Development of a Machine Learning-Based Radiometric Bias Correction for NOAA's Microwave Integrated Retrieval System (MiRS)

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Background & Motivation

- The Microwave Integrated Retrieval System (MiRS) is NOAA's operational microwave-only satellite retrieval system. It aims to provide a single consistent source for many microwave retrieval products, such as vertical profiles of temperature and moisture, from different satellites with various instrumental configurations.
- MiRS relies on a forward model, the Community Radiative Transfer Model (CRTM), to provide simulated radiances and implements a one-dimensional variational (1DVAR) algorithm to determine the atmospheric state which best fits the radiometric measurements.
- The current radiometric bias correction uses a Histogram Adjustment Method, which performs well at characterizing the average global differences between measurements and retrievals (static method). However, the local variations of systematic errors in CRTM are not accounted for.
- New method: a machine learning-based approach to the radiometric bias correction, a Neural Network (NN).
- The goal of using NN is to learn the bias structure from historical collocations of observed and simulated brightness temperatures, along with the estimated corresponding atmospheric and surface state. The NN model, once trained, can then be used in near real time for bias correction during the MiRS retrieval process.

Methodology

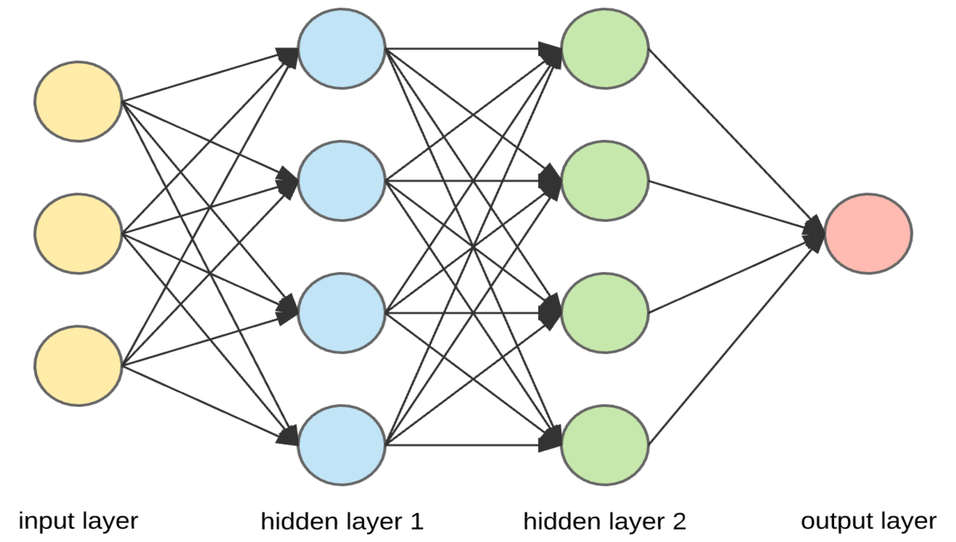

Figure 1. Neural Network Schematic

A NN has been developed for ATMS/SNPP. The architecture is:

- Number of hidden layers: 2
- Number of neurons (or nodes) in each hidden layer: 200
- Activation function: Rectified Linear Unit (ReLU)

Input features:

- Brightness temperature (TB) of the measurements,
- Satellite viewing angle,
- latitude,
- other geophysical parameters such as cloud liquid water (CLW), total precipitable water (TPW), and skin temperature (Tskin).

Output:

- Brightness temperature bias

Training: 12-days dataset

- Jan-14, Feb-15, Mar-25, Apr-01, May-11, Jun-04, Jul-15, Aug-01, Sep-01, Oct-20, Nov-01, Dec-01

