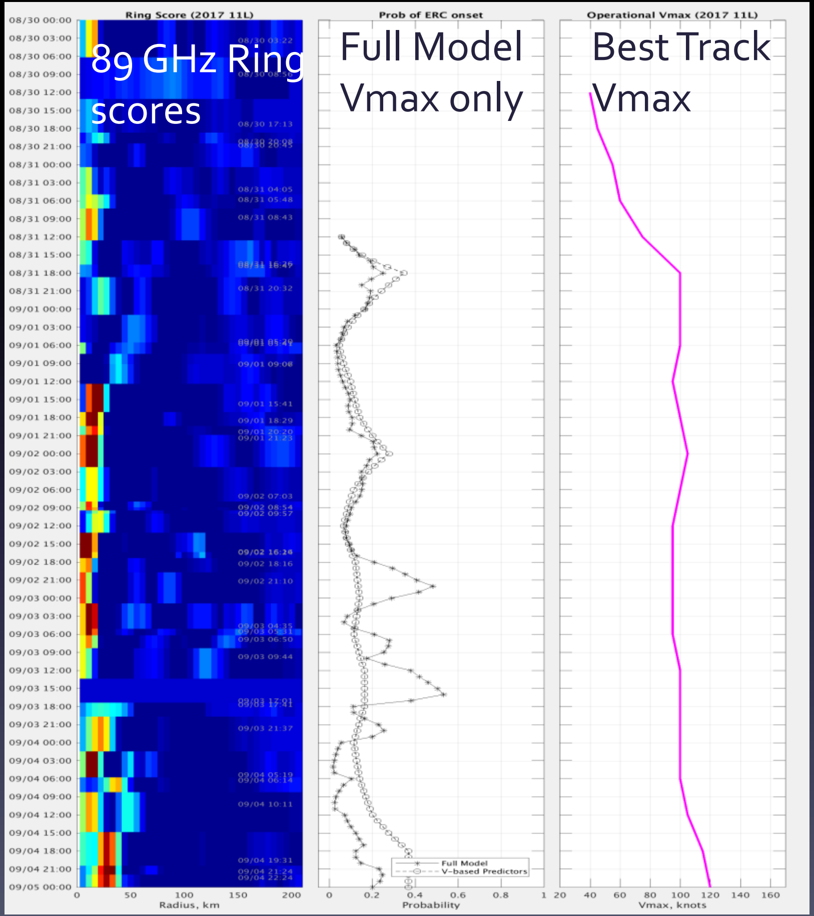
Updated web products

- Incorporate lessons learned to update product description page
- Created archive page for direct links

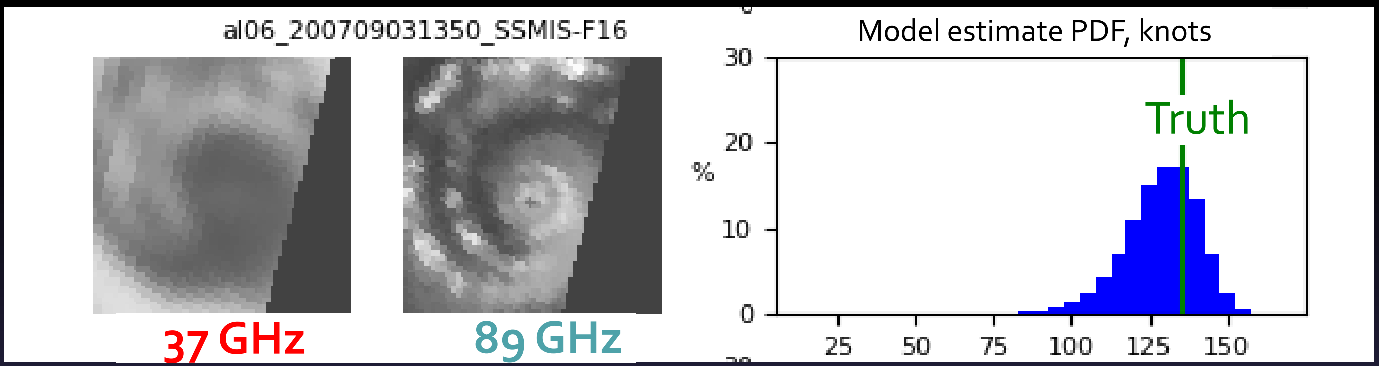
Held virtual product training for JTWC in 2020

