Using Convolutional Neural Network (CNN) to Enhance Spatial Resolution of ATMS Images

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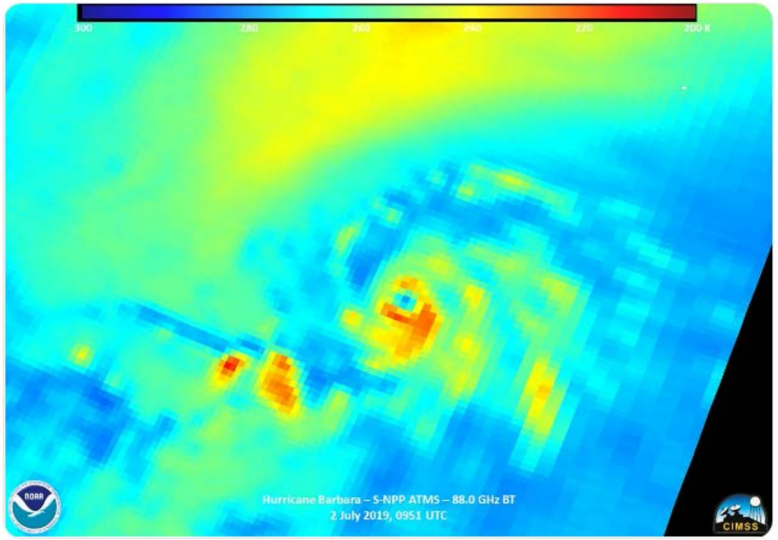
Outline

- Motivation
- Data preparation
- Super Resolution CNN Model
- Preliminary Results
- Conclusion

Motivation (i)

Joint Polar Satellite System (JPSS)
@JPSSProgram
Follow

This morning, #SuomiNPP's ATMS instrument viewed beneath the top level of #HurricaneBarbara's clouds with its microwave sensor, seeing a very well-defined eye as the hurricane strengthened. Hurricane Barbara is now a Category 4.

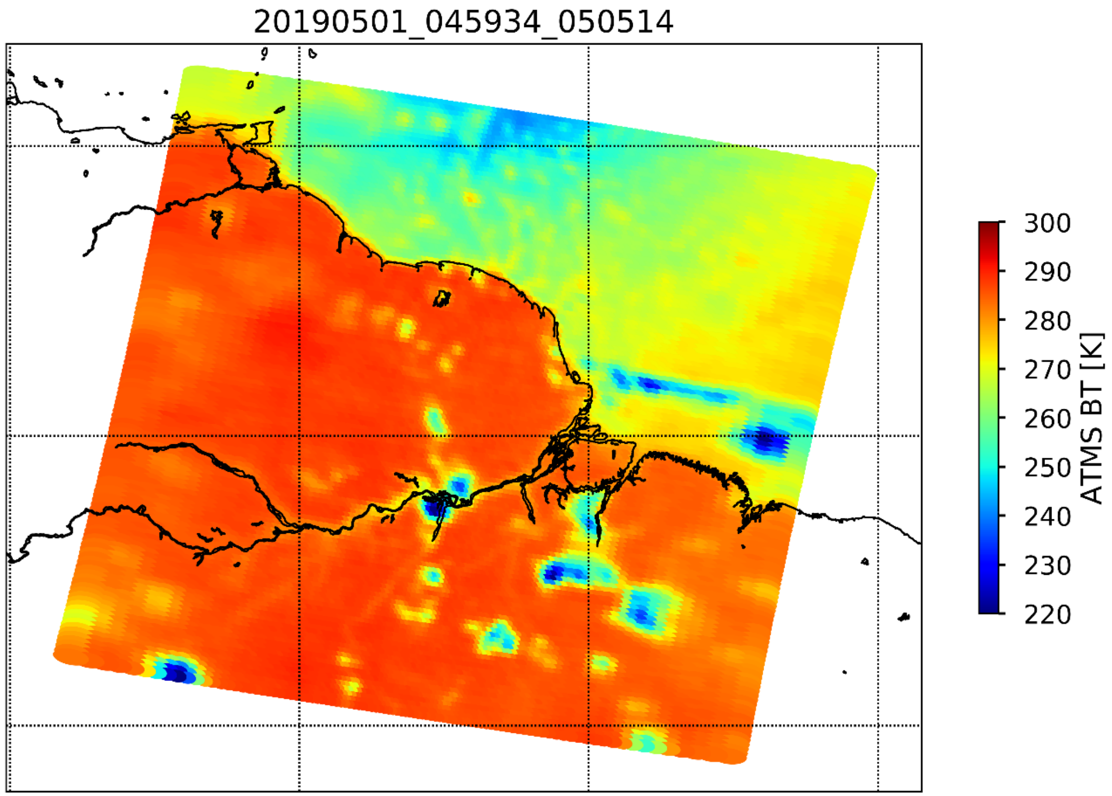


8:35 AM - 2 Jul 2019

- ATMS instrument (e.g., 89 GHz) can view beneath the cloud for hurricane structures. However, compared to optical sensor (e.g. VIIRS), the image resolution is really poor.

- With the enhanced images (that have improved spatial resolution), it will make the hurricane structures clearer.

Motivation (ii)



