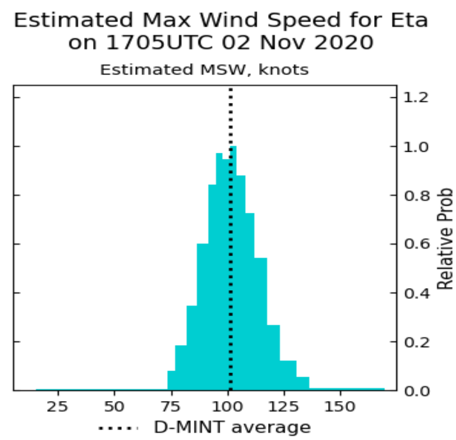
D-MINT (Deep learning - Multispectral INtensity of TCs)

D-MINT is neural network applied to GEO IR imagery and LEO passive microwave (MW) imagery, along with selected environmental variables to estimate TC intensity (max sustained 1-min. 10-m wind, MSW).

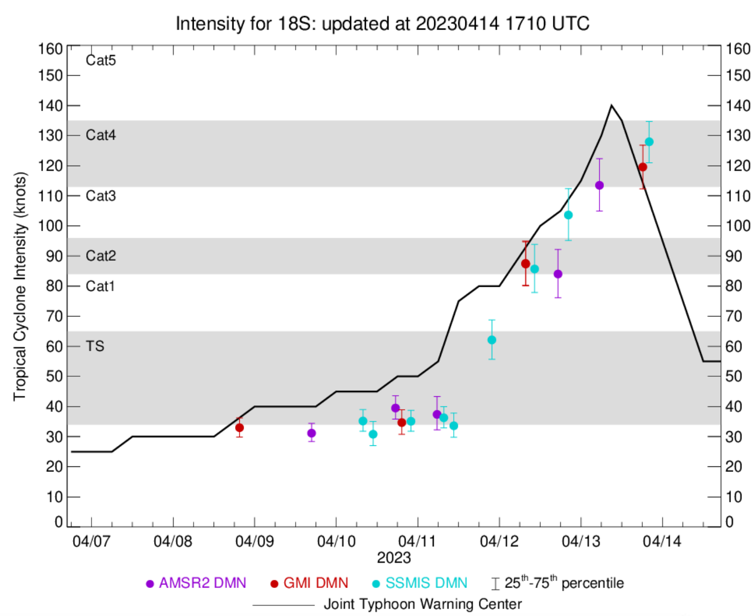
D-MINT is operated in real-time and processed for every available LEO MW overpass from SSMI-S, AMSR-2, and GMI, when the overpass covers at least 65% of the TC in the image and the corresponding IR imagery is available. Given the latency of MW data, D-MINT is usually processed and its output available 1-3h after the LEO overpass time.

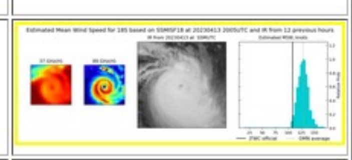
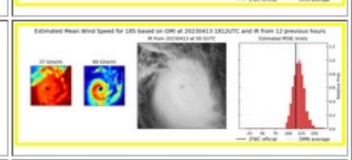
Output Graphics

The resulting model output is a histogram of TC intensity probabilities for 15 different percentiles: 1st, 2nd, 5th, 10th, 20th, …, 90th, 95th, 98th, and 99th. The D-MINT current intensity (MSW) is calculated from the inner average (30th to 70th percentile intensities), which has the best record for accuracy. An example for Hurricane Eta (2020) is shown to the right.



In real-time output graphics (example for TC Isla (2023) shown to the right), the estimated current D-MINT intensity is plotted as a circle with whiskers out to the 25th to 75th percentile intensities. Wider whiskers mean D-MINT is less certain of the intensity estimate. The working best track intensity from NHC or JTWC is depicted with a black line. A table of the average intensity and 25th to 75th percentile intensities is also available.



Date	Time	MW Sensor	Average (30th-70th percentile)	25th percentile	75th percentile	Image
20230413	2005 UTC	SSMISF18	**128 kts**	121 kts	135 kts	
20230413	1812 UTC	GMI	**120 kts**	112 kts	127 kts	