Established training dataset for EPac model

Started porting work. Move graphics production away from MATLAB to Python

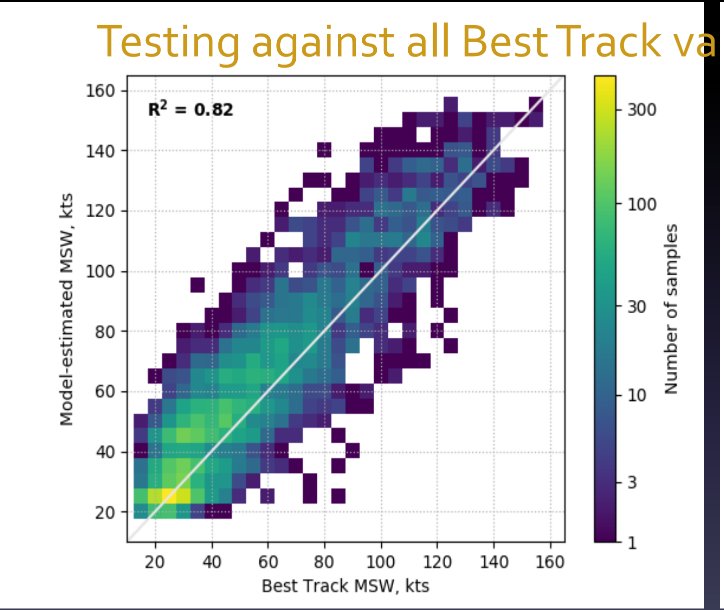


The Deep Learning intensity model: 'DeepMicroNet'

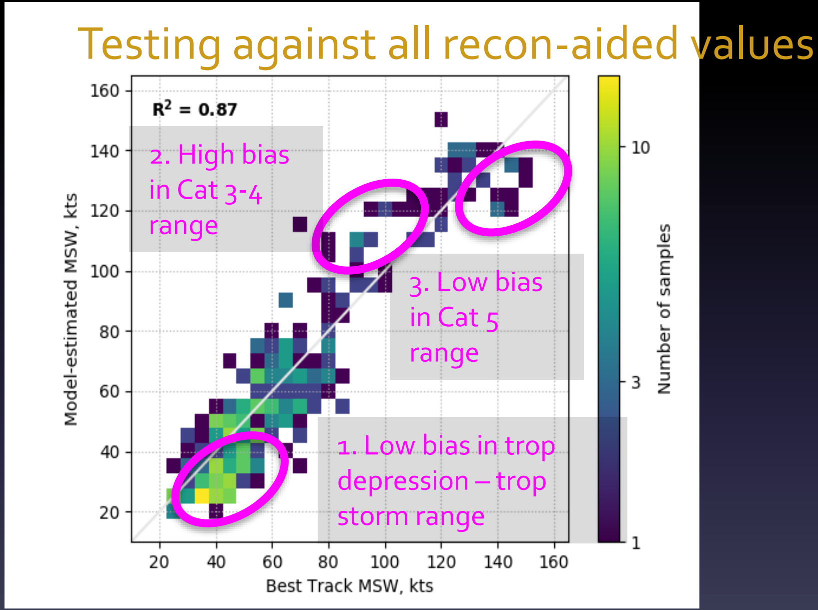


- Takes 37 and 89 GHz imagery as input, produces *probabilistic* output of TC intensity

Model statistics



RMSE = 14.6 kt



RMSE = 10.6 kt