A Remapping Technique of FY-3D MWRI Using Deep Learning for Better Use in Data Assimilation

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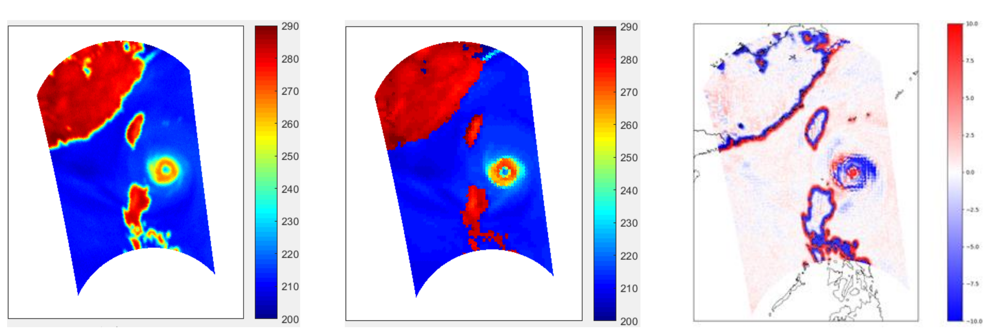
Introduction

Satellite microwave radiances have wide applications in earth remote sensing and have helped to improve global weather forecasts through the direct assimilation of observed data. Data assimilation accumulate the satellite observation data into the NWP model state by taking advantage of consistency constraints with laws of time evolution and physical properties, which can output an analysis field that is closest to the true state of the atmosphere at a given time as the initial state of NWP. However, the assimilation of these spaceborne, multichannel passive microwave measurements often suffered from the representativeness error due to the mismatch between the observation footprints and the NWP model grids. The representativeness error is a component of observation error in the context of data assimilation. The representativeness error is refer to the basic difference between the modelled representation of an observation and what is actually observed. For the assimilation of the spaceborne microwave brightness temperature data, the observation footprints usually extend over many model grid points due to the wide beam width of radiometer antenna. In data assimilation process, the mismatch between the observation footprints and the NWP model grids will introduce the additional representativeness error in the difference of Observation Minus Background (OMB), which can result in the decline of the accuracy of the analysis field.



a. 18.7GHz Synthetic T_A *b. 18.7GHz Background T_B* *c. TA minus Background T_B*

Fig.1 The mismatch between the observation and background T_B

This paper is devoted to develop and validate a new CNN-based microwave measurement (MWMR) remapping algorithm to reduce the representativeness error due to the mismatch between the observation footprints and the NWP model grids in data assimilation. For this purpose, the proposed algorithm is applied to remap FY-3D MicroWave Radiation Imager (MWRI) observation data, and the impact of the remapped MWRI observation on data assimilation is evaluated through Observation Minus Background (OMB) diagnosis with GRAPES 4D-Var system.