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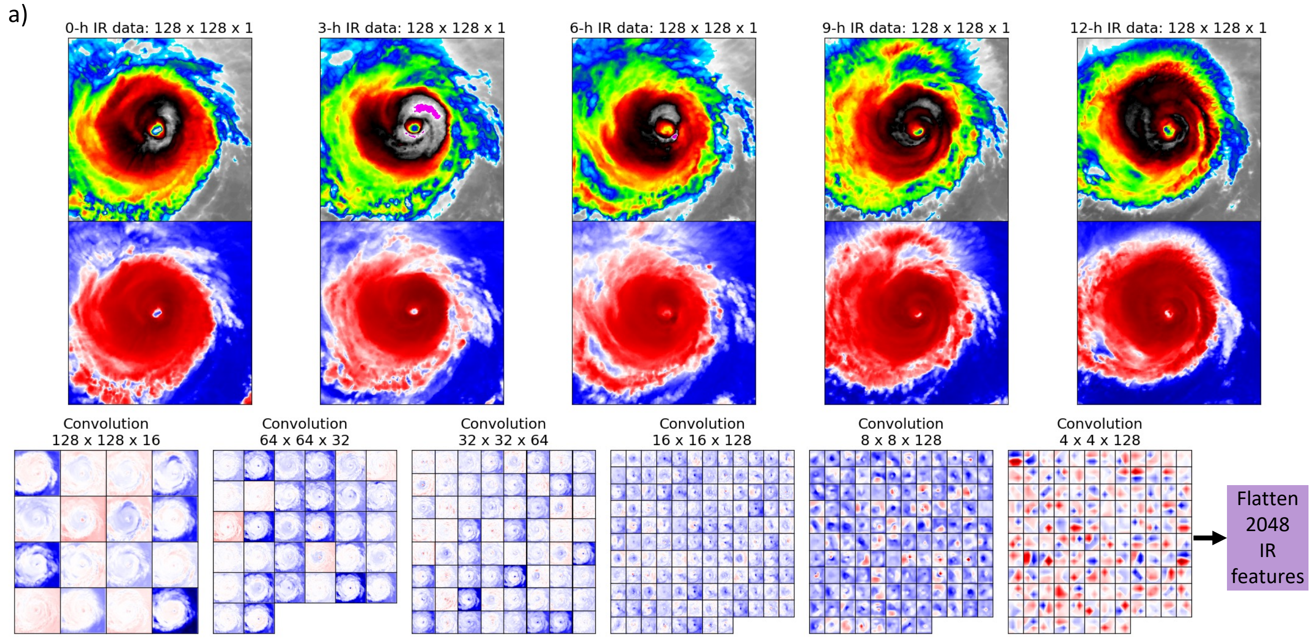
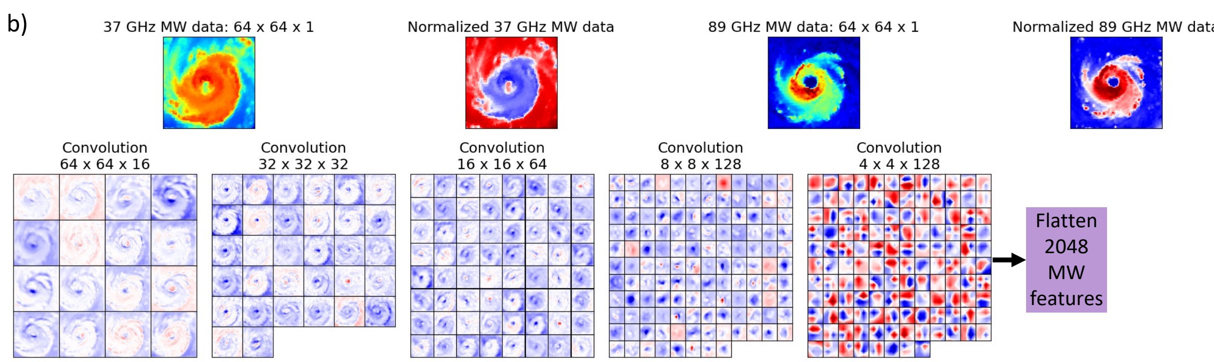
Model Technical Details

IR imagery:



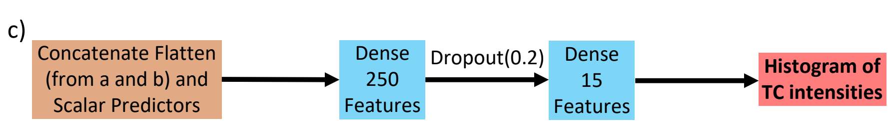
D-MINT uses 5 normalized normalized IR window (10.3 μm) images over the previous 12 hours (or fewer if not all are available). While the above image displays each IR image as an individual 128x128x1 input for clarity, the actual IR image input into D-MINT is 128x128x5. Thus, D-MINT can identify differences between the IR images (detailed later).

MW imagery:



D-MINT uses normalized 37- and 89-GHz MW images. These image sizes are smaller than the IR at 64x64x2.

Scalar Predictors:



The final inputs into D-MINT are scalar predictors from the SHIPS lsdiag files.

D-MINT is trained on global tropical cyclones.