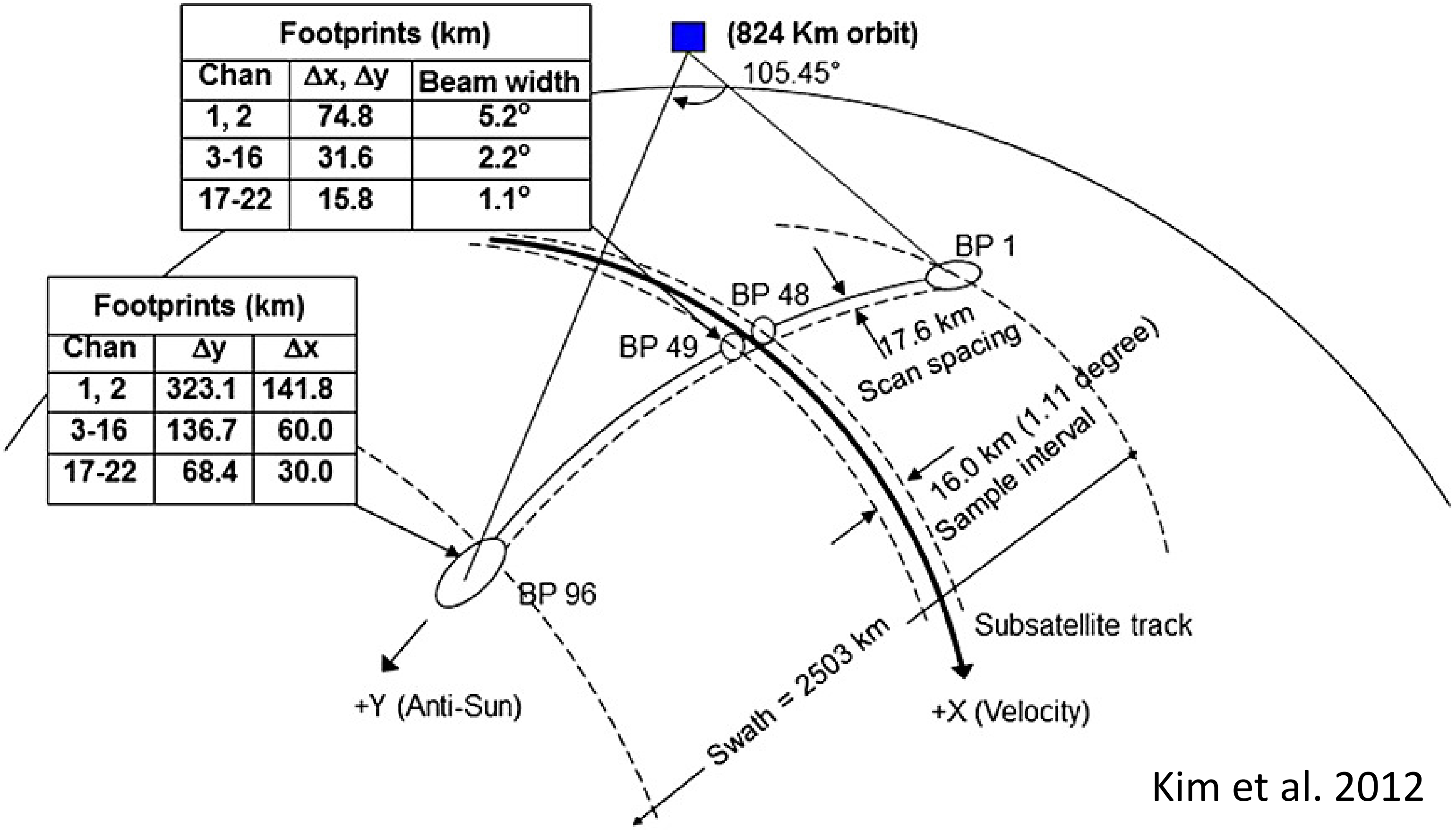
- Given low resolution ATMS image channel (2.2°), it is very hard to accurately retrieve the coastline from ATMS for geolocation assessment.

- The enhanced image (with improved spatial resolution) will be helpful for geolocation assessment.

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

ATMS Scan Pattern

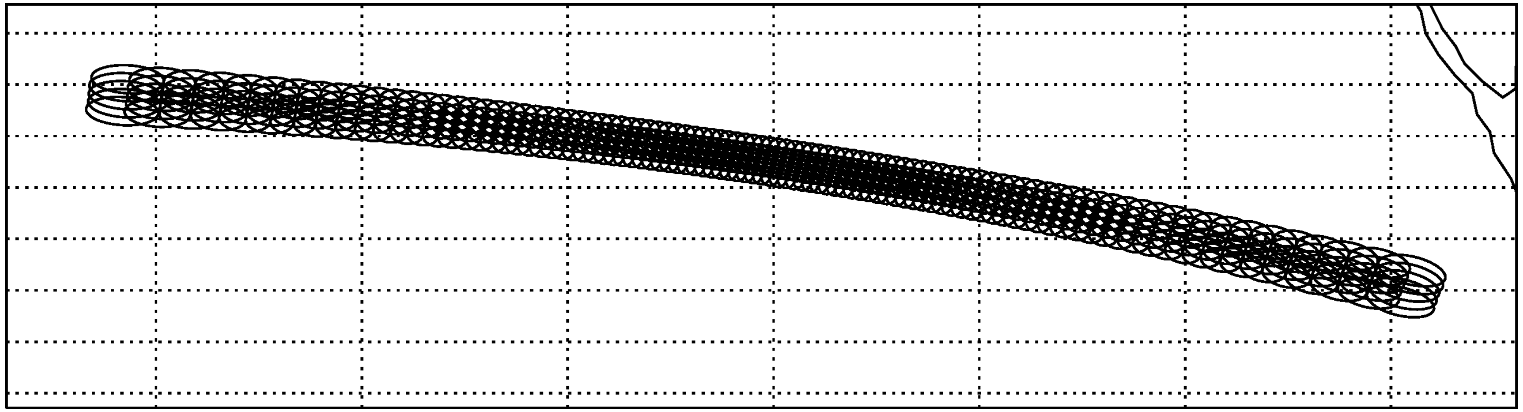


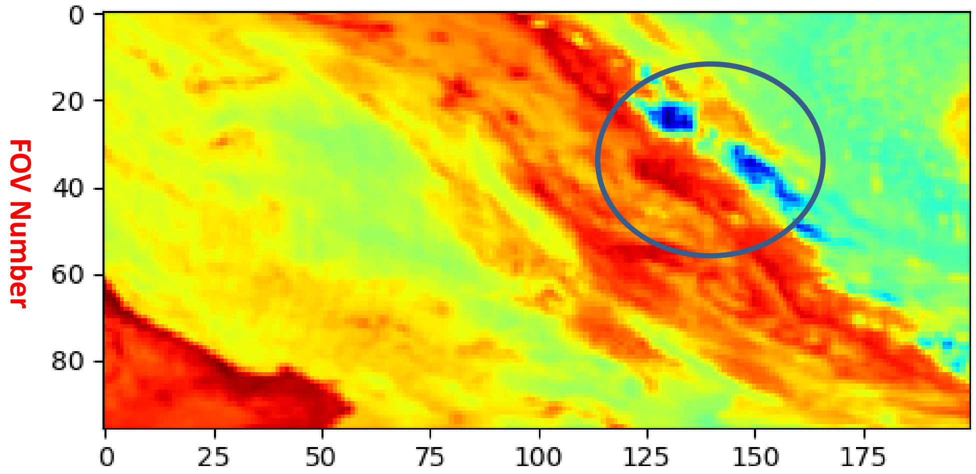
Footprints (km)		
Chan	Δx, Δy	Beam width
1, 2	74.8	5.2°
3-16	31.6	2.2°
17-22	15.8	1.1°