Training Dataset Generation

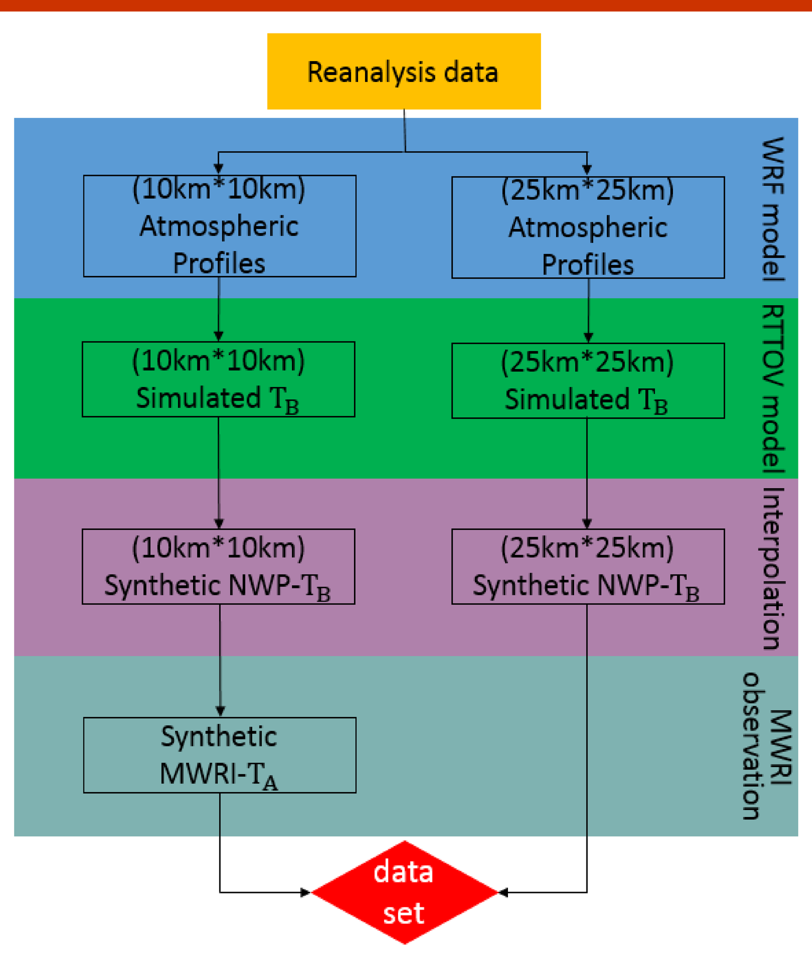


Fig.2 The flow chart of the dataset generation process.

To generate training dataset, three operations are performed:

1) One set of atmospheric profiles are generated to match the resolution of GRAPES model grids, while another set of profiles with higher resolution are for the simulation of MWRI-T_A,
2) the RTTOV model is used to simulate the upwelling brightness temperature at top of atmosphere. The simulated brightness temperature are then interpolated to the MWRI sample grids,
3) The synthetic NWP-T_B with higher resolution is simulated with degradation model to generate the synthetic MWRI-T_A data of the training dataset.