North Atlantic	Eastern North Pacific	Western North Pacific	North Indian Ocean	Southern Hemisphere	Global
8578	9253	14,296	1190	7814	**41,131**

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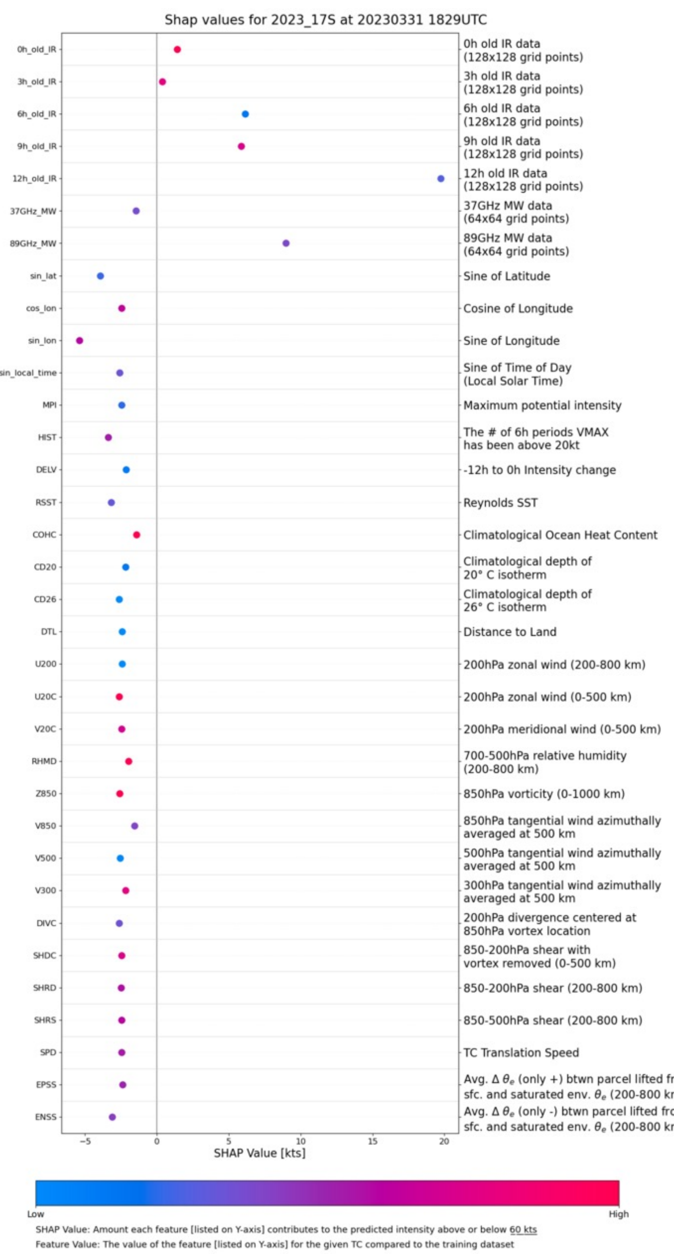
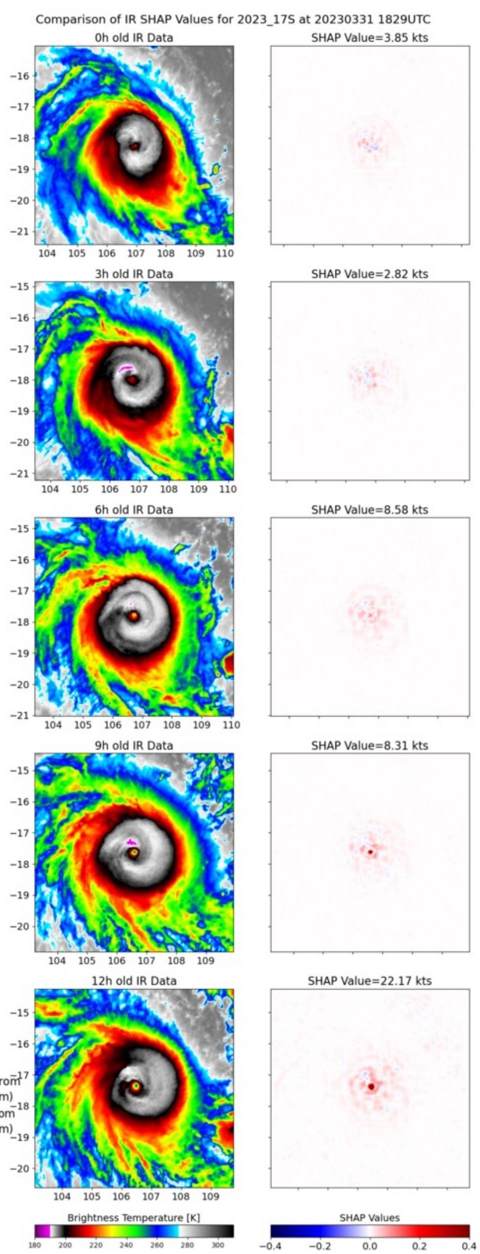
Diagnosing the D-MINT intensity estimates: A Brief Guide to SHAP Values