Testing: 20191001

NN Results

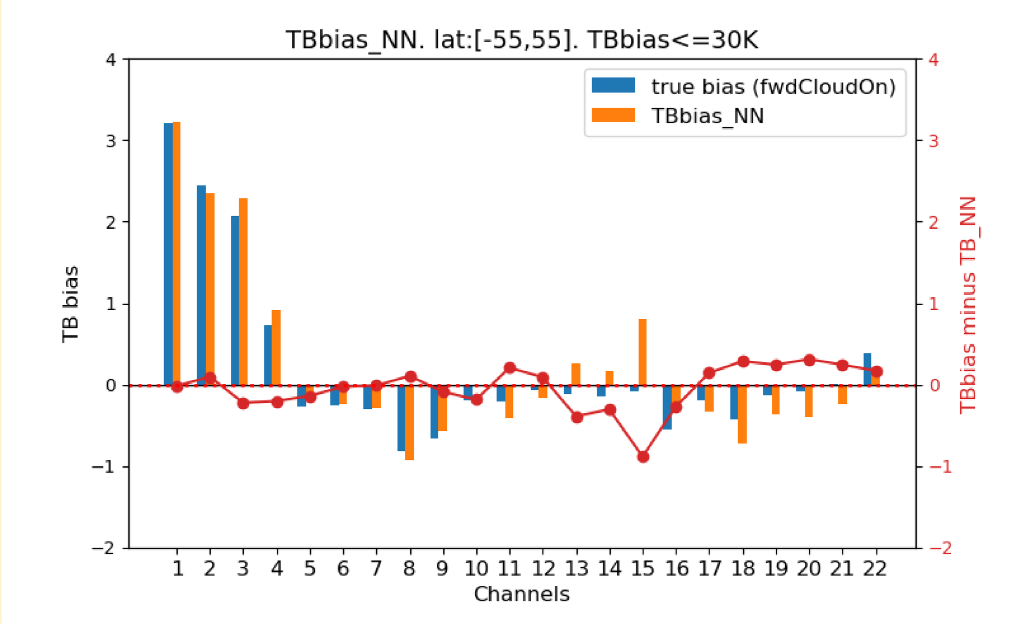

Figure 2. Mean TBbias of each ATMS channel, for latitude [55°S-55°N], when true TBbias is less than 30K.

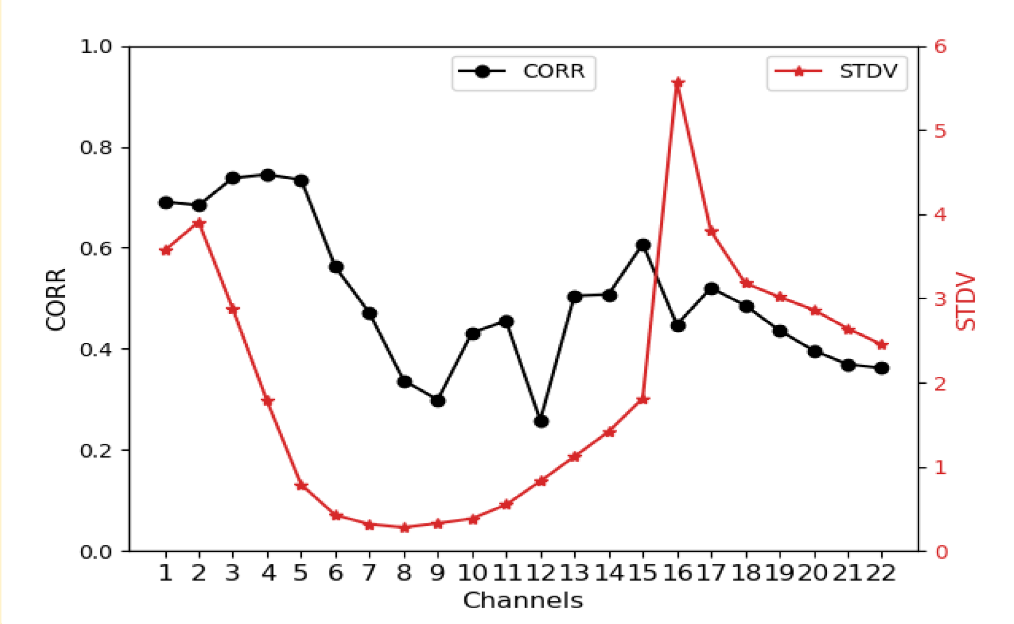

Figure 3. Correlation (black) and standard deviation (red) of TBbias, NN vs. true. For latitude [55°S-55°N], when true TBbias is less than 30K.