Architechture of MWMR Network

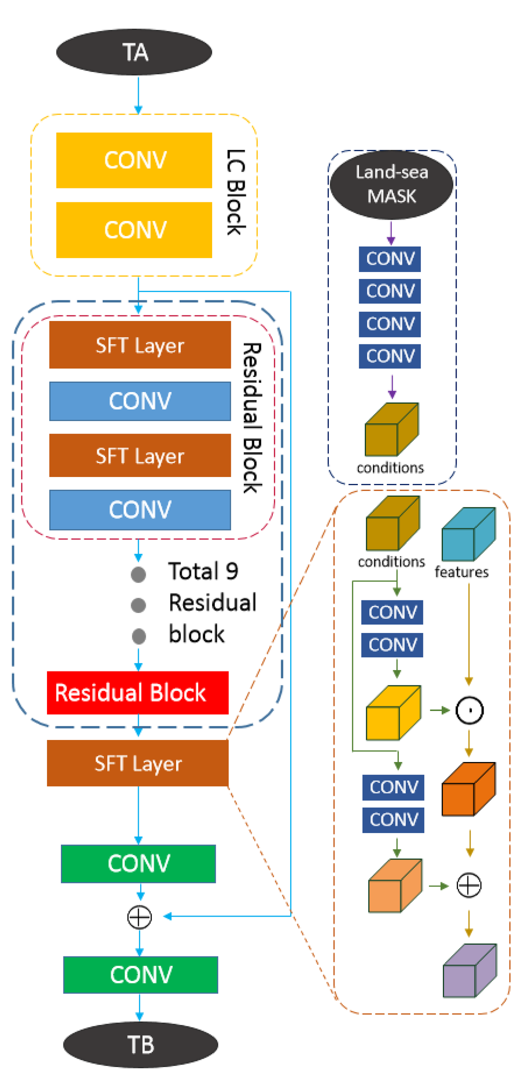
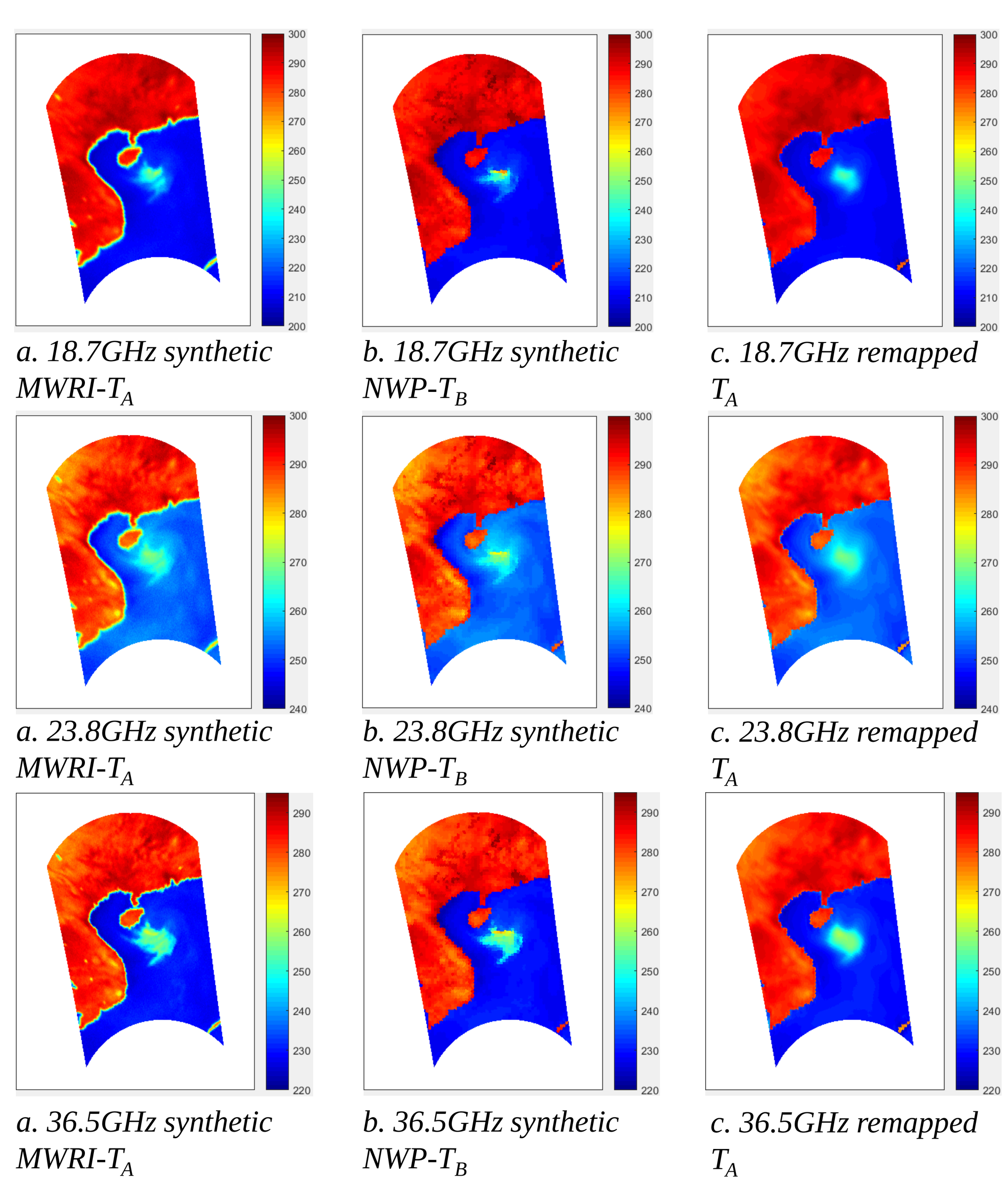


Fig.3 The architecture of MWMR network

MWMR network consists of two parts: a condition network and a residual network.