The power of the deep learning model comes from the ability to form complex, nonlinear relationships between images and the environment in order to predict an unknown feature (TC intensity). However, this power also complicates our ability to interpret the reasoning used by the model. To address this, the SHapley Additive Explanation (SHAP) method *approximates* the nonlinear model as a linear model, in order to give a rough idea of the sensitivities of the model result to each input. We have organized a set of diagnostic graphics to show *a first-order approximation* of how the model arrives at its answer. In the next pages we'll break down the three elements of the SHAP diagnostic graphic.

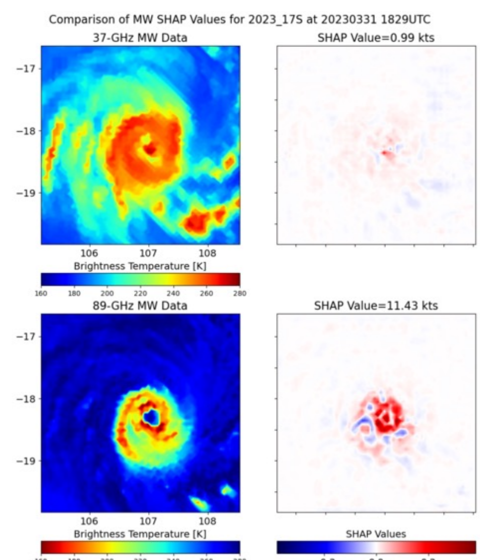
1. Full input breakdown



2. IR contribution



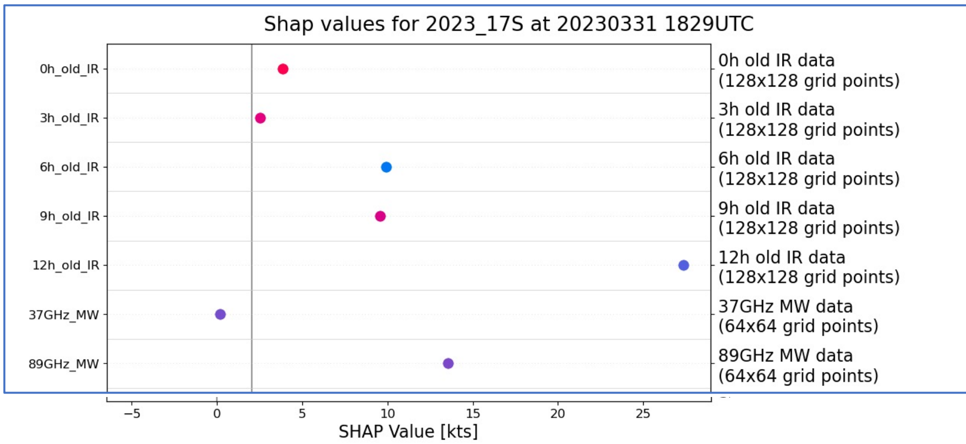
3. MW contribution

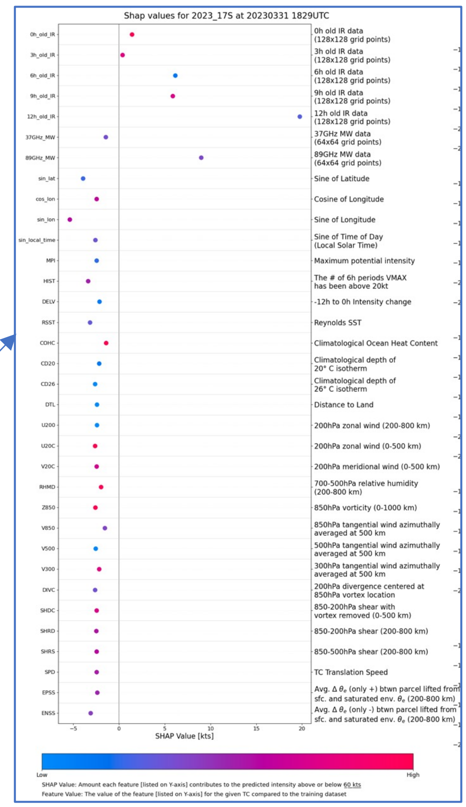


Why use IR imagery from 0 to 12 hrs old? We found this to be more accurate than models with any more or less IR imagery as their inputs. Adding this context of recent TC history seems to help prevent overfitting to the latest single image.