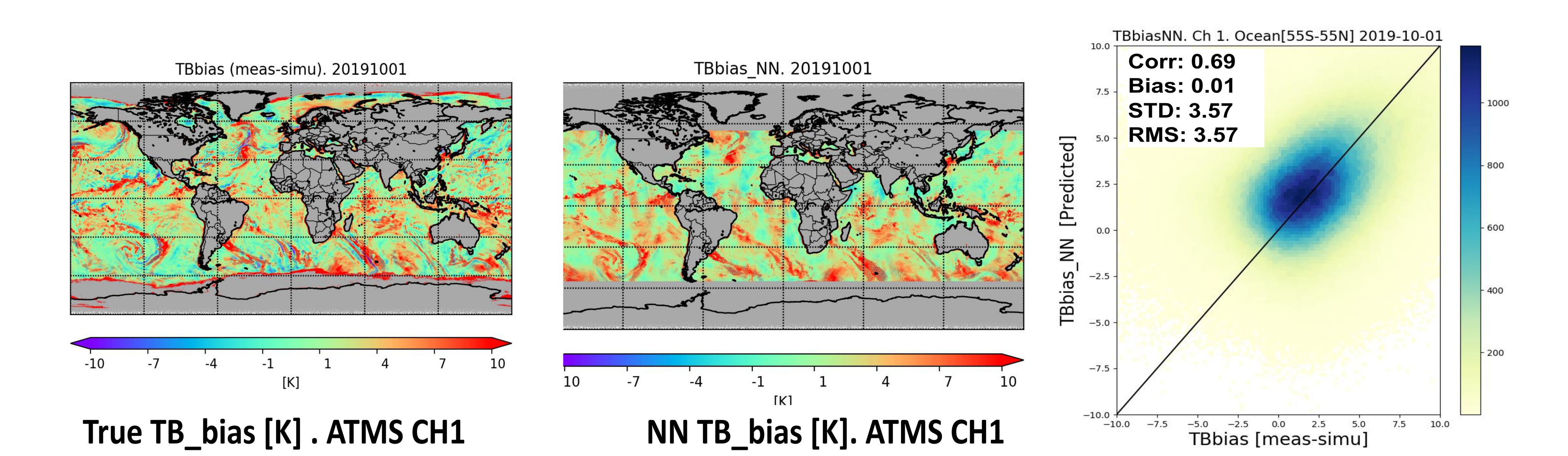

Figure 4. NN TBbias verification for ATMS/SNPP Channel 1 (23.8GHz). Latitude [55°S-55°N], true TBbias is less than 30K.