Footprints (km)		
Chan	Δy	Δx
1, 2	323.1	141.8
3-16	136.7	60.0
17-22	68.4	30.0

Kim et al. 2012

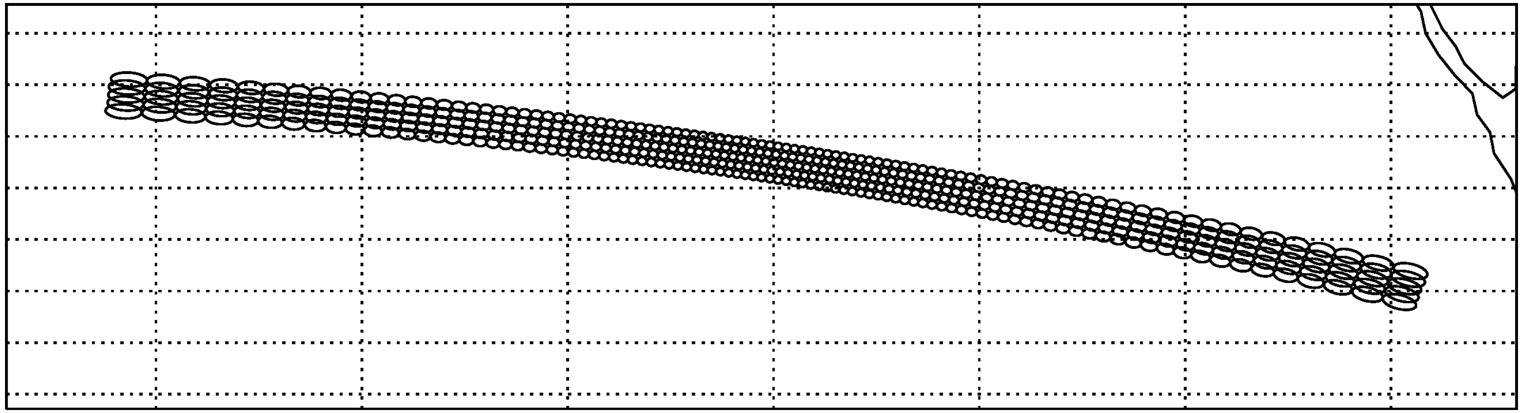
Over-Sample vs. Normal Sample

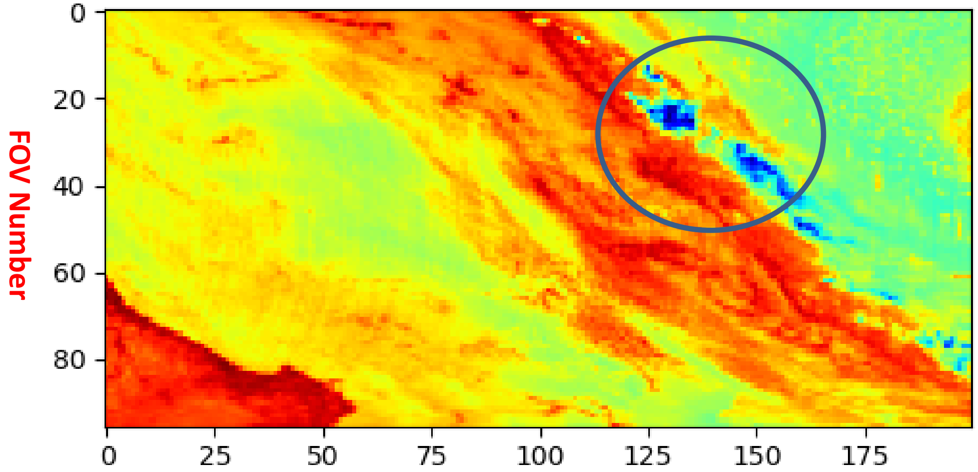




2.2° FOV Size with 1.1 ° step angle, oversample

Blur effects



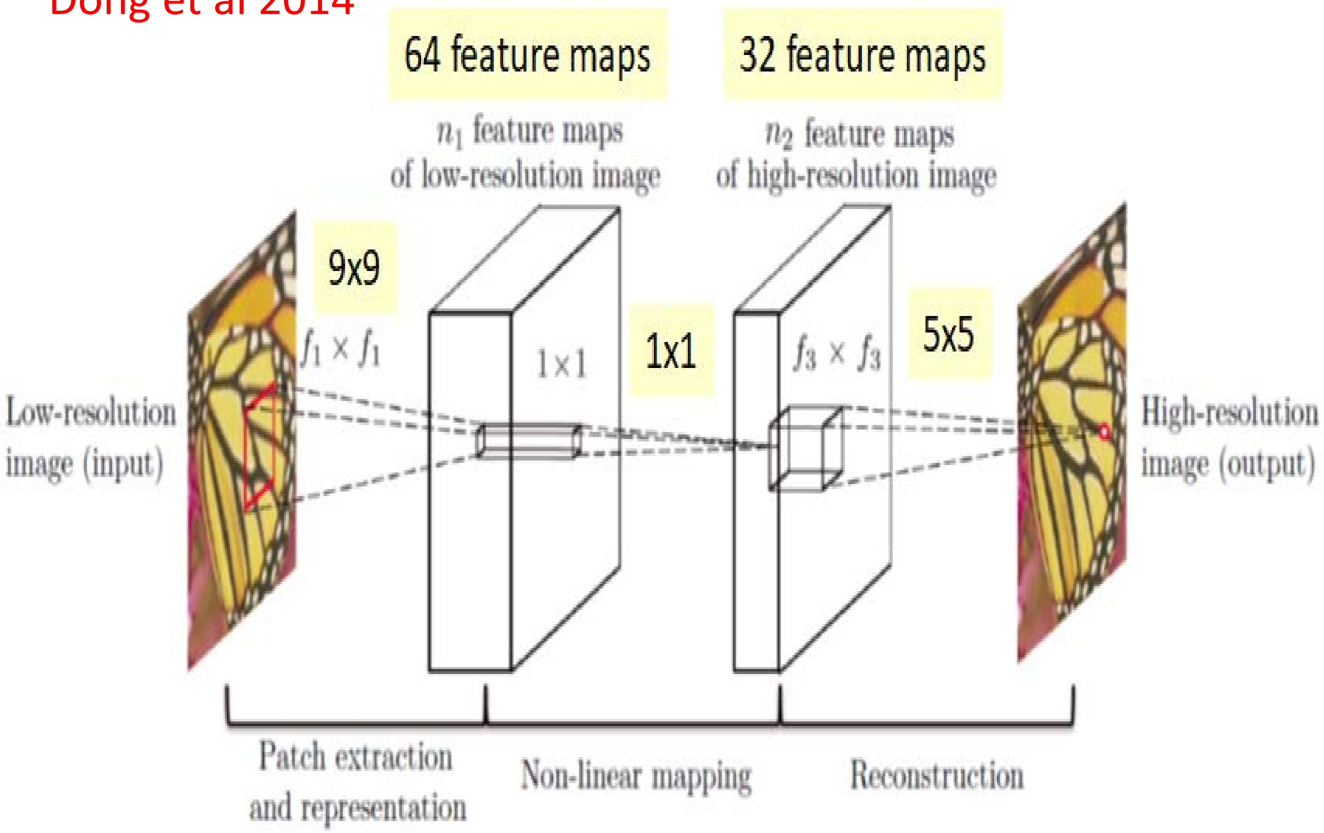


1.1° FOV Size with 1.1 ° step angle, normal sample

Feature enhanced

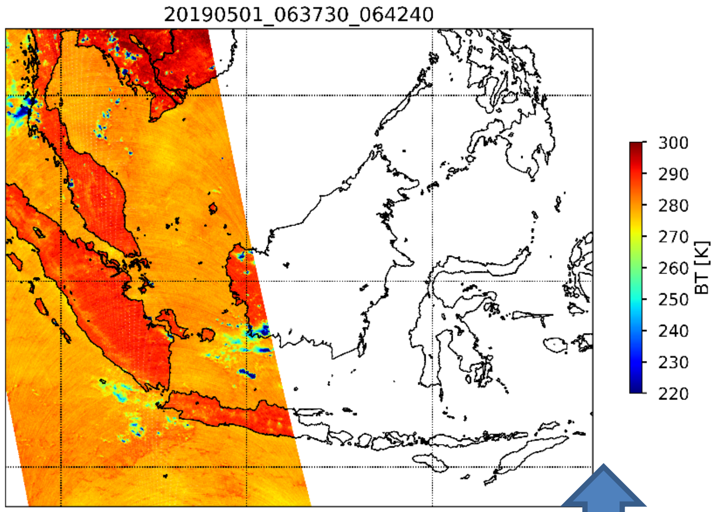
