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Generating High Temporal and Spatial Resolution Microwave Hurricane Image Products Using Artificial intelligence and Machine Learning Technique

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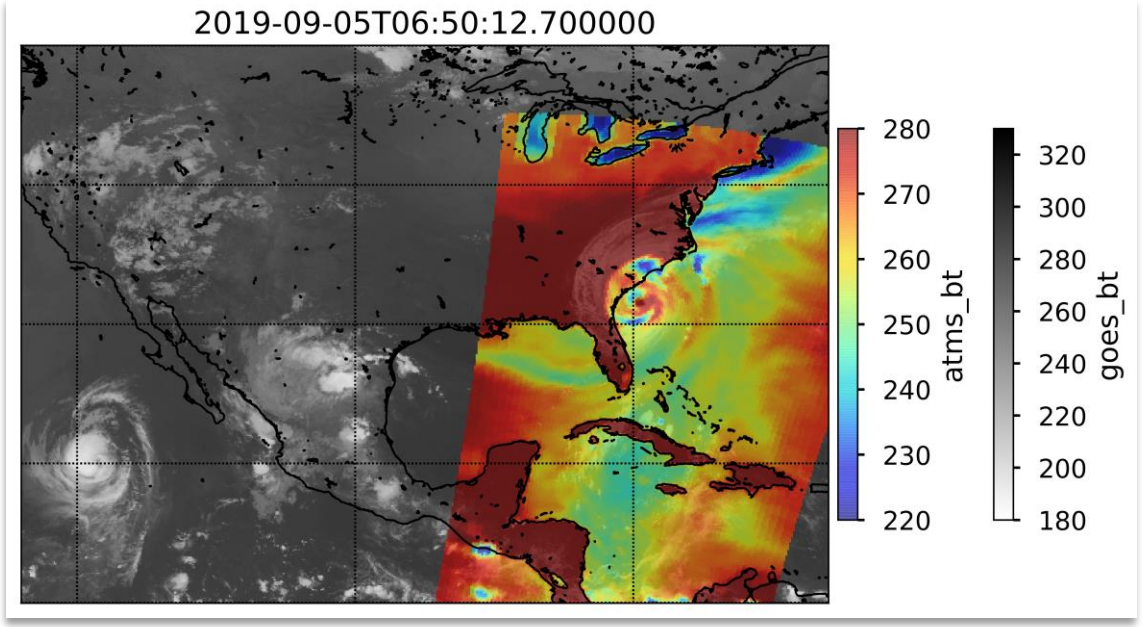
Project Background

- Microwave (MW) instruments (e.g., ATMS) have an ability to penetrate thick clouds and thus can “see” the inner structures of severe tropical cyclones (TCs) but has low image quality, which are only available on POES satellites (two times each day).

- The goal of this project is to generate high spatial and temporal resolution MW images by taking advantages of emerging artificial intelligence (AI) and machine learning (ML) techniques.

- MW image products can potentially benefit traditional Dvorak technique that makes use of infrared and visible images from polar-orbiting and geostationary satellites for TC intensity analysis.



Emerging AI & ML Ideas

- **Single Image Super Resolution**
  - Given an input of low resolution MW image (like ATMS), the model output high resolution MW images

- **Image-to-Image Translation (Pix2Pix2 model)**
  - Using GOES IR images to predict MW images.

- Optical Flow Morphing (still at the early stage)
  - Using continuous GOES images to derive optical flow fields, which drive the passing MW images to move

ATMS Channel List

Ch	Channel Central Freq.(MHz)	Polarization	Bandwidth Max. (MHz)	Frequency Stability (MHz)	Calibration Accuracy (K)	Nonlinearity Max. (K)	NEΔT (K)	3-dB Bandwidth (deg)	Remarks	Characterization at Nadir
1	23800	QV	270	10	1.0	0.3	0.5	5.2	AMSU-A2	Window-water vapor 100 mm
2	31400	QV	180	10	1.0	0.4	0.6	5.2	AMSU-A2	Window-water vapor 500 mm
3	50300	QH	180	10	0.75	0.4	0.7	2.2	AMSU-A1-2	Window-surface emissivity
4	51760	QH	400	5	0.75	0.4	0.5	2.2		Window-surface emissivity
5	52800	QH	400	5	0.75	0.4	0.5	2.2	AMSU-A1-2	Surface air
6	53596±115	QH	170	5	0.75	0.4	0.5	2.2	AMSU-A1-2	4 km ~ 700 mb
7	54400	QH	400	5	0.75	0.4	0.5	2.2	AMSU-A1-1	9 km ~ 400 mb
8	54940	QH	400	10	0.75	0.4	0.5	2.2	AMSU-A1-1	11 km ~ 250 mb
9	55500	QH	330	10	0.75	0.4	0.5	2.2	AMSU-A1-2	13 km ~ 180 mb
10	57290.344(f_o)	QH	330	0.5	0.75	0.4	0.75	2.2	AMSU-A1-1	17 km ~ 90 mb
11	f_o± 217	QH	78	0.5	0.75	0.4	1.0	2.2	AMSU-A1-1	19 km ~ 50 mb
12	f_o±322.2±48	QH	36	1.2	0.75	0.4	1.0	2.2	AMSU-A1-1	25 km ~ 25 mb
13	f_o±322.2±22	QH	16	1.6	0.75	0.4	1.5	2.2	AMSU-A1-1	29 km ~ 10 mb
14	f_o±322.2±10	QH	8	0.5	0.75	0.4	2.2	2.2	AMSU-A1-1	32 km ~ 6 mb
15	f_o±322.2±4.5	QH	3	0.5	0.75	0.4	3.6	2.2	AMSU-A1-1	37 km ~ 3 mb
16	88200	QV	2000	200	1.0	0.4	0.3	2.2	89000	Window H_2O 150 mm
17	165500	QH	3000	200	1.0	0.4	0.6	1.1	157000	H_2O 18 mm
18	183310±7000	QH	2000	30	1.0	0.4	0.8	1.1	AMSU-B	H_2O 8 mm
19	183310±4500	QH	2000	30	1.0	0.4	0.8	1.1		H_2O 4.5 mm
20	183310±3000	QH	1000	30	1.0	0.4	0.8	1.1	AMSU-B/MHS	H_2O 2.5 mm
21	183310±1800	QH	1000	30	1.0	0.4	0.8	1.1		H_2O 1.2 mm
22	183310±1000	QH	500	30	1.0	0.4	0.9	1.1	AMSU-B/MHS	H_2O 0.5 mm