1) The condition network takes land-sea mask as input, which are processed by four convolution layers. It generates intermediate conditions shared by all the SFT layers.
2) The residual network is built with a Linear Combination (LC) and 9 residual blocks with the SFT layers. The LC Block is designed to extract the overlap information, and the SFT layers take the shared conditions as input and modulate the feature maps.

MWMR Network Evaluation



a. 18.7GHz synthetic MWRI-T_A *b. 18.7GHz synthetic NWP-T_B* *c. 18.7GHz remapped T_A*

a. 23.8GHz synthetic MWRI-T_A *b. 23.8GHz synthetic NWP-T_B* *c. 23.8GHz remapped T_A*

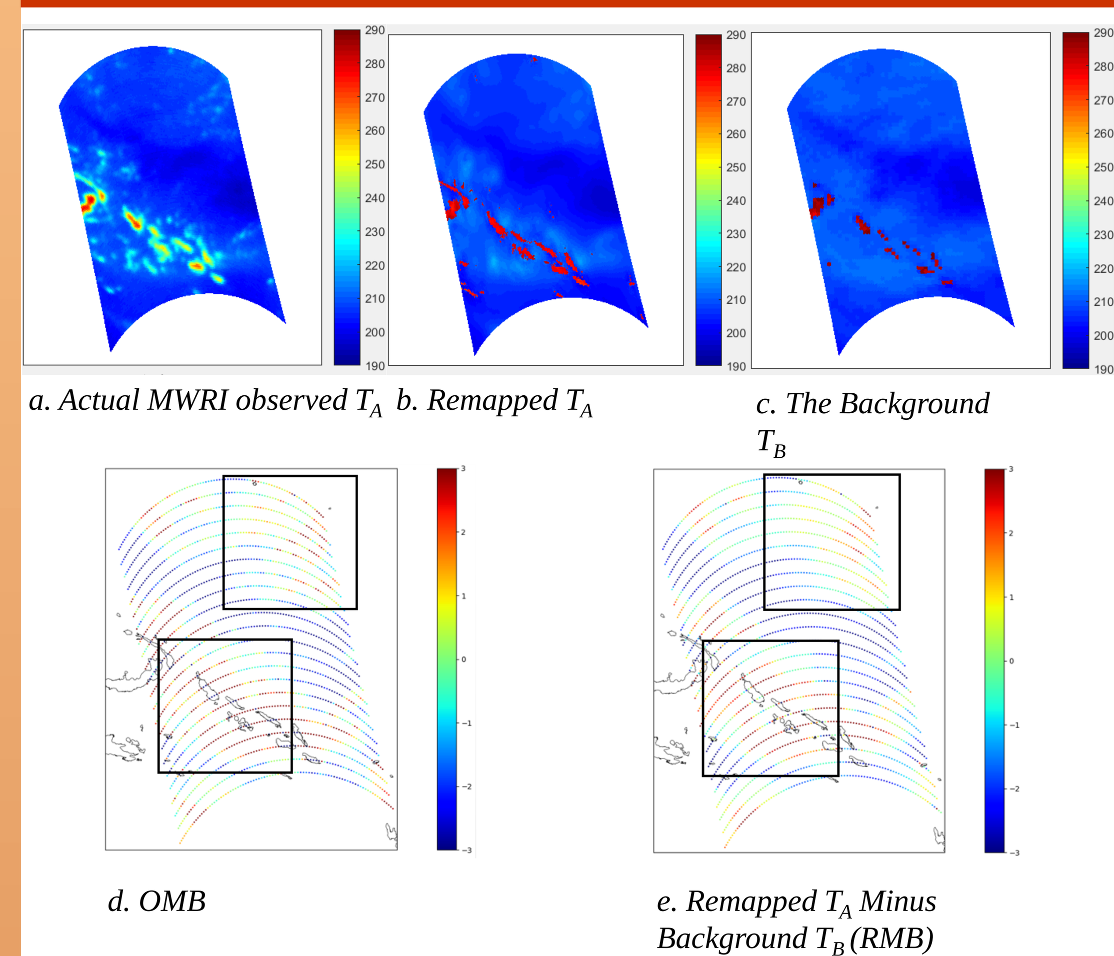
a. 36.5GHz synthetic MWRI-T_A *b. 36.5GHz synthetic NWP-T_B* *c. 36.5GHz remapped T_A*

Fig.4 The effect of MWMR network on the test set.