Super-Resolution Convolutional Neural Network (SRCNN)

Dong et al 2014

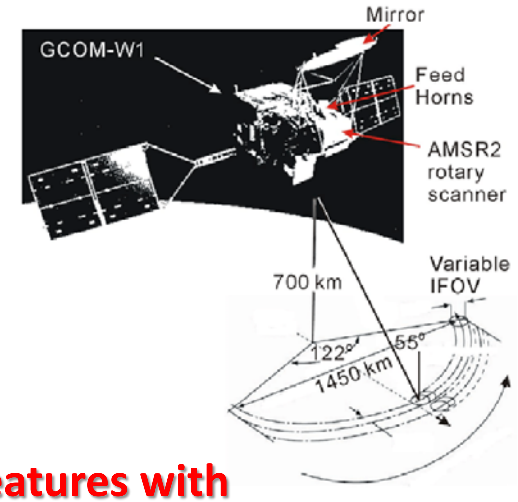


- Layer (type) Output Shape Param #
- ===
- conv2d_1 (Conv2D) (None, 24, 24, 128) 10496
- ____
- conv2d_2 (Conv2D) (None, 24, 24, 64) 73792
- ____
- conv2d_3 (Conv2D) (None, 20, 20, 1) 1601
- ===
- Total params: 85,889
- Trainable params: 85,889
- Non-trainable params: 0
- ____
- None