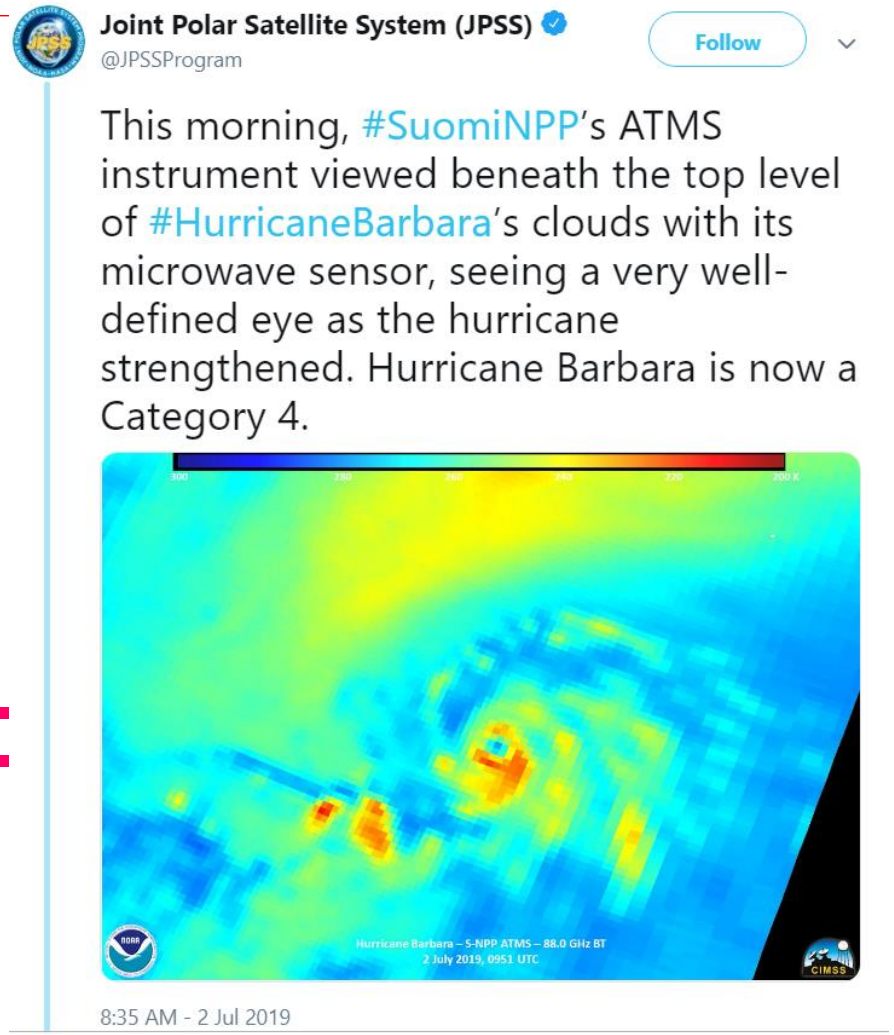
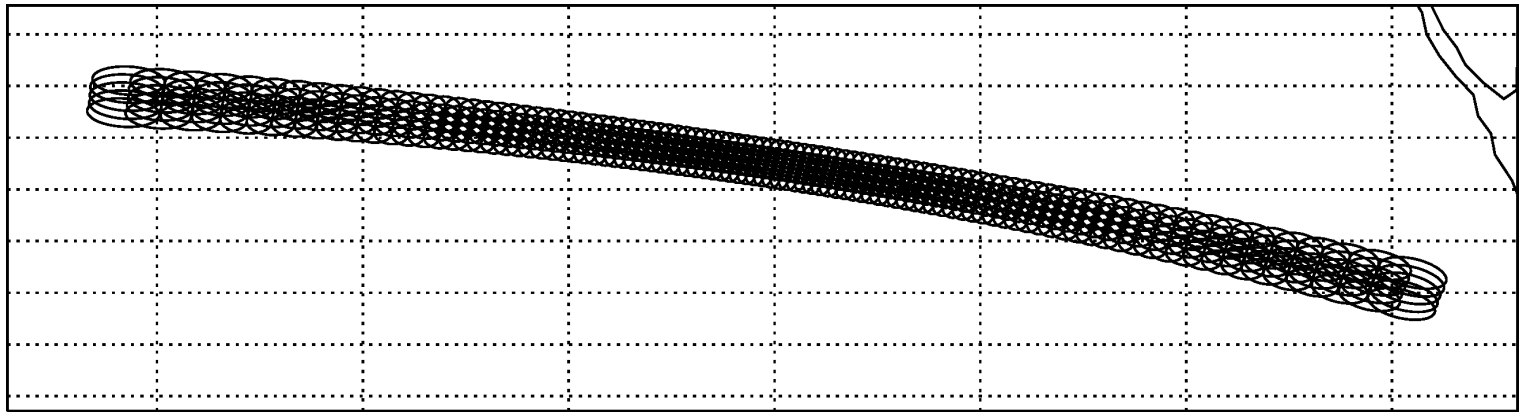
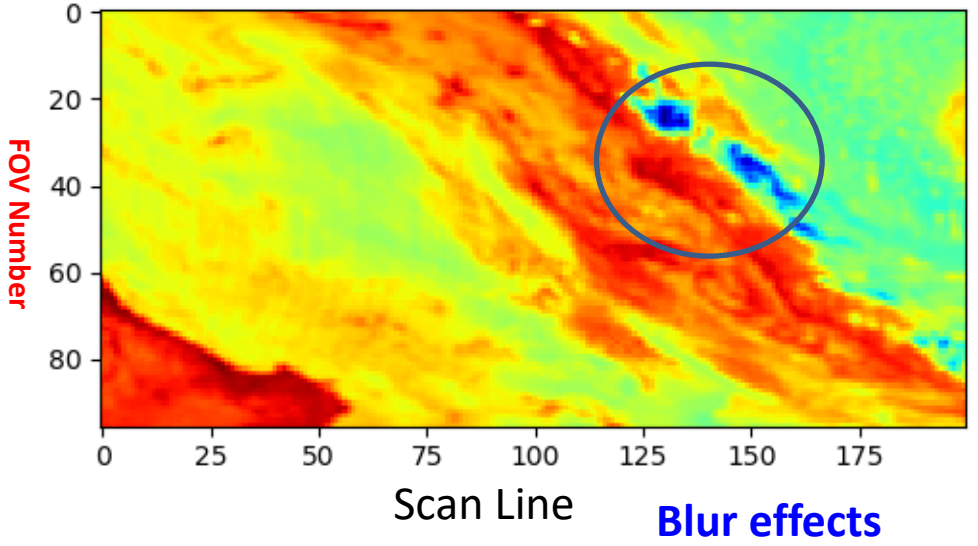


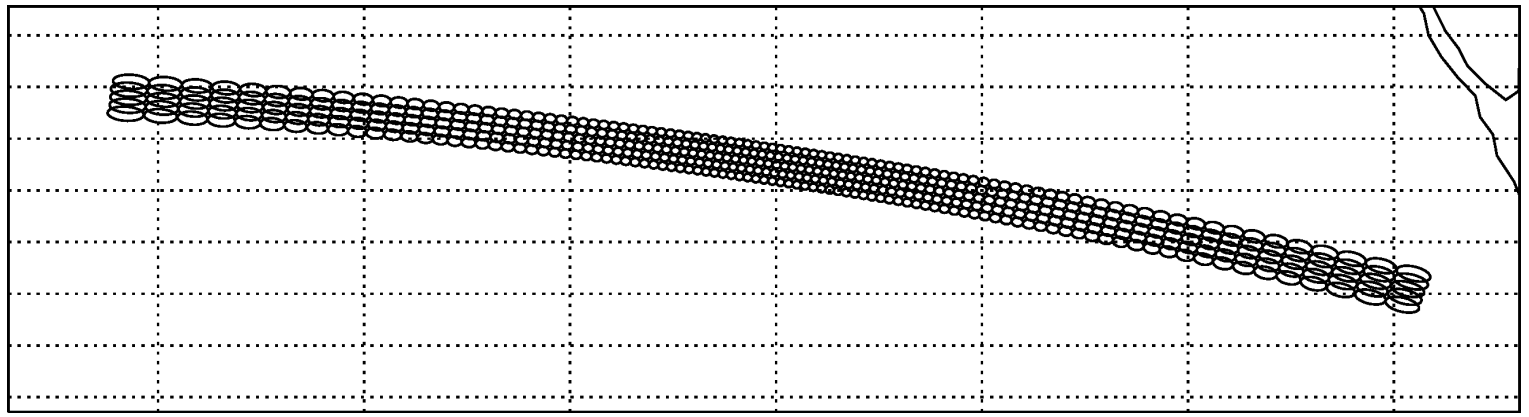
Image Quality Factor: 1) FOV Res. 2) Sample Rate



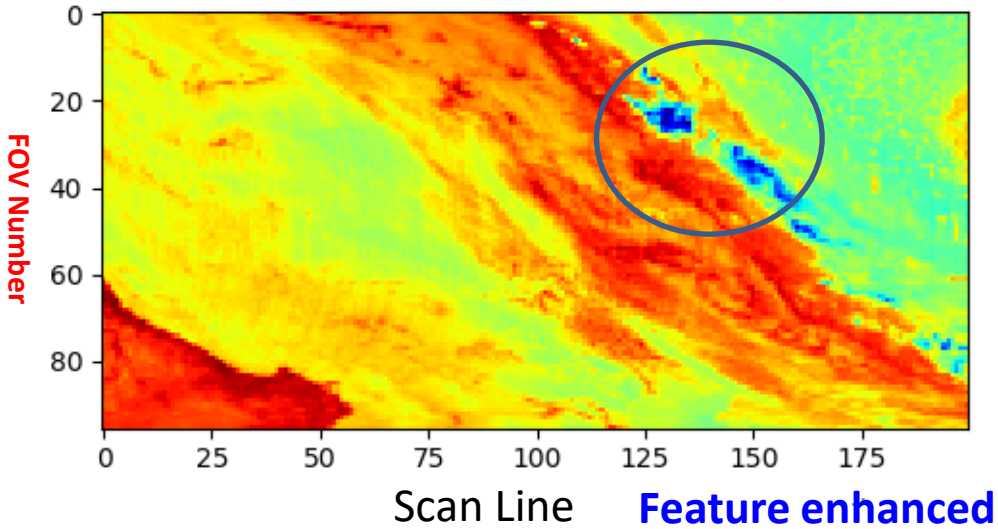
2.2° FOV Size with 1.1 ° step angle, 96 Samples Per Scan



Blur effects



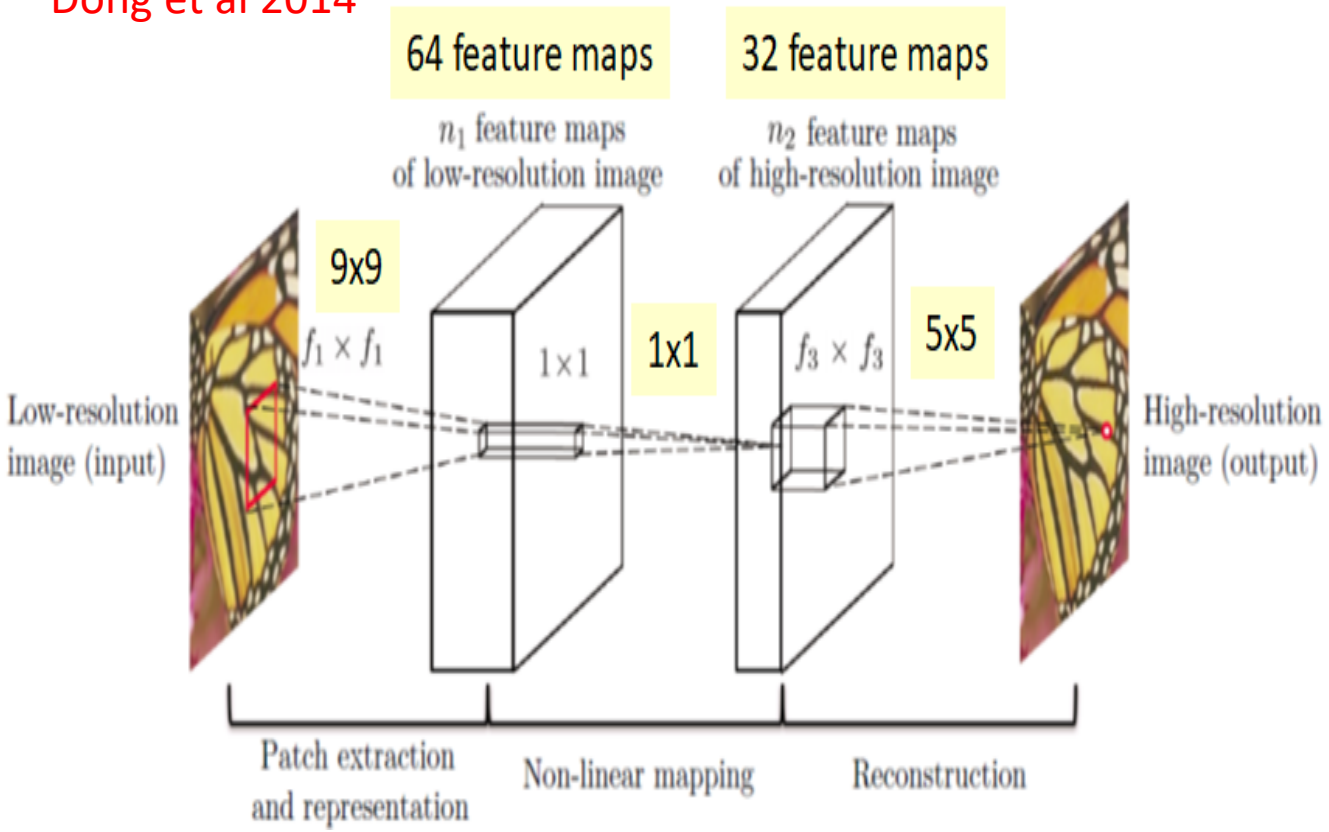
1.1° FOV Size with 1.1 ° step angle, 96 Samples Per Scan