Tab.1 The evaluation of the remapping effect on test set

Channel	Evaluation Metric	T_A	Remapped T_A
	RMSE/K	7.20	3.21
18.7-V	PSNR/dB	32.11	39.74
	SSIM	0.83	0.92
	RMSE/K	3.75	2.16
23.8-V	PSNR/dB	37.97	43.42
	SSIM	0.76	0.87
	RMSE/K	5.19	2.96
36.5-V	PSNR/dB	34.90	40.24
	SSIM	0.77	0.87

OMB Analysis Experiment



a. Actual MWRI observed T_A *b. Remapped T_A* *c. The Background T_B*

d. OMB *e. Remapped T_A Minus Background T_B (RMB)*

Fig.5 The example effect of MWMR network on the actual MWRI observed TA and the OMB experiment results of 18.7GHz.

Tab.2 Quantitative analysis of three channels MWRI data within latitude 30 for three tracks

Area	channel	OMB		RMB		Observed TA		Remapped TA	
		Mean (K)	Std (K)	Mean (K)	Std (K)	RMSE (K)	PSNR (dB)	RMSE (K)	PSNR (dB)
Off-shore	18.7-V	4.91	6.93	-0.26	3.02	8.49	41.34	3.03	45.81
	23.8-V	2.18	4.12	-0.59	2.93	4.66	43.94	2.99	45.87
	36.5-V	1.09	5.72	-1.16	2.87	5.82	42.98	3.09	45.73
open sea	18.7-V	0.52	3.54	-0.03	2.69	3.58	45.09	2.69	46.33
	23.8-V	-0.40	2.91	-0.59	2.45	2.93	45.95	2.52	46.61
	36.5-V	-1.11	4.82	-0.90	3.32	4.95	43.68	3.44	45.26

Fig. 5 shows that from the visual effect, the remapped T_A is much closer to the background T_B than the MWRI observed T_A. The boundaries between land and sea in the MWRI observed T_A are ambiguous, while they became clearer after remapping. And it can be seen from the comparison between OMB and RMB that the overall noise in the remapped T_A decreased a lot.

The OMB analysis experiment focused on the impact of MWMR remapping algorithm on the MWRI observed T_A of coastal area and clear sky. Based on the threshold of single beam width from the coastline, the pixels of the observed T_A can be divided into two categories: offshore and open sea, in which all data are under clear sky condition. Tab. 2 shows the mean and standard deviation (std) of OMB and RMB for the two categories of MWRI data within latitude 30 for three tracks.

The RMSE has dropped by 180.2%, 55.9% and 88.3% in the offshore area of the three channels, respectively. And the RMSE has dropped by 33.1%, 16.3% and 43.9% in the open sea area of the three channels, respectively. These results verified that MWMR remapping algorithm can quantitatively reduce the representativeness error of MWRI observed data, especially the data in the coastal area.

Discussion

The experiment results suggest three conclusions.

1)The bias and standard deviation of OMB with the CNN-based remapped MWRI observation was quantitatively reduced compared with the raw measurements in GRAPES 4D-Var, which indicates the reduction of the observation's representativeness error. It's hopeful to better assimilate MWRI brightness temperature data in the future.

2)The MWMR network's good behaviors on synthetic data set and the actual MWRI observed T_A shows the CNN-based algorithm's good robustness, and it's expected to be applied to more space-borne microwave remote sensing data.