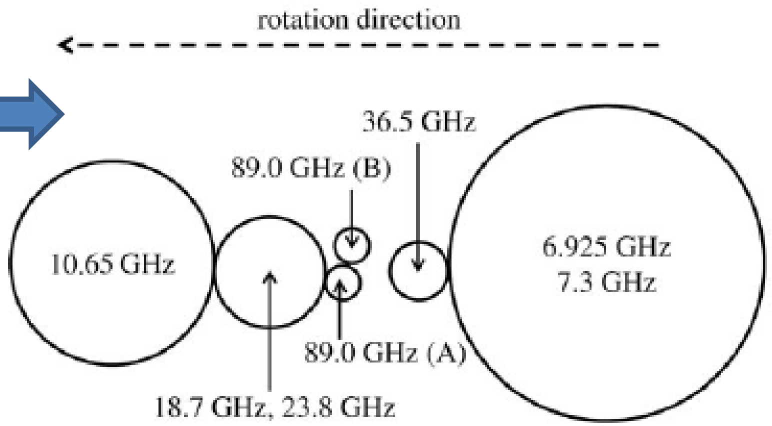
Generating Training Dataset



AMSR-2 89GHz Image

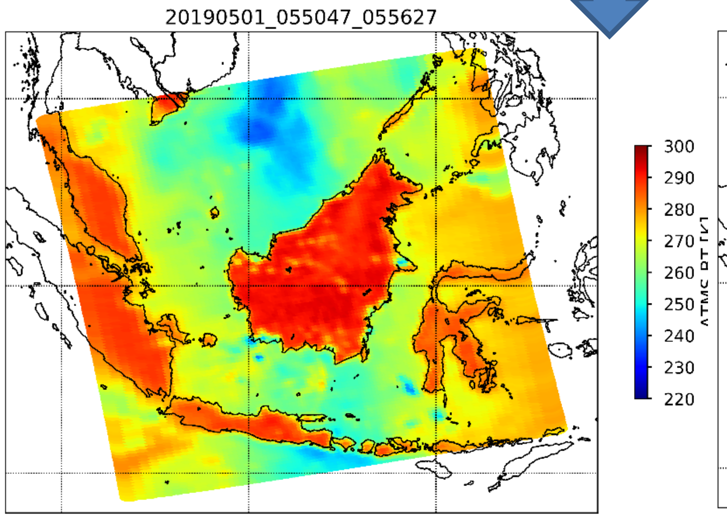


Maeda et al. 2016

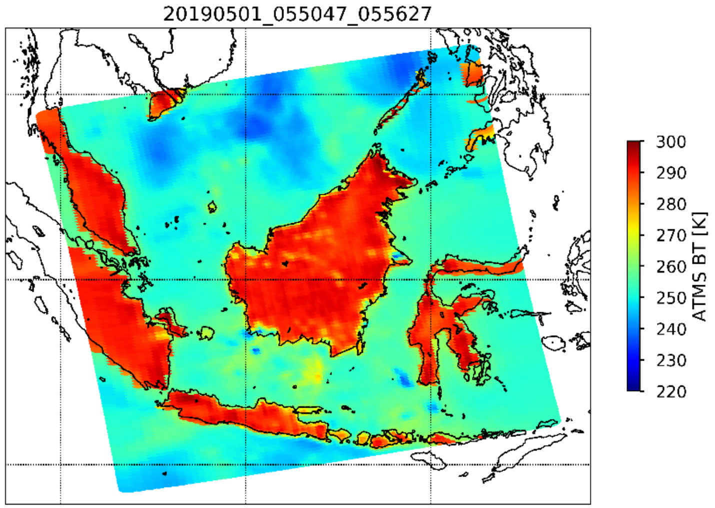


Similar features with different resolution and view angle

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

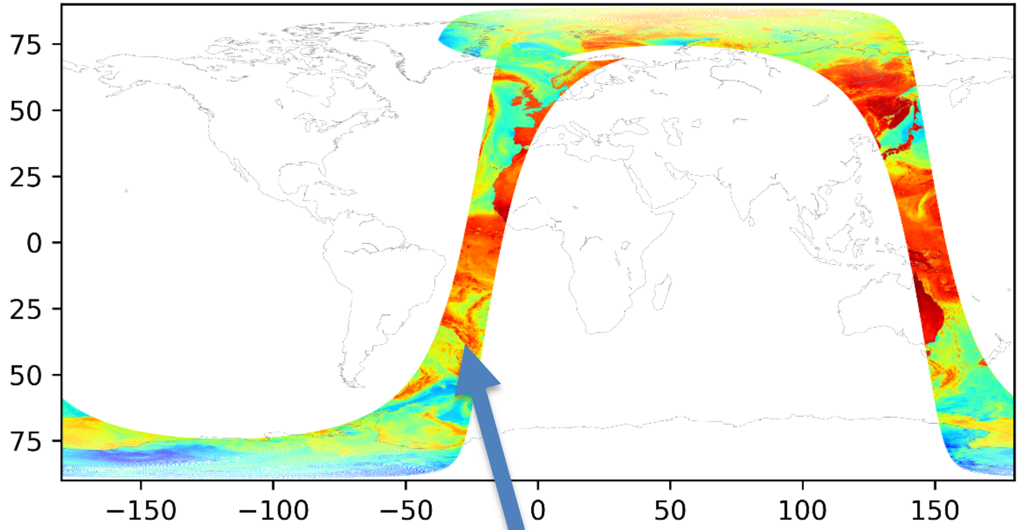


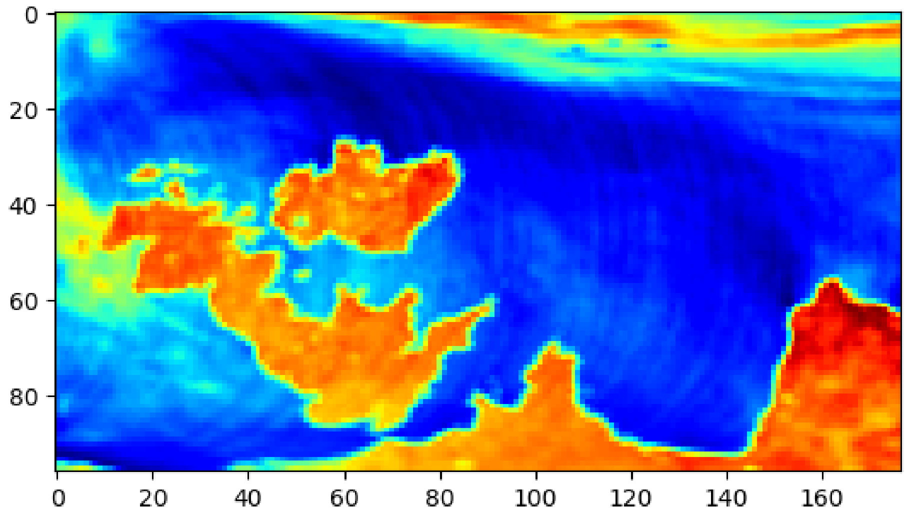
89GHz Image (original)



89GHz Image (Limb-corrected)

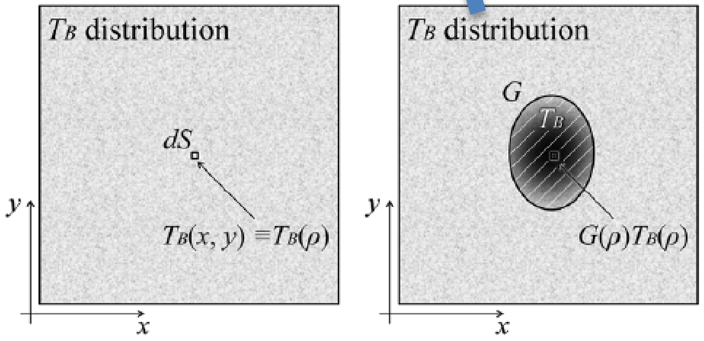
Using AMSR-2 to simulate Low (1.1°) and High (2.2°) resolution ATMS data



