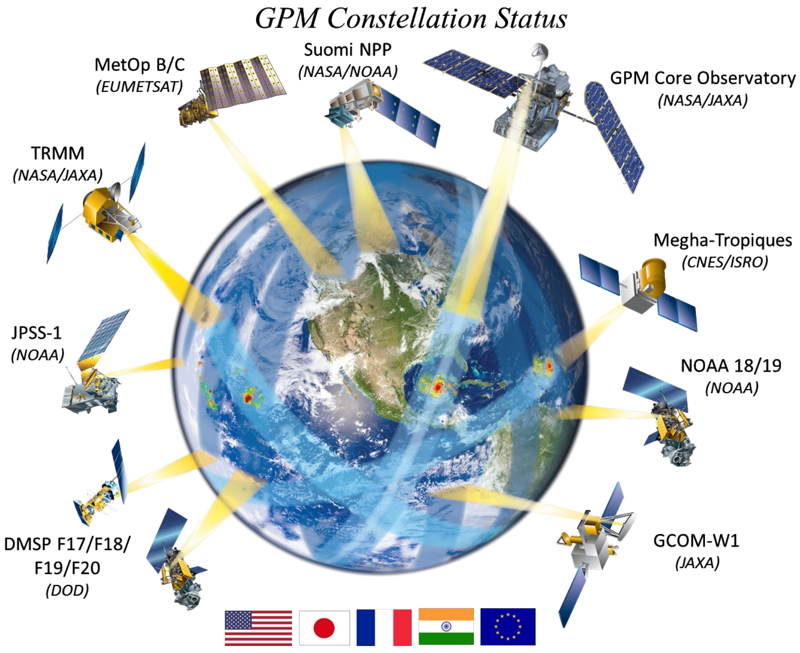
“Parametric Rainfall Algorithms from Microwave sensors - what’s ready and what’s not”



Christian Kummerow
Paula Brown
Simon Pfreundschuh
Ryan Gonzalez
and many other students