Feature enhanced

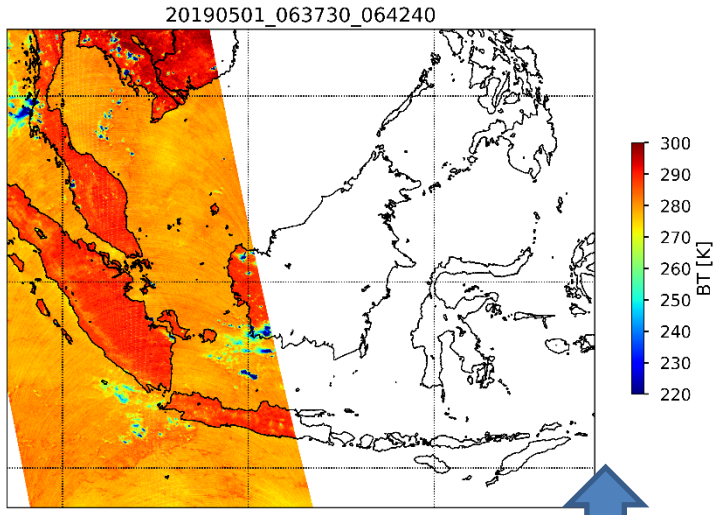
Super-Resolution Convolutional Neural Network (SRCNN)

Dong et al 2014

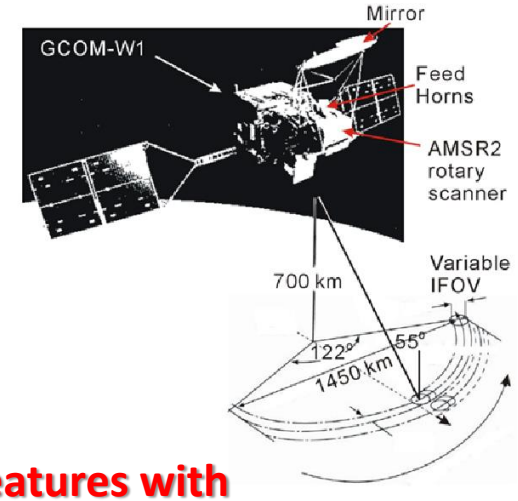


- Layer (type) Output Shape Param #
- ==========
- conv2d_1 (Conv2D) (None, 24, 24, 128) 10496
- _____
- conv2d_2 (Conv2D) (None, 24, 24, 64) 73792
- _____
- conv2d_3 (Conv2D) (None, 20, 20, 1) 1601
- ==========
- Total params: 85,889
- Trainable params: 85,889
- Non-trainable params: 0
- _____
- None

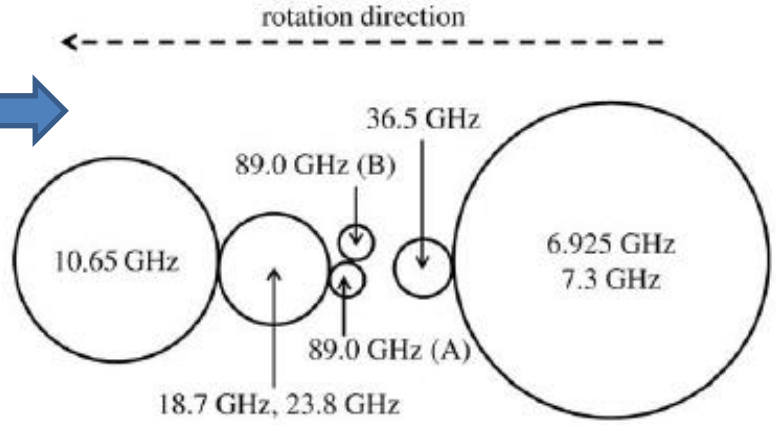
Generating Training Dataset using AMSR2



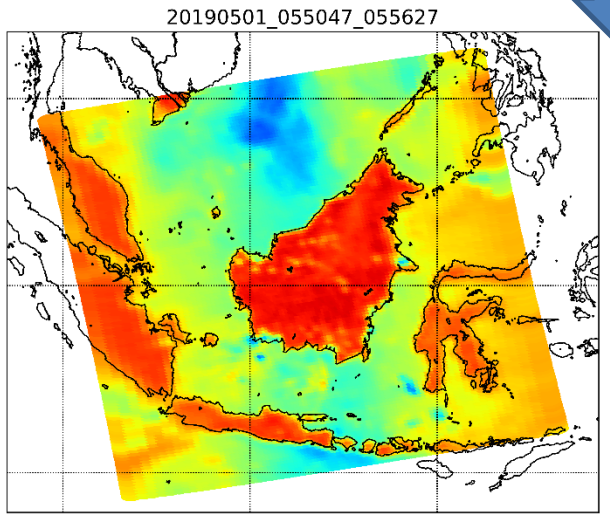
AMSR-2 89GHz Image

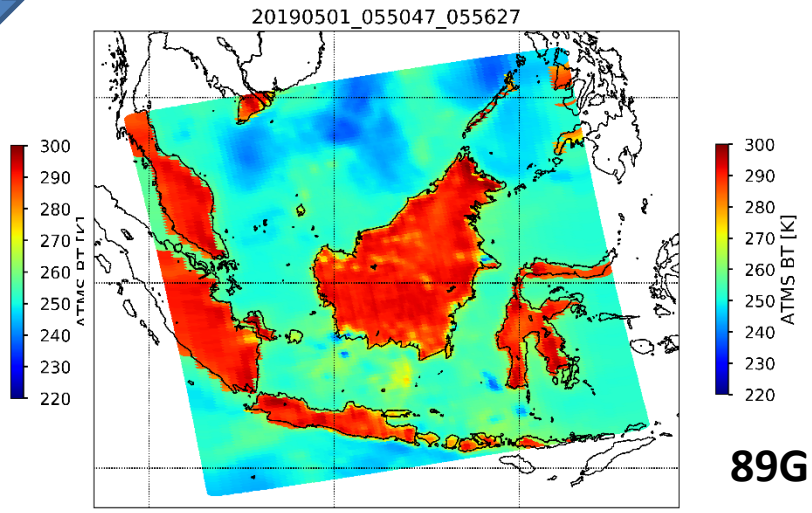


Maeda et al. 2016



Similar features with different resolution and view angle



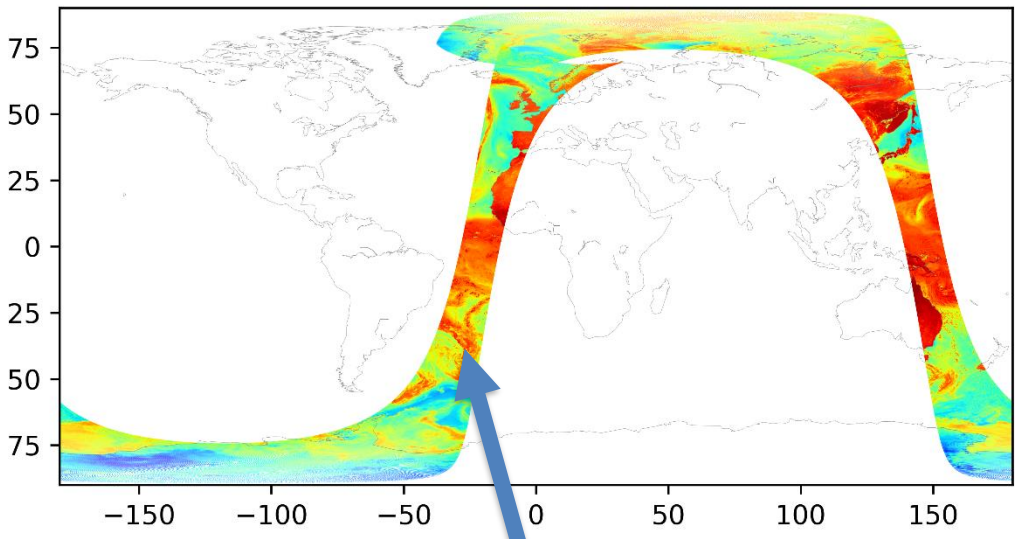


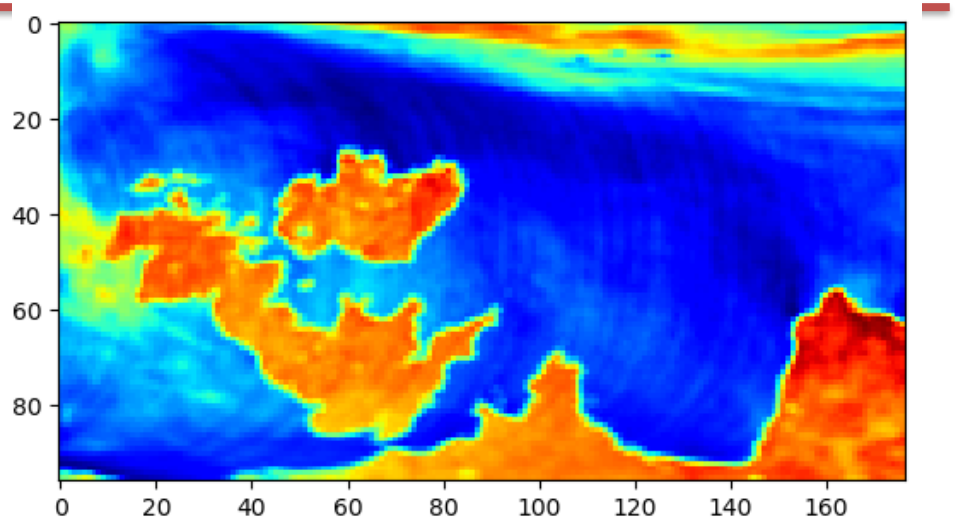
Using GCOM-W1 AMSR-2 89GHz
High resolution data (3 by 5 km)