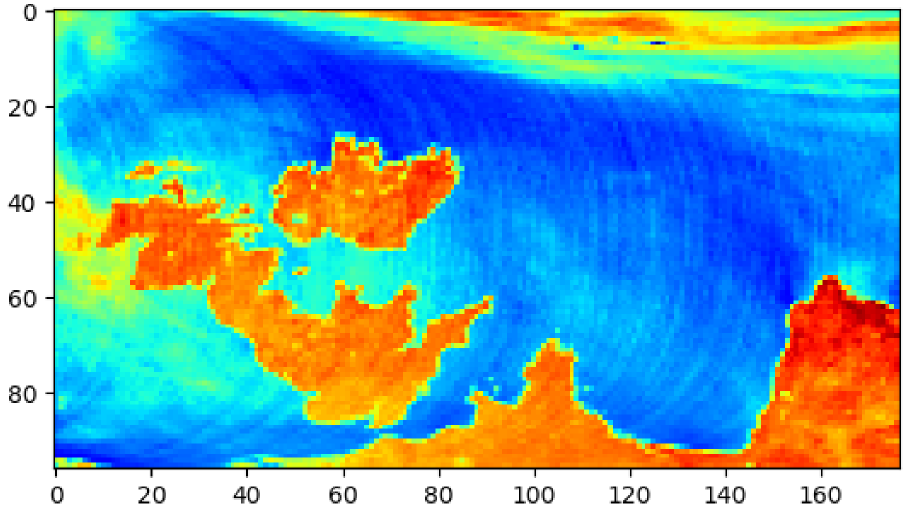


2.2 degree with 96 FOV 3/8 seconds scan rate

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

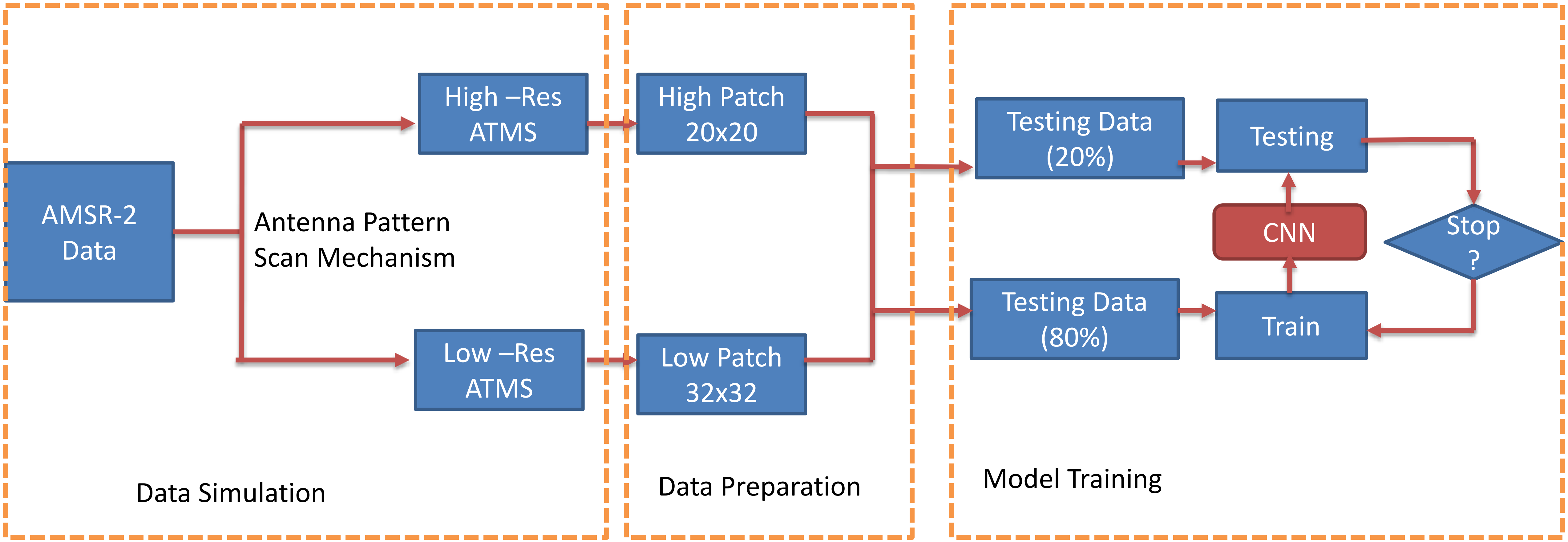


$$T_B = \int\int G(x,y)T_B(x,y)dxdy \equiv \int_S G(\rho)T_B(\rho)dS$$

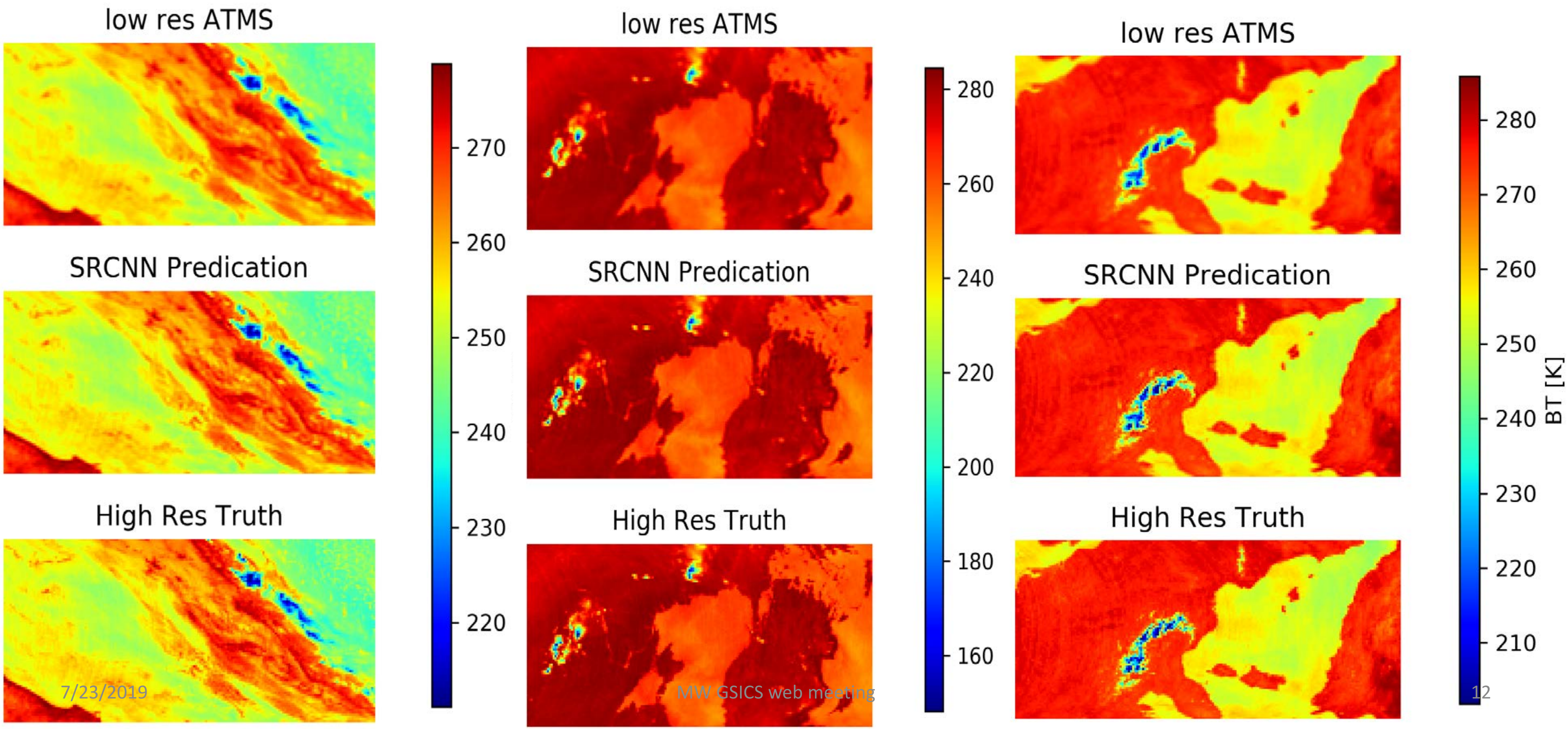


1.1 degree with 96 FOV 3/8 seconds scan rate

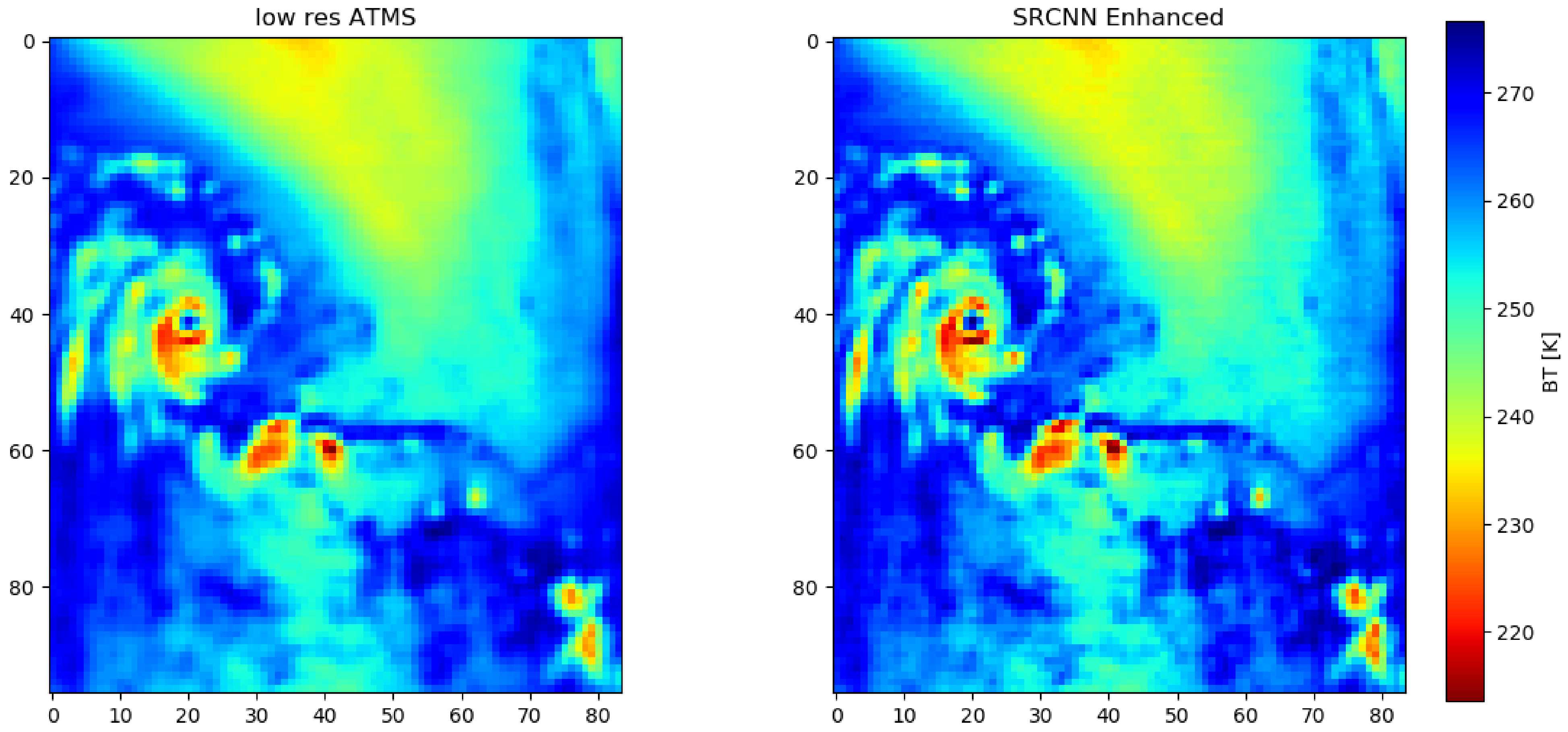
Algorithms Flow Chart