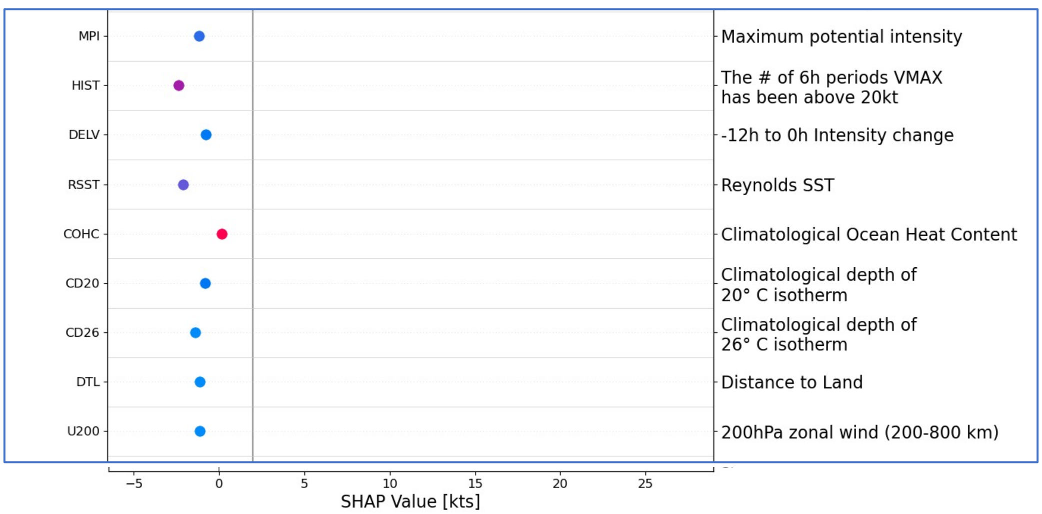
D-MINT (Deep learning - Multispectral INtensity of TCs)

1. Full input breakdown



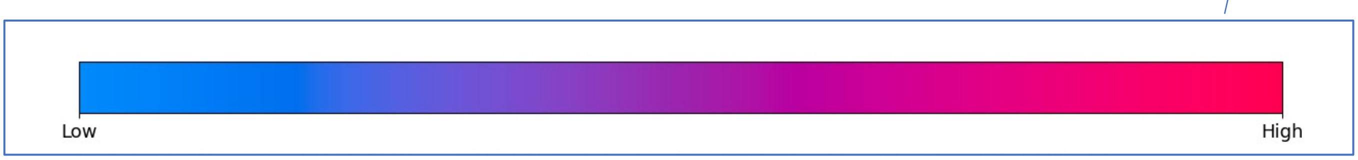


The top rows summarize the contributions of the satellite imagery to the final estimate. Each point on the chart stands for the amount that the image adds to the final estimate (**starting at a baseline 60 knots**).



The remaining rows summarize the contributions of the environmental/historical predictors to the final estimate. Refer to these to pick out

1) **Whether the environment/history is generally favorable or unfavorable**
2) **Whether it identifies any contributors that are uniquely influential**
3) **Whether any contributor may be in error**



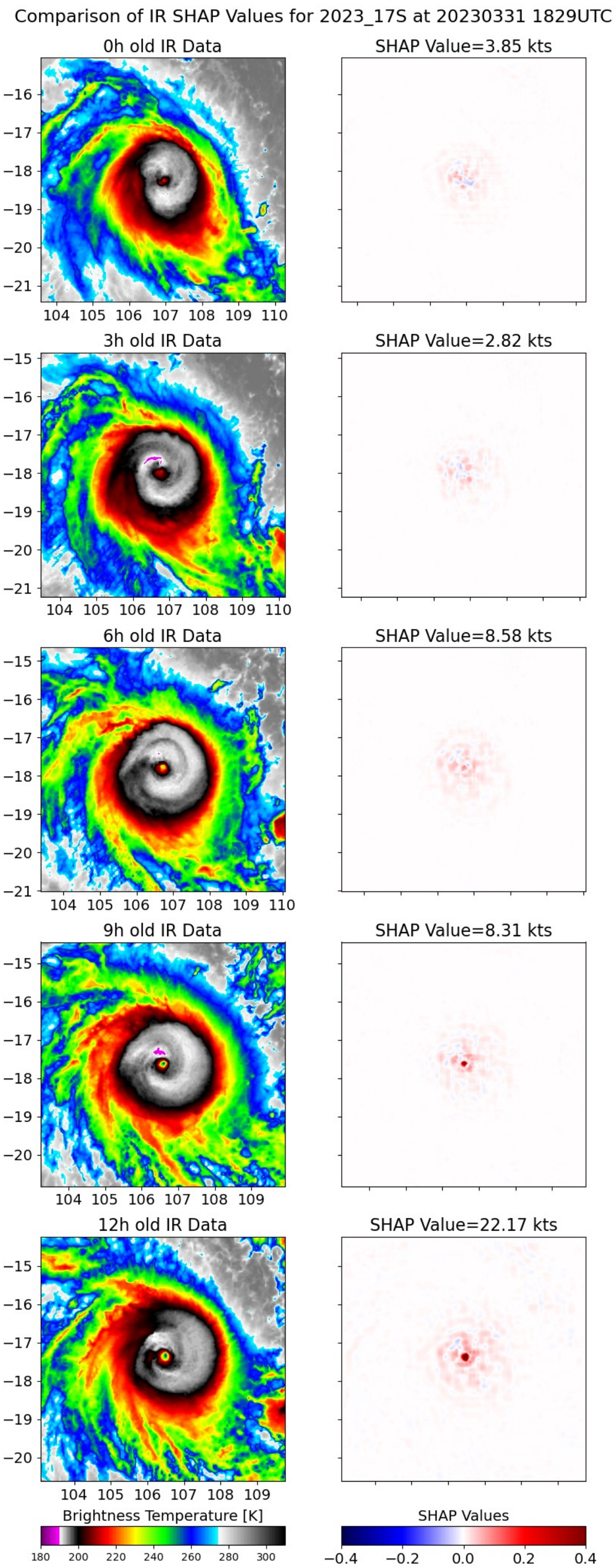
Finally, the color of each point indicates its value above or below the climatological average for TCs. For instance, the Distance to Land is blue, indicating a relatively short distance.