89GHz Image (Limb-corrected)

89GHz Image (original)

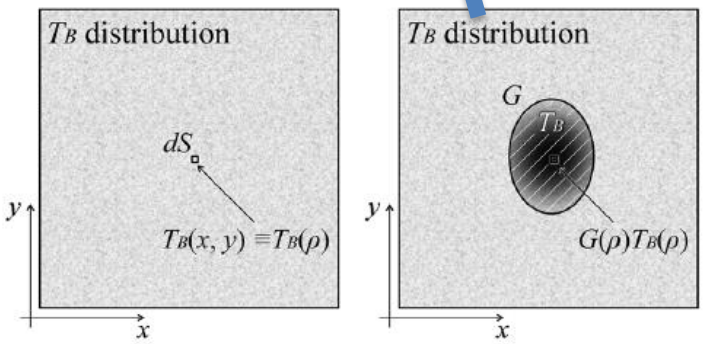
Using AMSR-2 to simulate High (1.1°) and Low (2.2°) resolution ATMS data



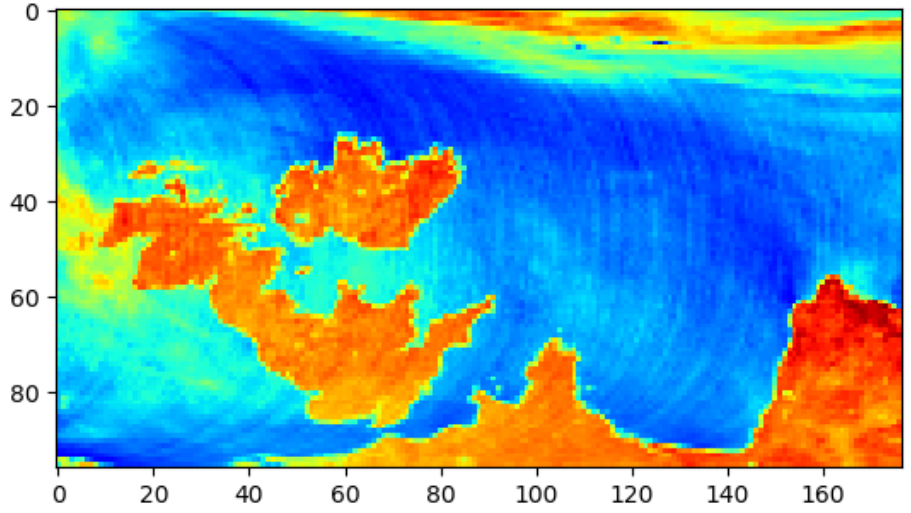


2.2 degree with 96 FOV 3/8 seconds scan rate

Convolved with AMSR-2 images with ATMS antenna pattern (1.1 and 2.2 degree)