MiRS Retrieval Results

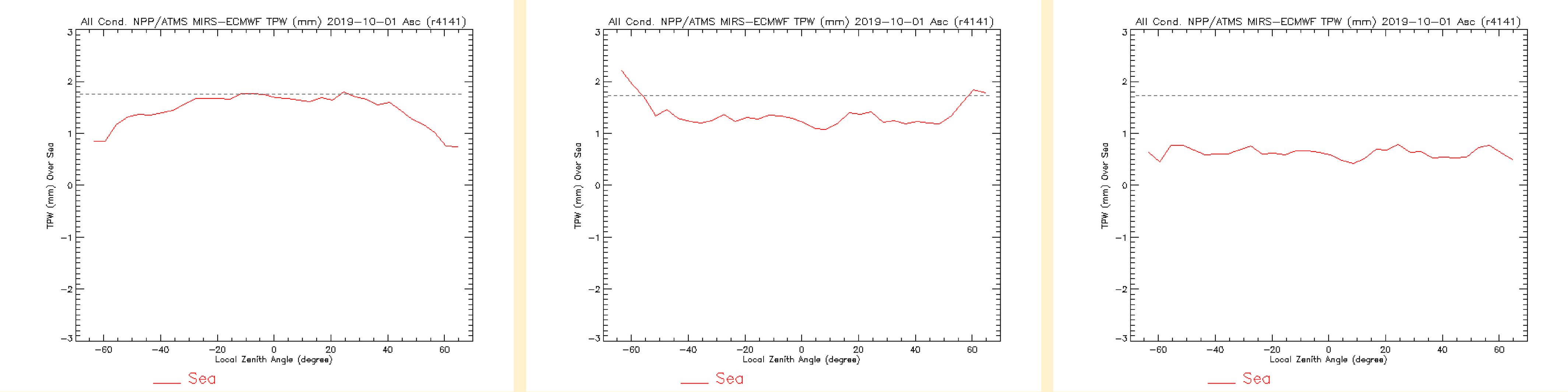

Figure 5. Figure 5. MiRS TPW Over Ocean. From left to right: Static, Perfect, and NN experiments

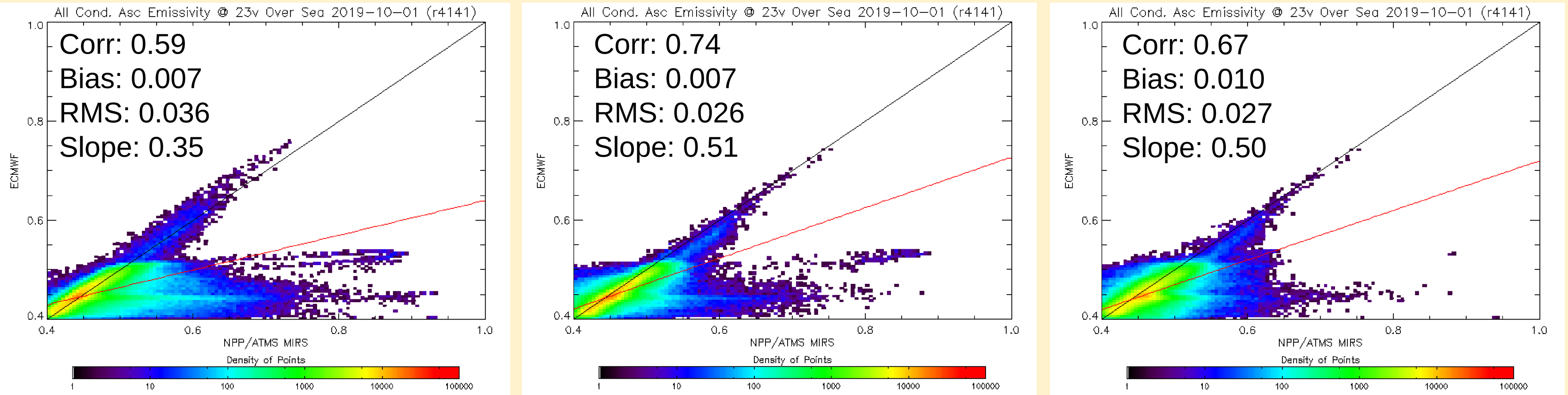

Figure 6. MiRS Emissivity Over Ocean (23.8GHz). From left to right: Static, Perfect, and NN experiments

MiRS Retrieval Results (*cont.*)