As for the image contribution coloring (top plot), we have simply set the colors to match our coloring of image brightness temperatures, where blue means warmer and red means colder.

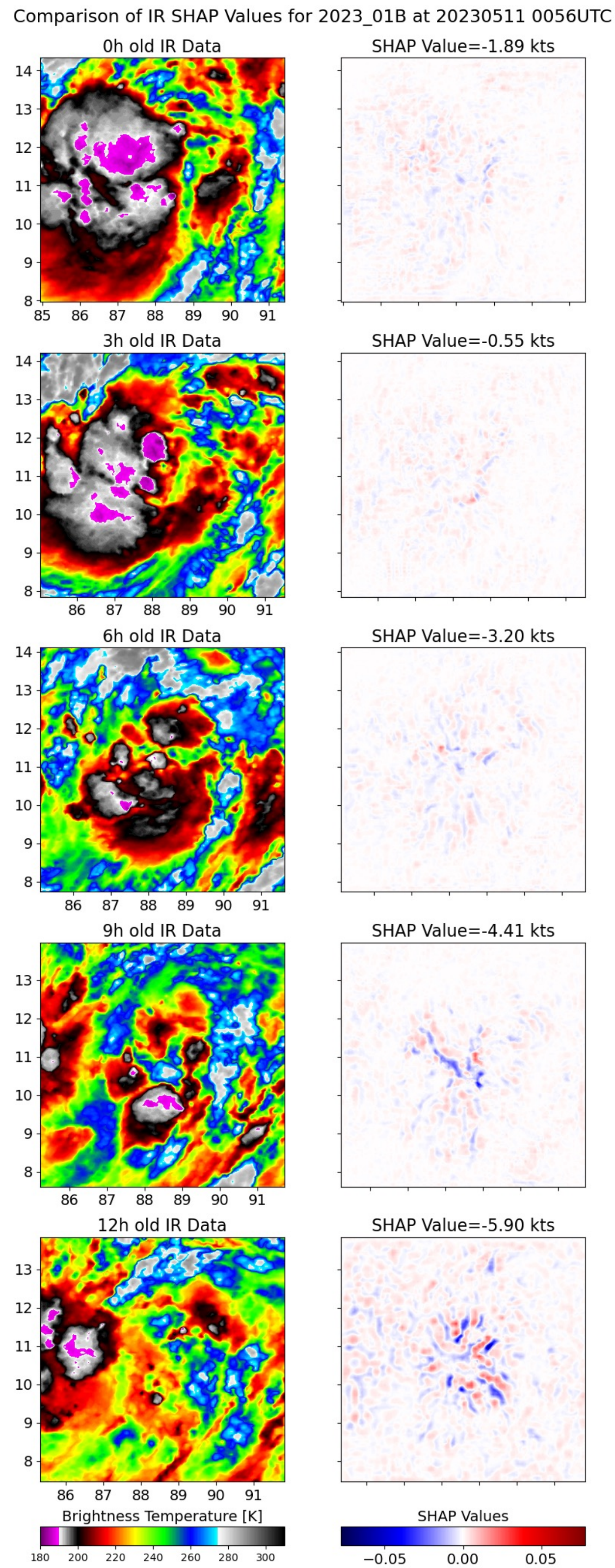
D-MINT (Deep learning - Multispectral INtensity of TCs)

2. IR contribution (spatial SHAP values)

Strong tropical cyclone
105 kt max. sustained winds (1 min.)