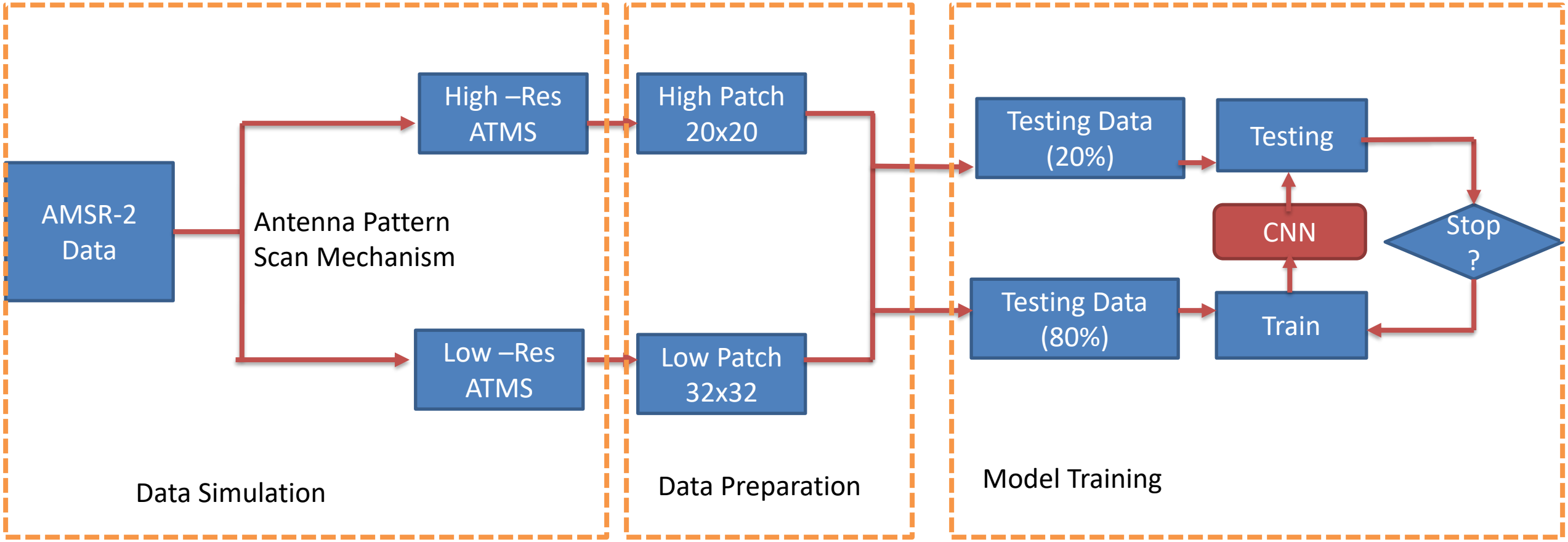


$$T_B = \int\int G(x,y)T_B(x,y)dxdy \equiv \int_S G(\rho)T_B(\rho)dS$$

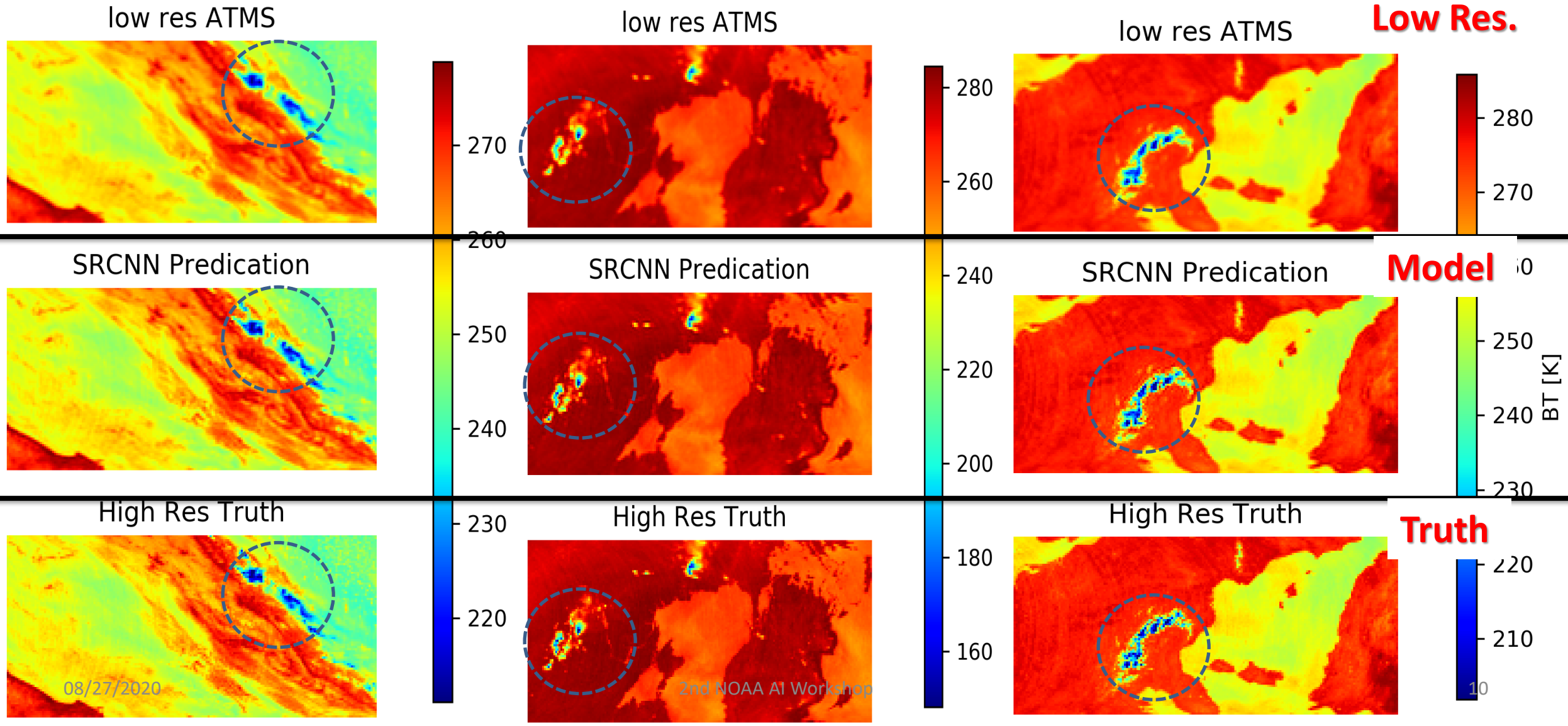


1.1 degree with 96 FOV 3/8 seconds scan rate

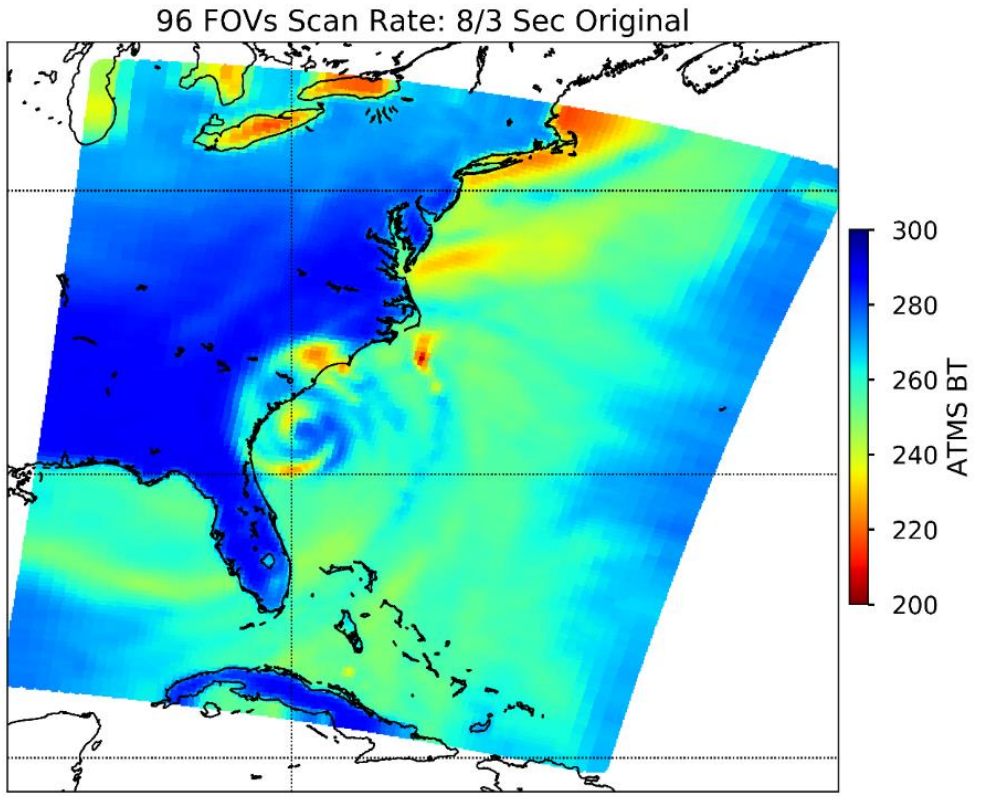
Algorithms Flow Chart

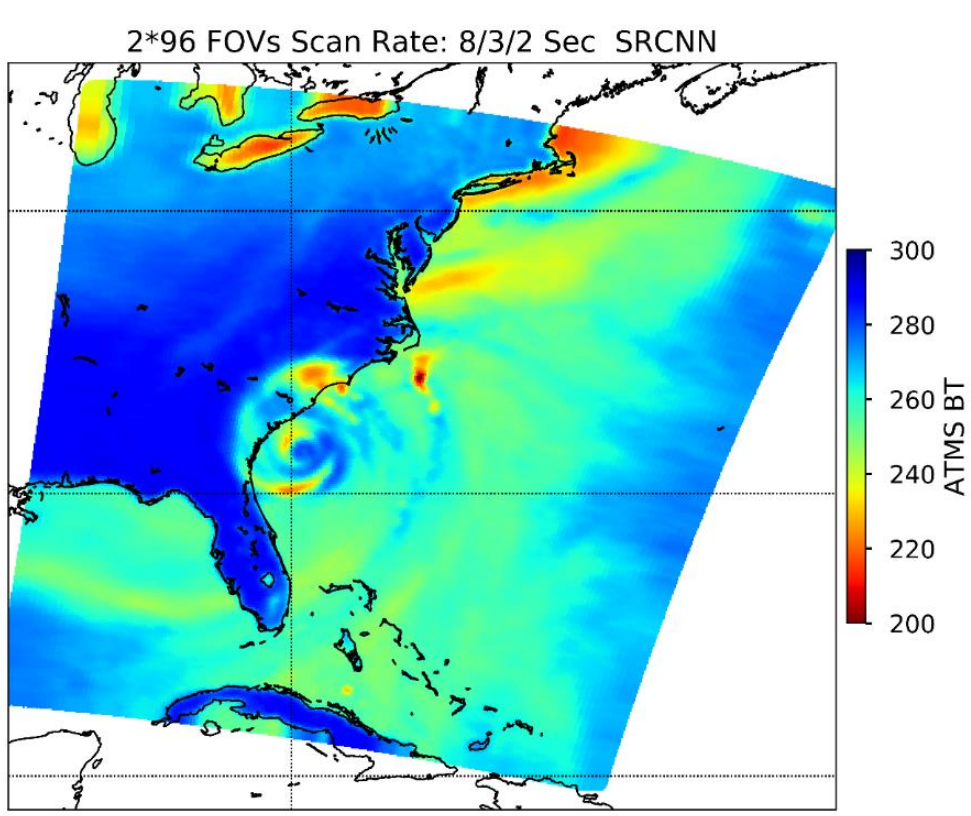


Validation with Testing Data



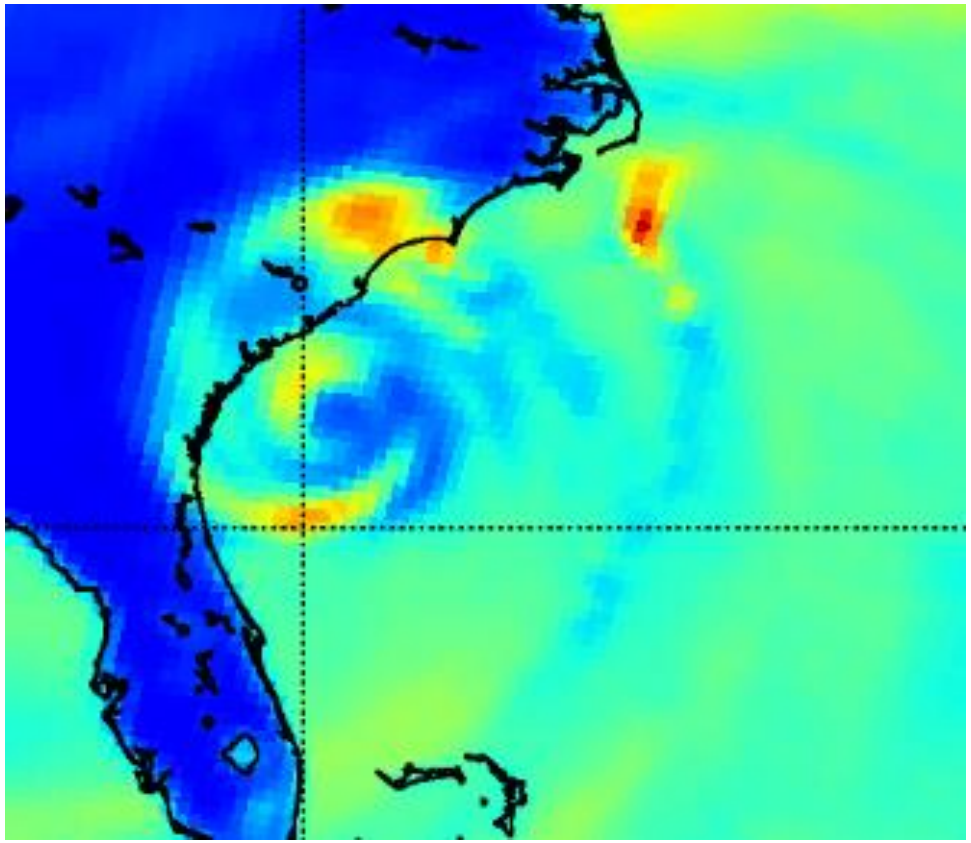
Hurricane Dorian Channel
ATMS Image 89 GHz on Sep 5 2019