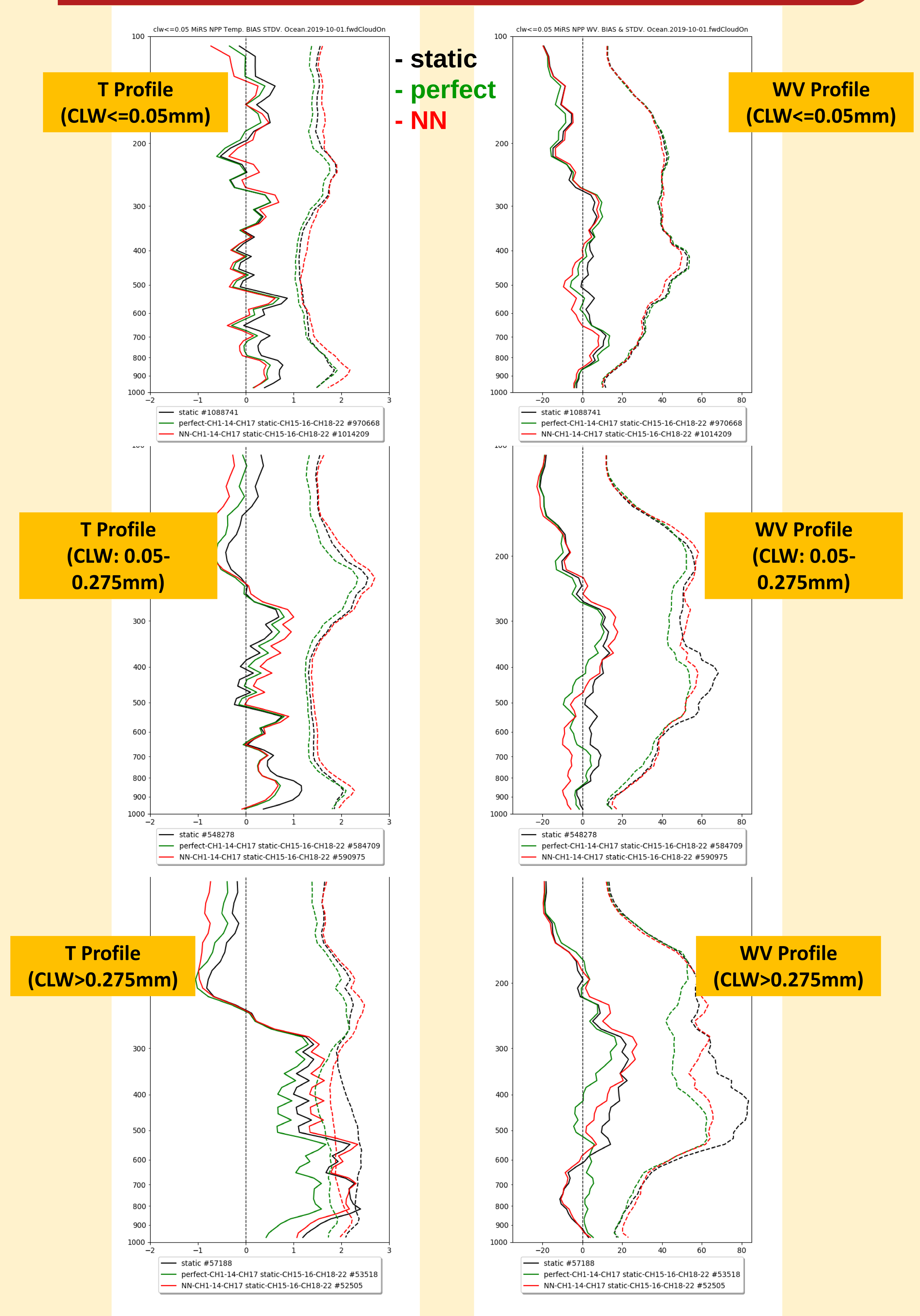

Figure 7. MiRS temperature (left) and water vapor (right) profiles stratification by CLW

Summary & Future Works

- A new NN-based approach to estimate the observed TB bias structure was developed. The NN represents TB bias very well, at least for surface channels such as 23.8GHZ (Figure 4), and for water vapor channels at 183.31GHz (not shown).
- Applying either true or NN-estimated TBbias to MiRS leads to generally positive impact on atmospheric temperature and water vapor profiles than static method (Figure 7). Significant improvement can be observed
  - for temperature bias where CLW is larger than 0.275mm, under 300hPa
  - for water vapor standard deviation where CLW is larger than 0.05mm, between 300-600hPa
- The TPW shows smaller bias and scan-dependency using NN-estimated TBbias (Figure 5).
- The emissivity was improved for surface channels, such as 23.8GHz (Figure 6).
- **Future Works:** Improving NN is possible by using more input features such as atmospheric temperature profiles, water vapor profiles, and by fine-tuning of the NN architecture, such as number of hidden layers, nodes, and activation functions (Undergoing).