Weak tropical cyclone
30 kt max. sustained winds (1 min.)



Most recent IR image

D-MINT inputs five IR imagery time frames together. *However, the images are always significantly autocorrelated*, so a high contribution from one time frame does not rule out the influence of other time frames. On the left case, the strongest signal comes from the 12 hr old eye. However, you can interpret this as a signal of the eye strength from all five images because their eyes are so similar, and you can think of it as the SHAP algorithm choosing the easiest signal to emphasize among several at the exact location.

Oldest IR image

Unlike in the Full Input Breakdown, the blue-to-red colors are the pixelwise *SHAP values* for the IR images. These SHAP values sum up to the number listed above each image, which is plotted on the Full Input Breakdown.

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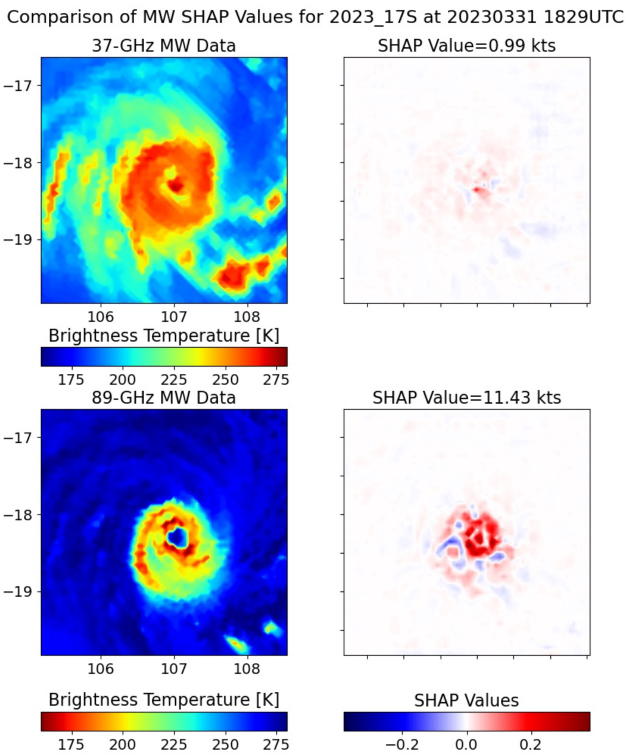
3. MW contribution (spatial SHAP values)

These plots work the same as the IR contribution plots, except that there is only the 0h image. Just note that the SHAP color scale is not the same between IR and MW and will also vary from case to case.

Strong tropical cyclone

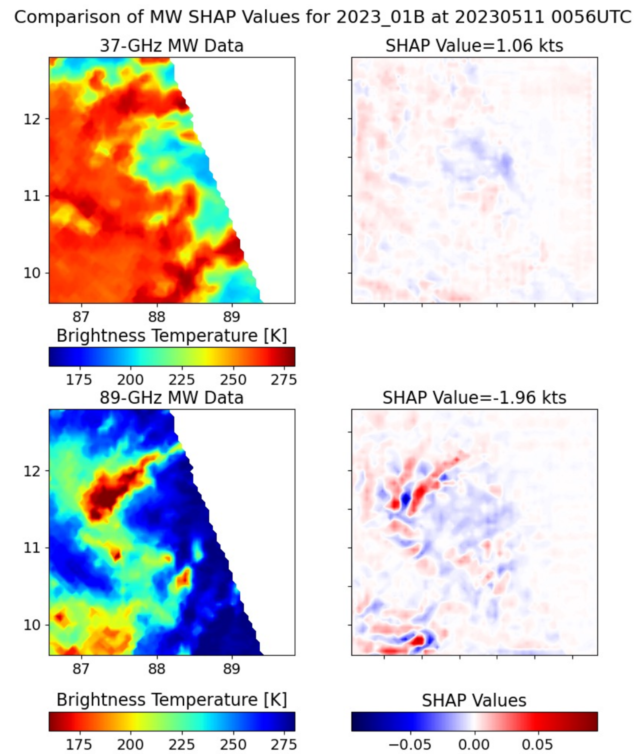
105 kt max. sustained winds (1 min.)



Here we see that the model inferred a strong signal from the inner eyewall gradients. The 37 GHz imagery was much less significant than the 89 GHz imagery.

Weak tropical cyclone

30 kt max. sustained winds (1 min.)



The model finds signals at the high-gradient edges in both images, but note that the magnitudes are relatively low, indicated by the low total value listed at the tops of the images and by the lower min and max of the SHAP color scale.