NOAA Precipitation Workshop
March 1, 2023

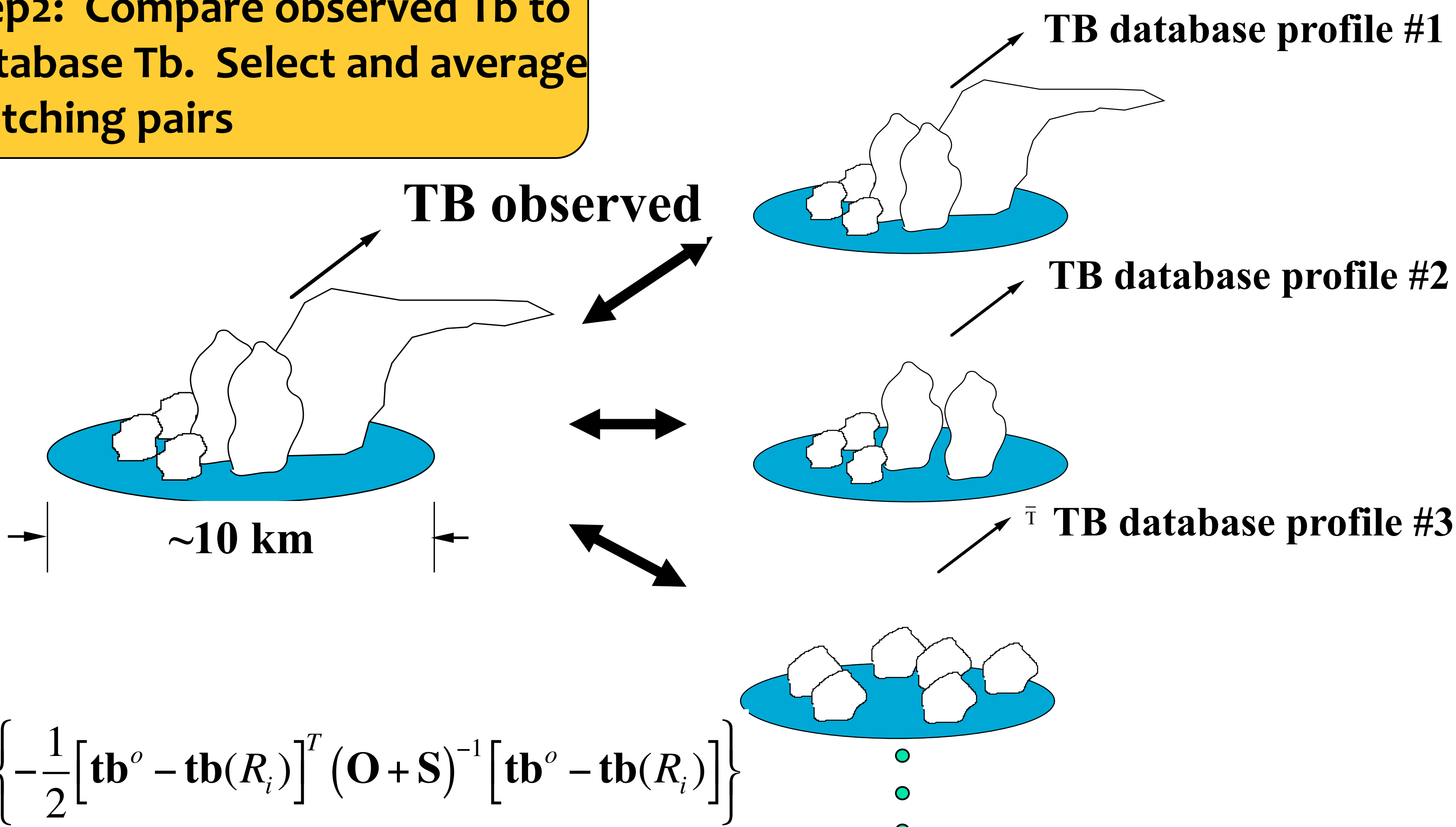
The Goddard Profiling Algorithm

- ☆ Running operationally at NASA for TRMM and GPM
- ☆ Uses a Bayesian framework with a common a–priori database for all sensors. Readily adaptable for any new sensor★
- ☆ Recently changed to ML in lieu of the Bayesian inversion. This exploits the prior data slightly better than the Bayesian scheme.

The GPM radiometer algorithm – GPROF

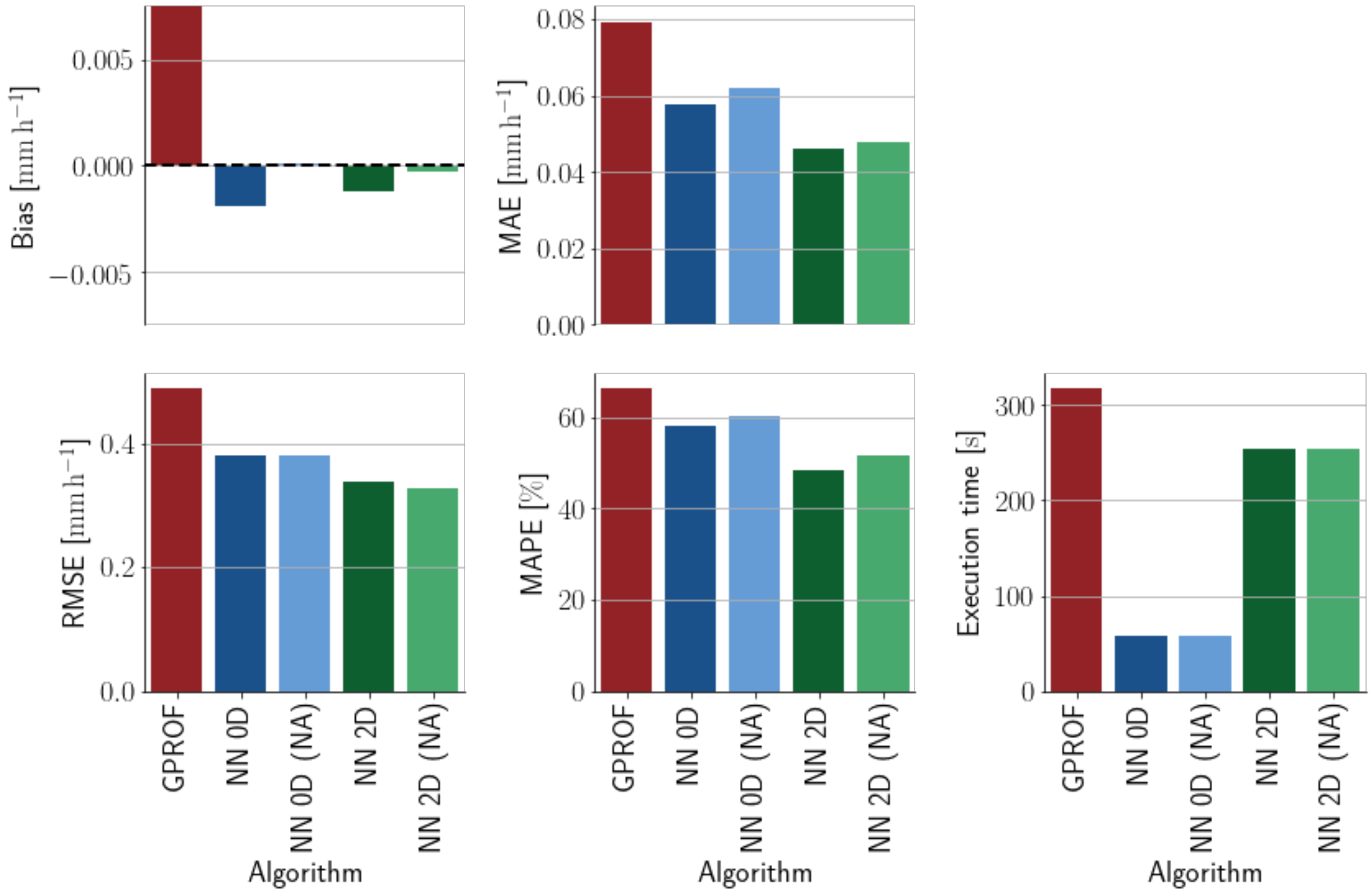
Step 1: Use GPM CORRA product to derive set of "Observed" profiles that define an a-priori database of possible rain structures.