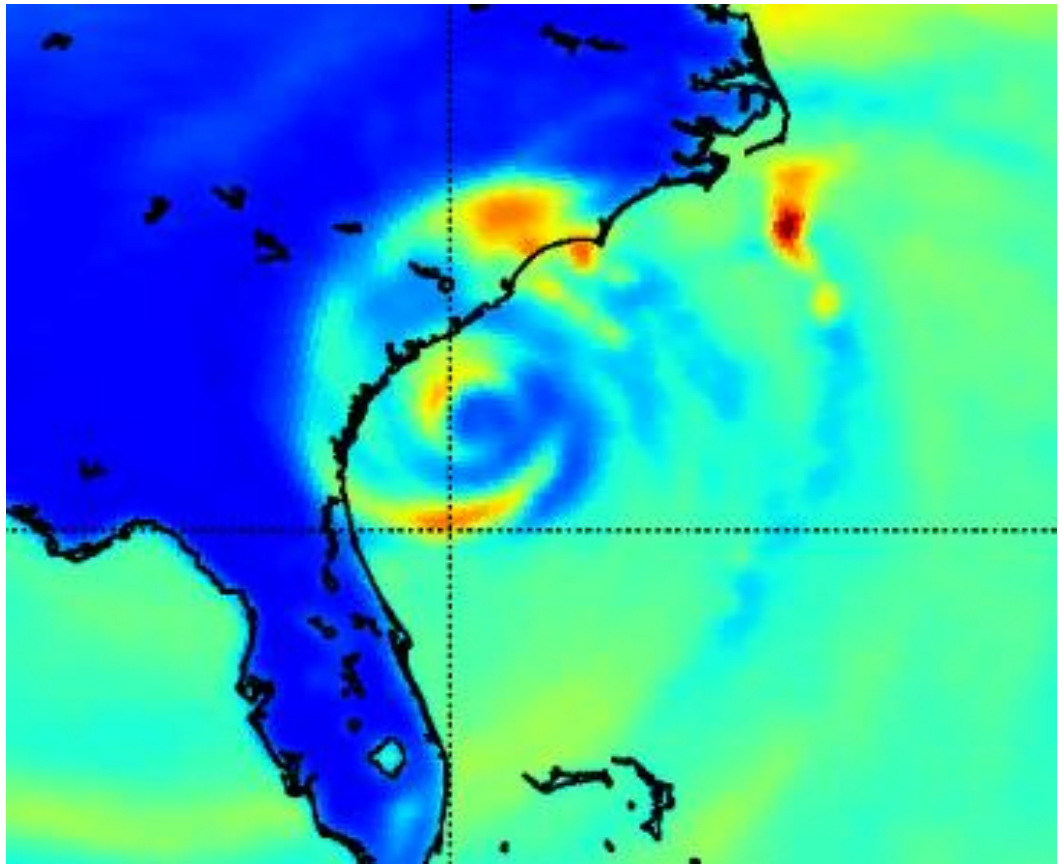


- **FOV Resolution: 2.2 Degree → 1.1 Degree**
- **Sample Rate: 96 → 102 per scan**

Zoom In

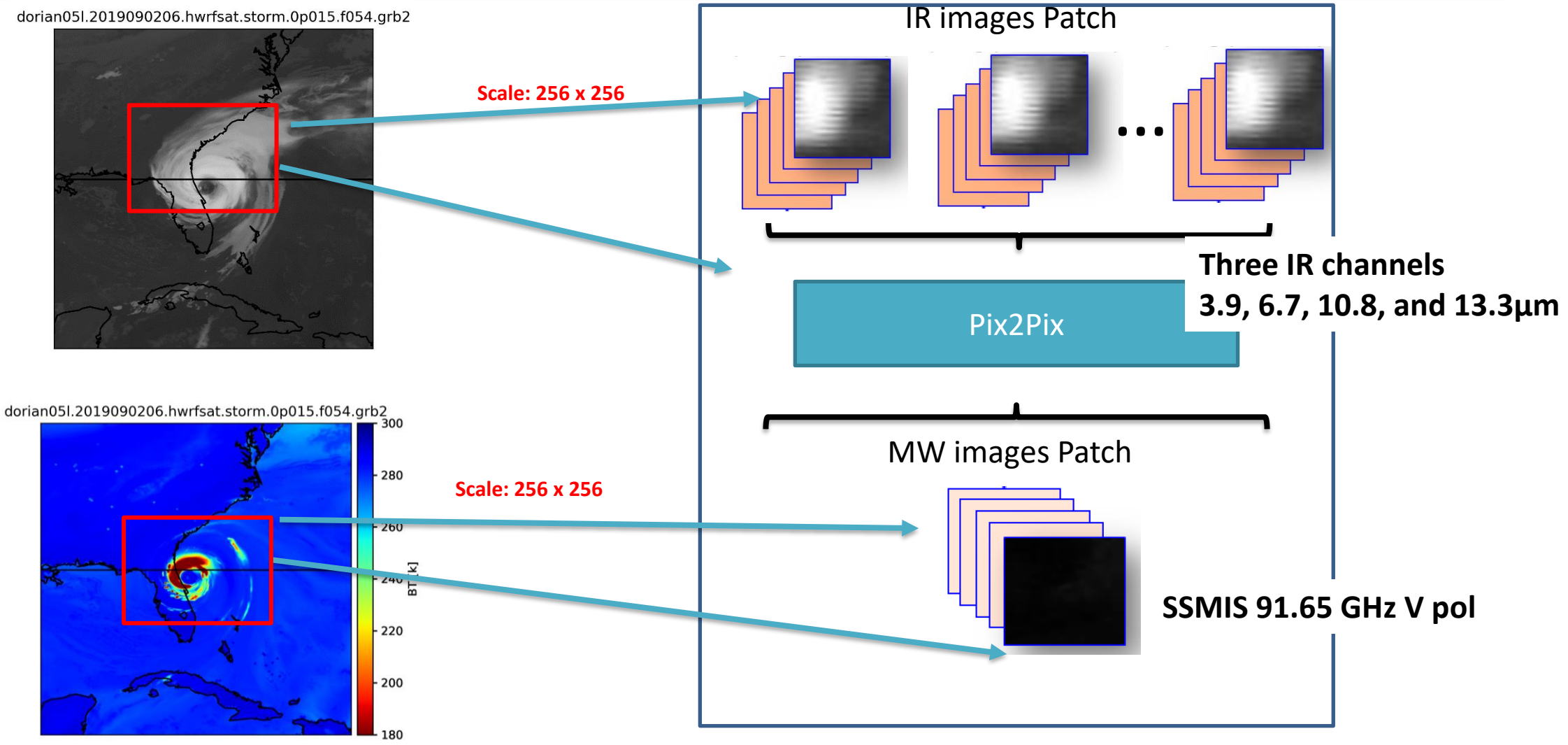


Original



AI Model Enhanced

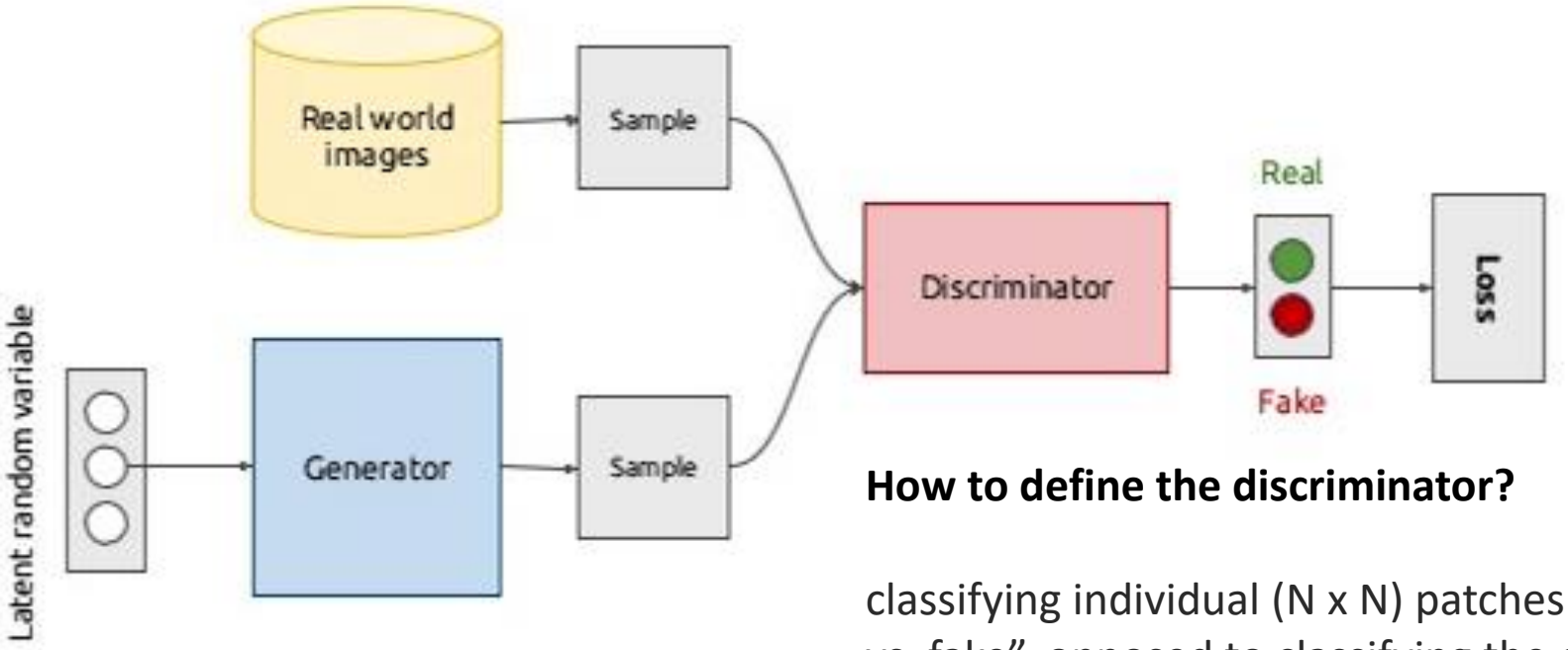
Image-to-image Translation



Using Pix2Pix2 Framework to covert IR to MW

Structure of GAN Model – Pix2Pix2

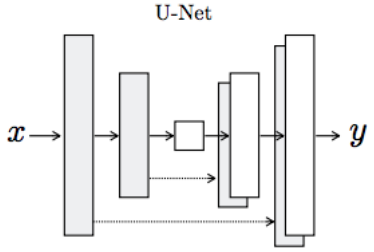
- https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016



How to define the discriminator?

classifying individual (N x N) patches in the image as “real vs. fake”, opposed to classifying the entire image as “real vs. fake”. N can be controlled dependent on which details you like to achieve. Here we choose N=70 in 256x256 images.