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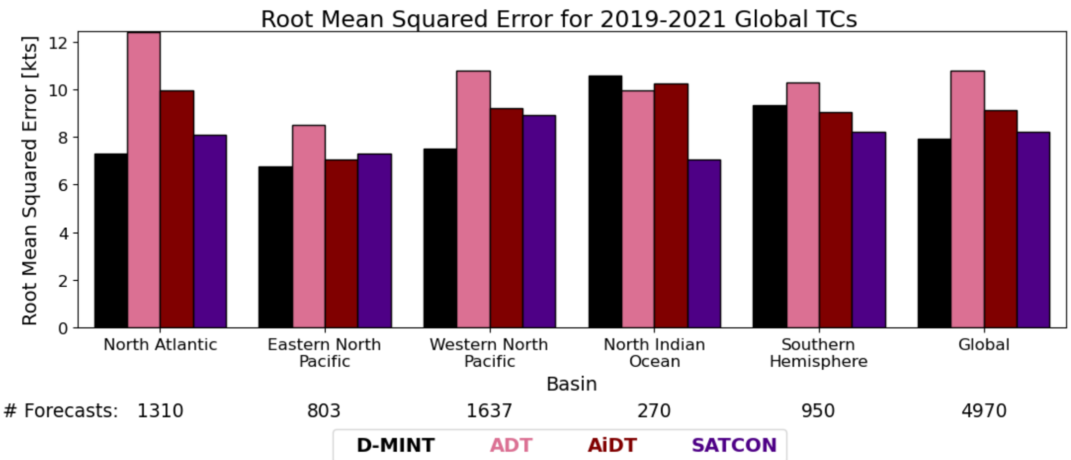
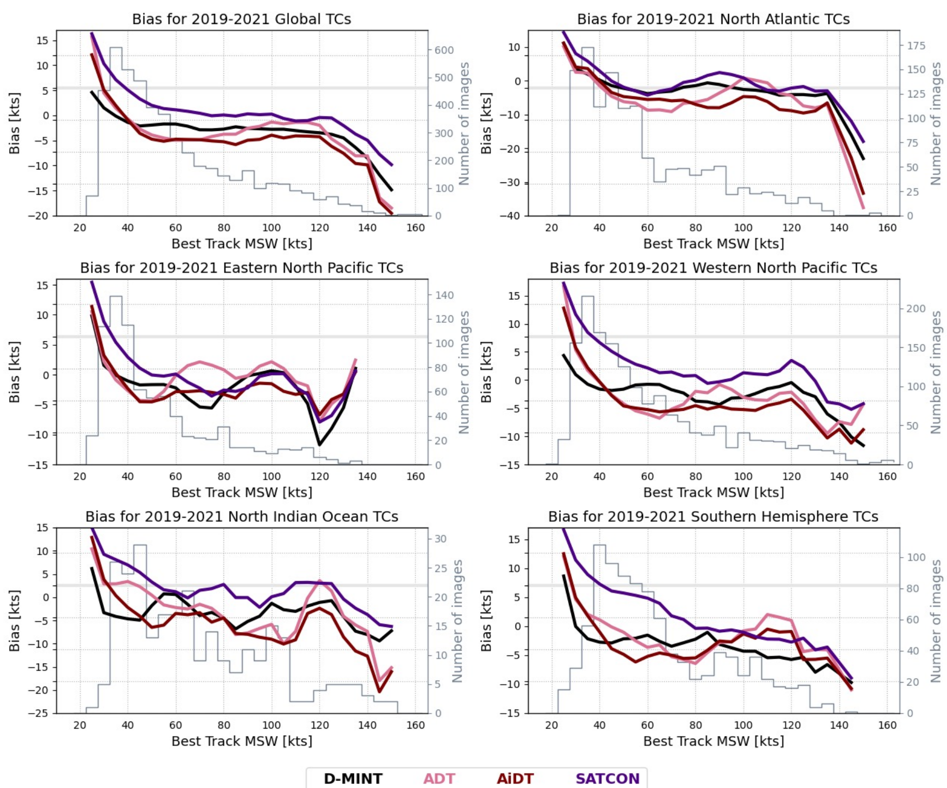
Model Performance Statistics



D-MINT has the lowest error in the North Atlantic, Eastern and Western Pacific. For the North Indian Ocean, it has the highest error. Only ADT has a higher error in the Southern Hemisphere.



Compared to ADT, AiDT and SATCON, D-MINT is the least biased for weak TCs (< 40 kts). It is the second-least biased option for strong TCs (> approx. 120 kt), after SATCON.

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Reference: Griffin, S. M., A. Wimmers, and C. S. Velden, 2023: Predicting Short-term Intensity change in Tropical Cyclones using a Convolutional Neural Network. *In Review*