Validation with Testing Data

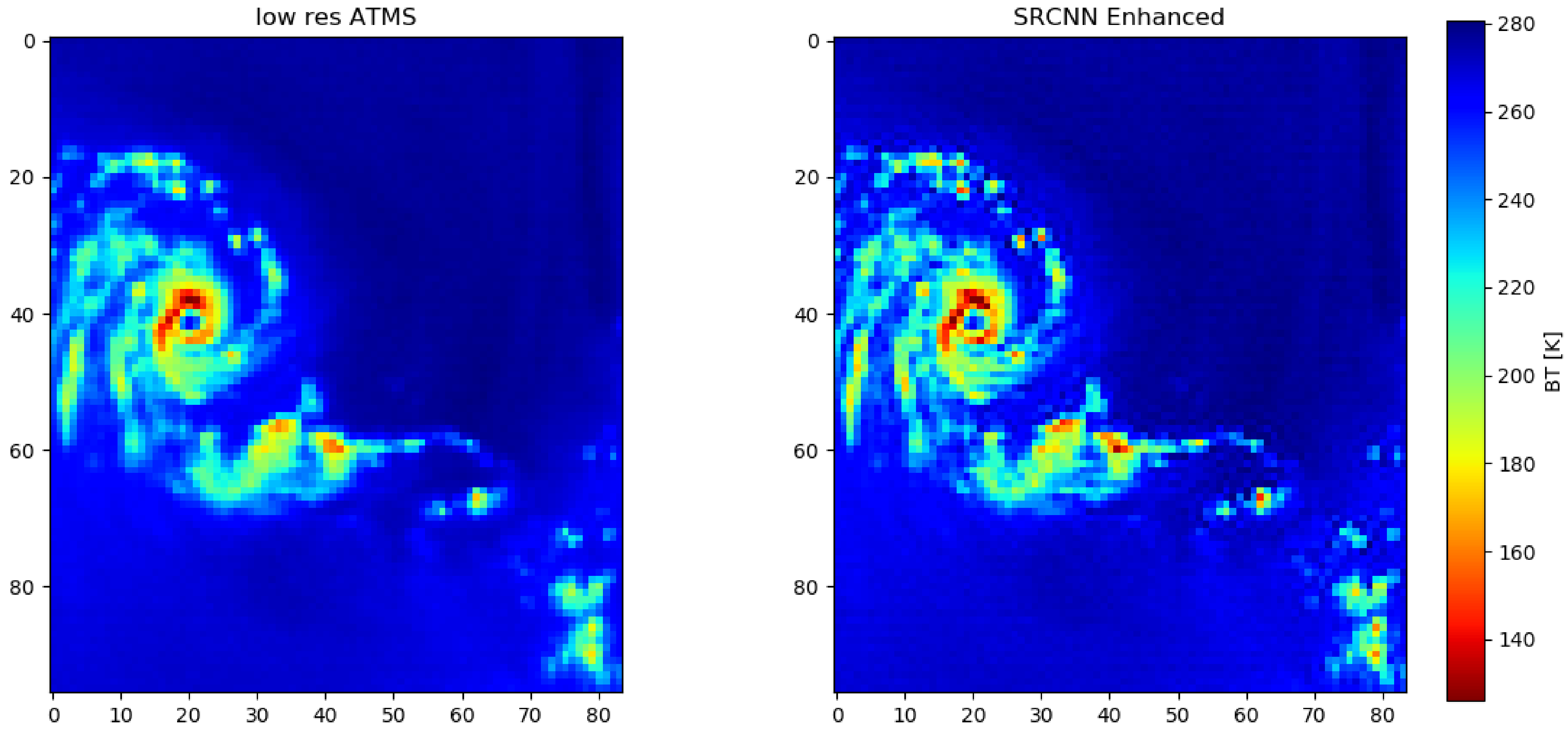


Testing Using ATMS Data (89 GHz)



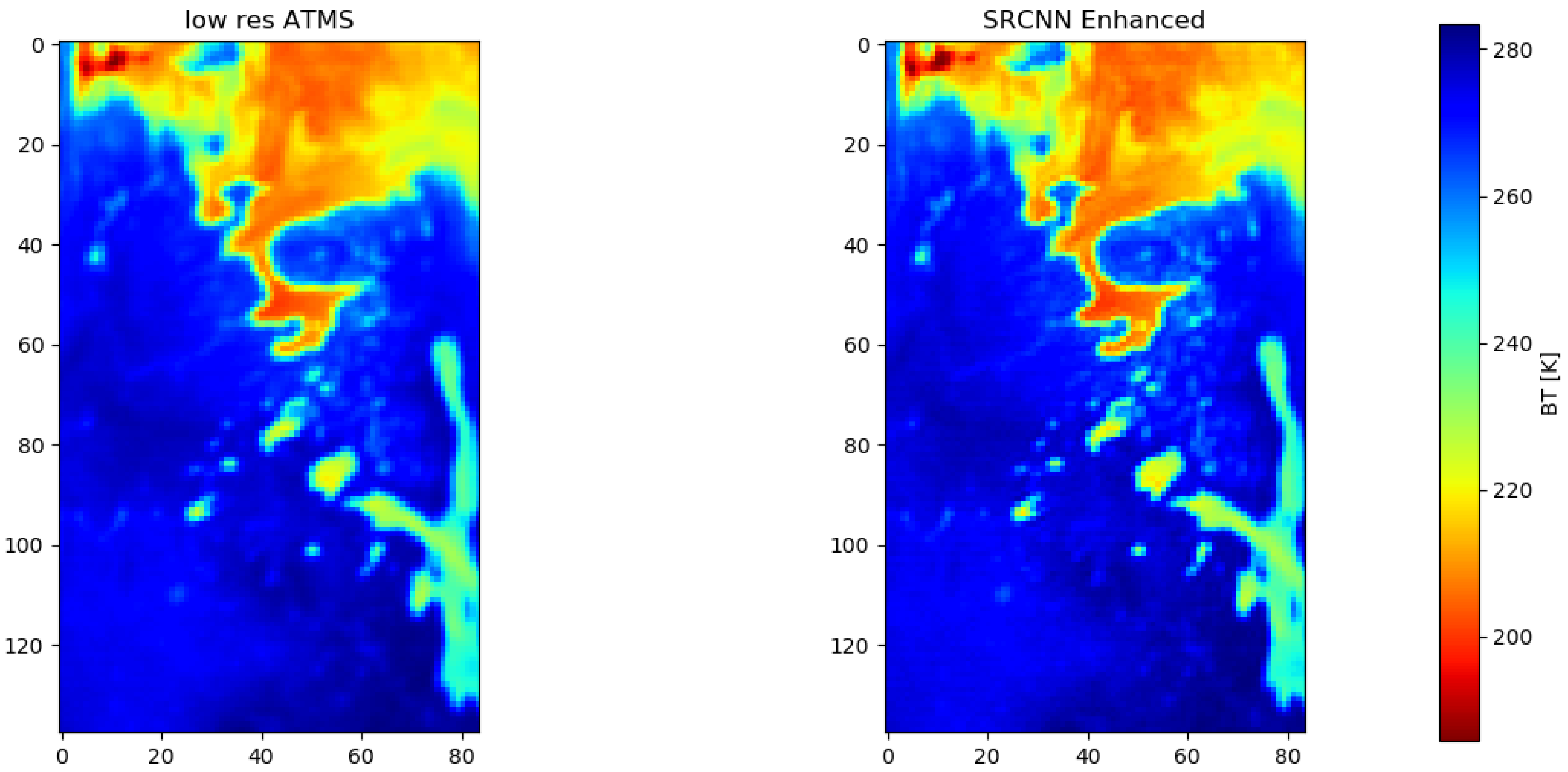
SNPP ATMS data on 2019/07/02 0949-0953

Testing Using ATMS Data (Ch 18)



Supersized !!! Model works well for 1.1 Degree channels!

Testing Using ATMS Data (Ch 16)



JPSS ATMS data on 2019/06/06 0002-0007

Conclusion Remarks

- Preliminary results indicate that the model works well for ATMS image resolution enhancement (2X).
- The model seems to work well for other surface channels also.
- Future work
  - Quantitatively assess signal-to-noise ratio
  - Quantitatively and Mathematically compare with Backus-Gilbert (B-G) method
  - Build model for 4X resolution enhancement
  - How does Enhanced ATMS data impact on precipitation retrievals?