How to define the generator?



Training and Validation Dataset

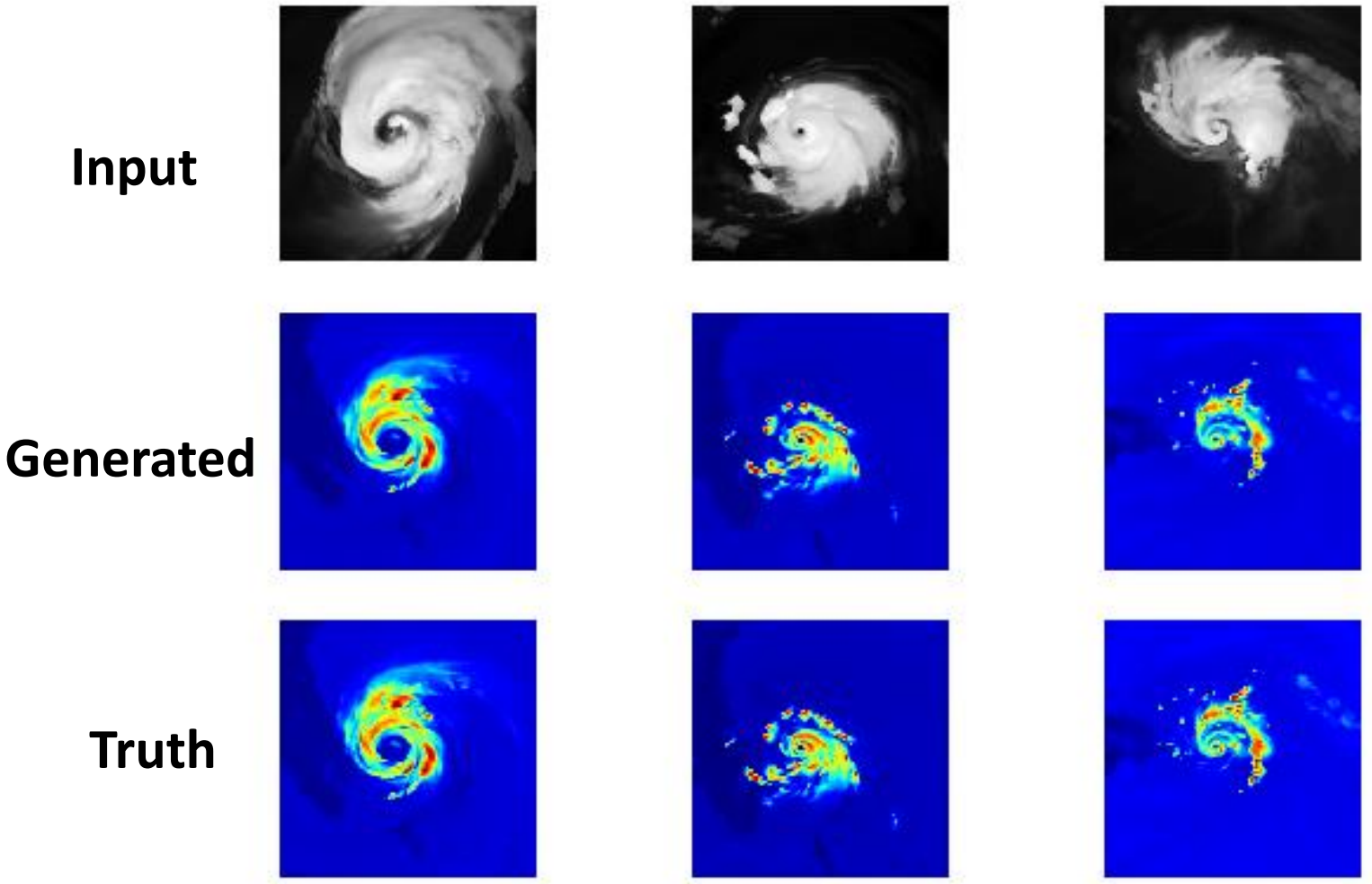
- HWRF Unified Post Processor(UPP) Simulated Satellite Images
  - Resolution (D2, 6km, 850 km × 850 km)
    - On grids, Model Resolution
  - Viewing angle
    - Set as zero, nadir only
  - Channels:
    - IR GOES-13 (IR): 6.7, 10.8, and 13.3 µm
    - SSIMIS 91.65 GHz V
  - Outputs
    - Every 6 hours for future every 6 hour's forecasting
    - For example 1200 – f06, f12 f18 ….

- Training Dataset:
  - Hurricane Dorian (08/24-09/07 2019)

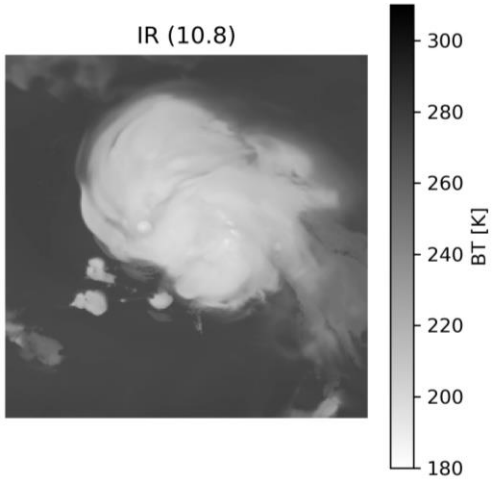
- Validation Dataset:
  - Hurricane Humberto (09/13-09/20 2019)

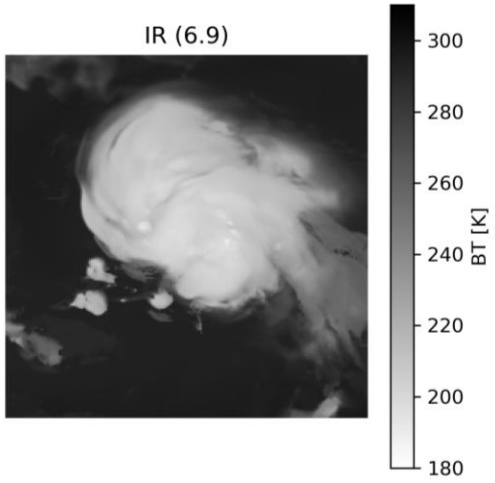
- Testing Dataset:
  - Real Satellite data from GOES16 ABI clipped from storm center
  - Hurricane Dorian (08/24-09/07 2019)

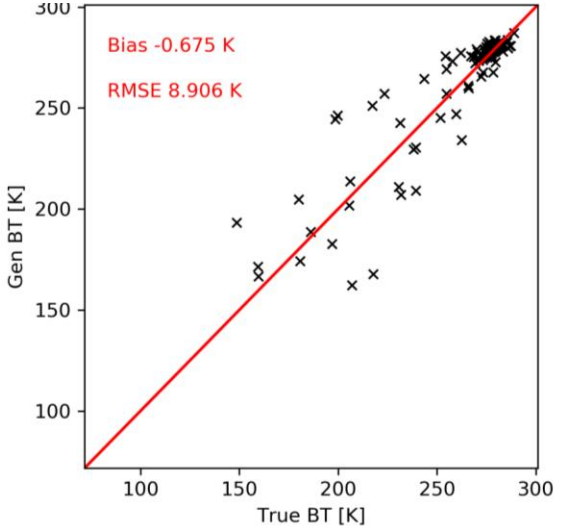
During Training Process



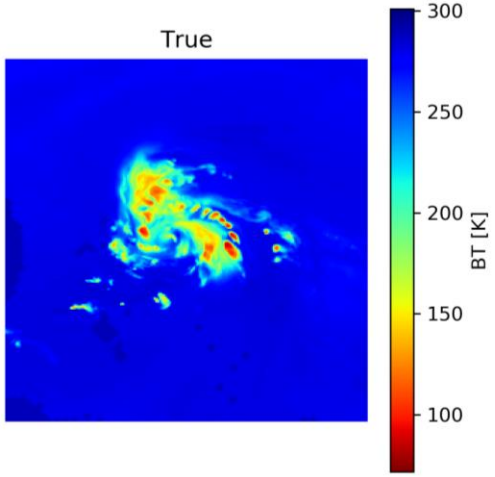
Independent Validation – HWRF Data
Hurricane Humberto – 09/2019

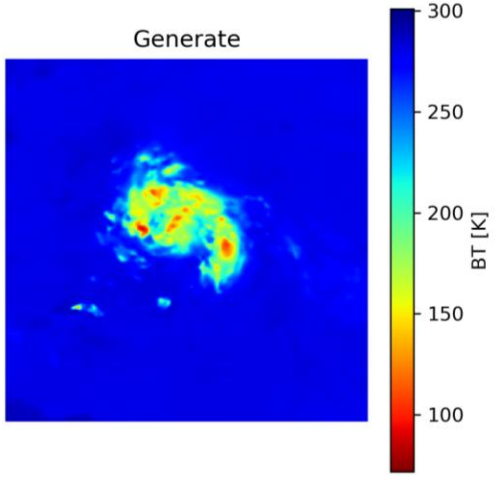






16x16 pixel average



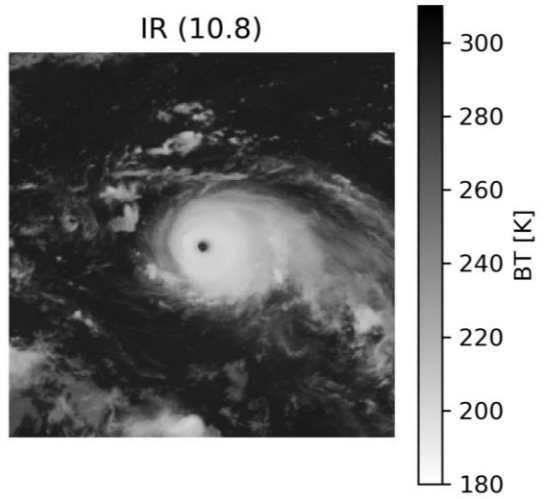


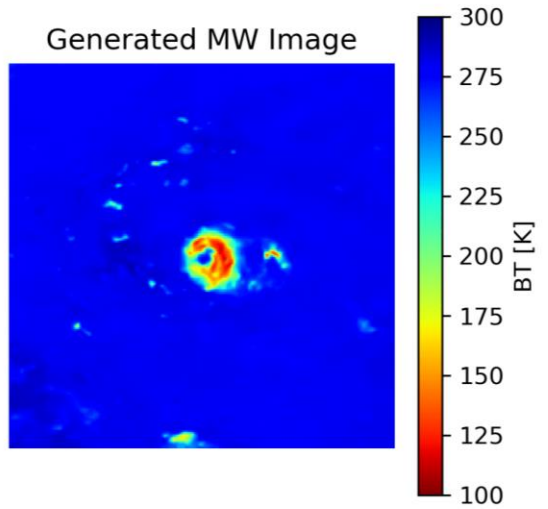
Generally speaking, the model can basically reproduce MW image with overall structures but still cannot capture the fine structures within TCs.

The scatter plot shows correlations but still has relatively large bias and RMSE.

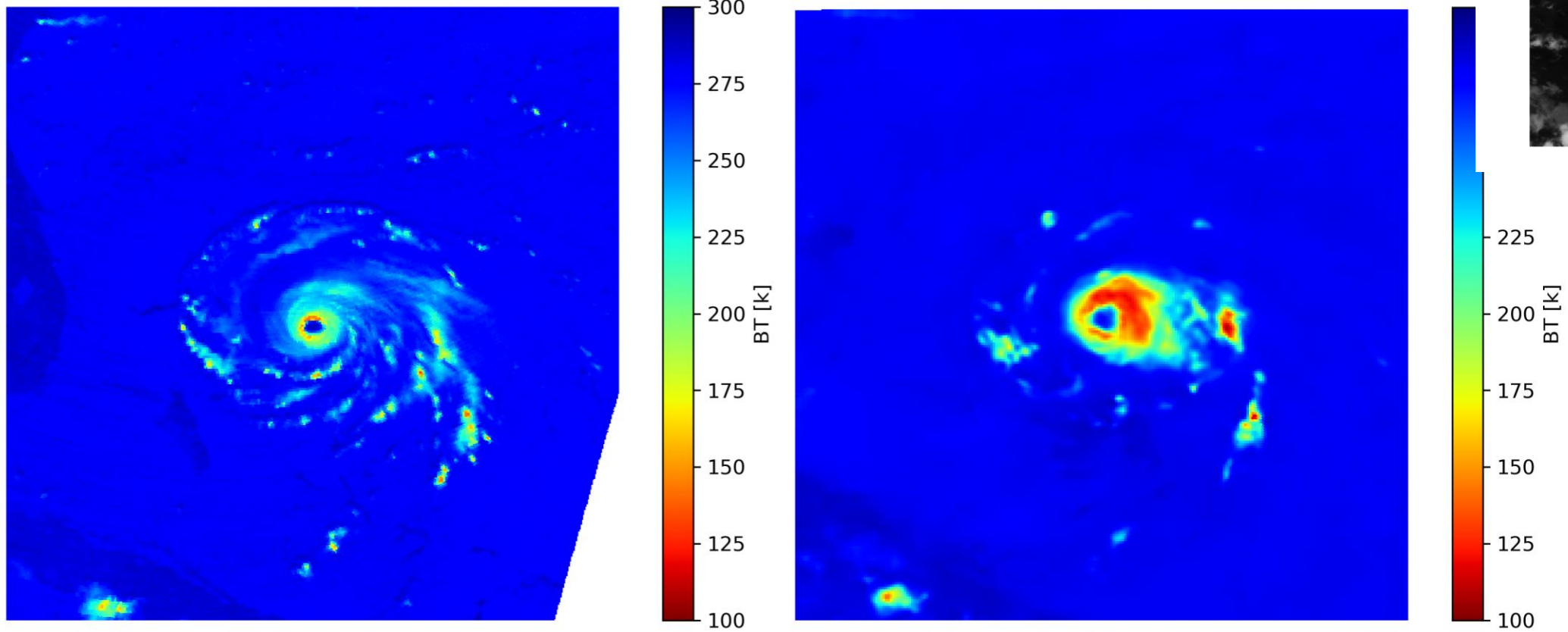
Real Satellite Data – GOES 16 ABI Hurrican Dorian 2019/09

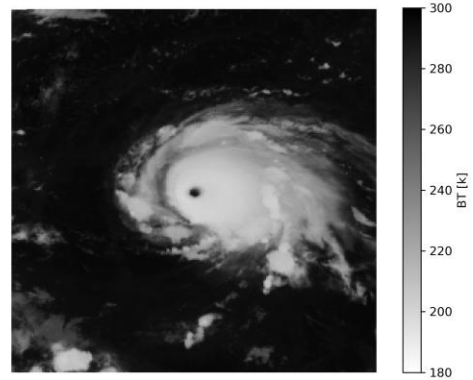
- The GOES16 ABI three channels of 6.7, 10.7, 13.3 μm are clipped along the TC centers
- The real satellite data are input into the AI model to produce the MW images
- The AI model is trained use the HWRF simulated data
- The data for Hurricane Dorian from 09/01 to 09/02 in 2019 are used to test.



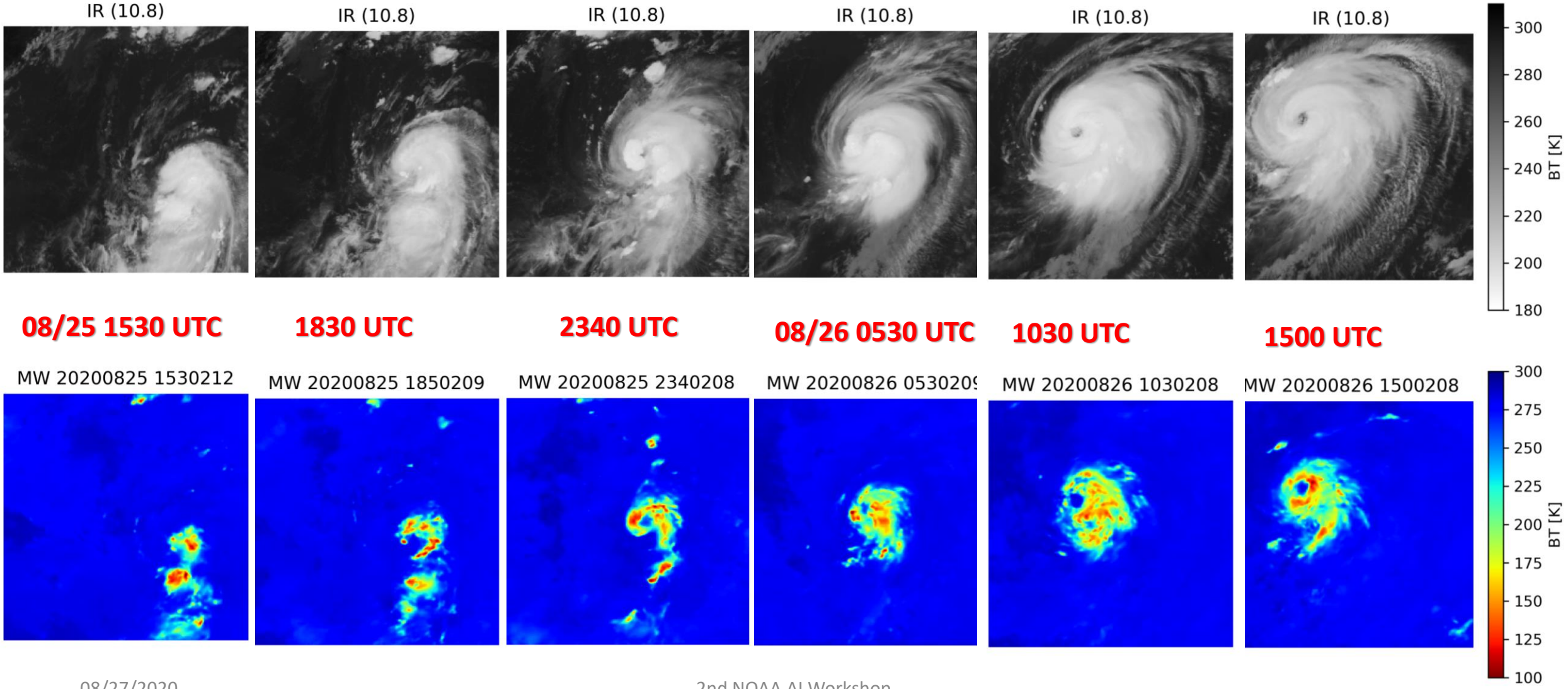


AI model produced Image *vs* AMSR2





Hurricane Laurel



Conclusion and Final Remarks

- Several methods from AI & ML are tested to generate high temporal and spatial resolution MW images for hurricane applications.

- The single image super resolution works very well to improve image quality from ATMS instrument onboard JPSS.

- The image-to-image translation model that converts IR images into MW image shows some potentials.
  - Overall images look OK but still need to improve fine structure predication
  - The AI-model generated MW images can benefit forecasters to monitor hurricanes.