Step2: Compare observed Tb to Database Tb. Select and average matching pairs

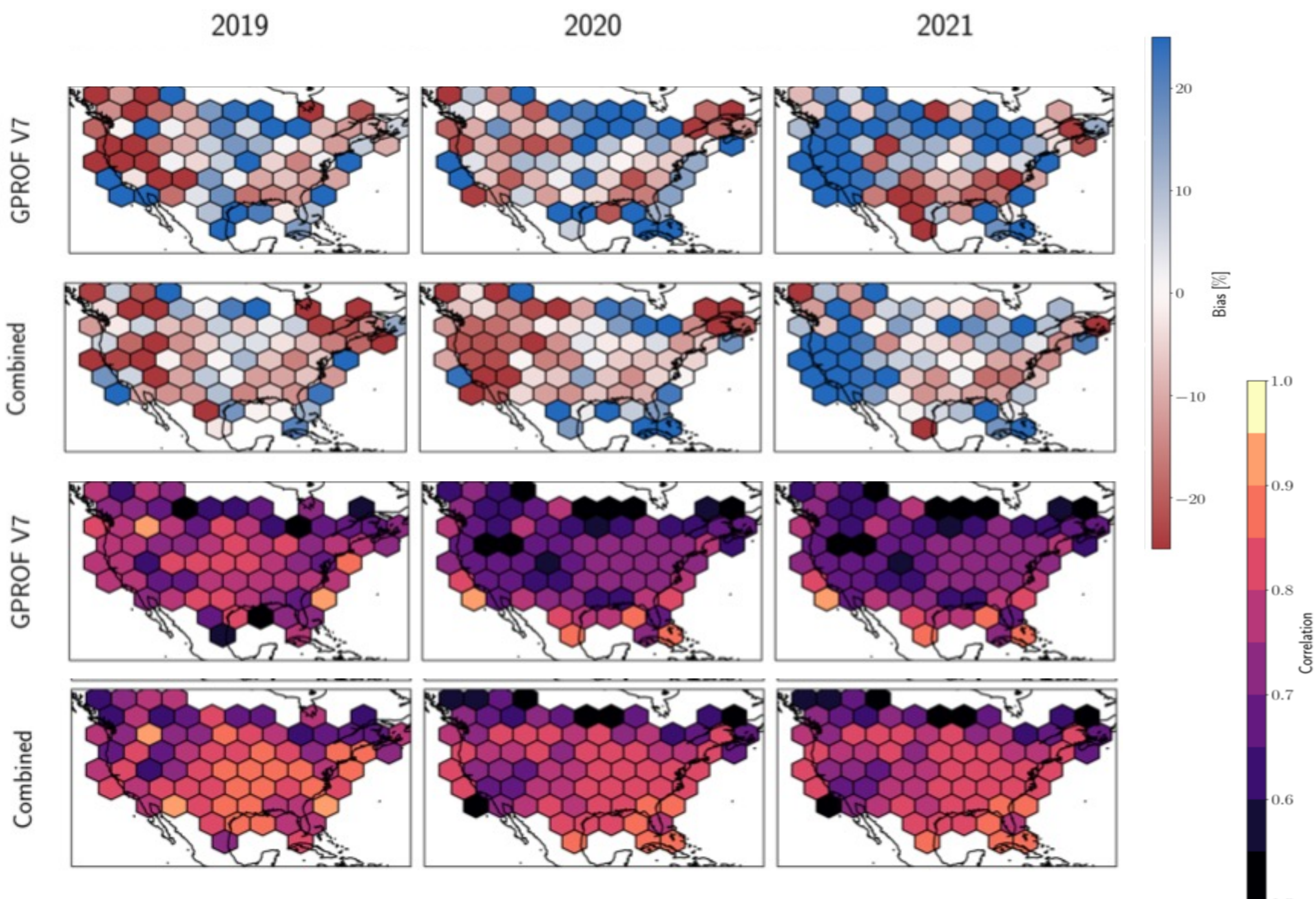


$$J_i = \exp\left\{ -\frac{1}{2} \left[\mathbf{tb}^o - \mathbf{tb}(R_i) \right]^T \left(\mathbf{O} + \mathbf{S} \right)^{-1} \left[\mathbf{tb}^o - \mathbf{tb}(R_i) \right] \right\}$$

Retrieval performance (surface precipitation)



Regional Bias/Correlation vs MRMS



Assumptions/Caveats

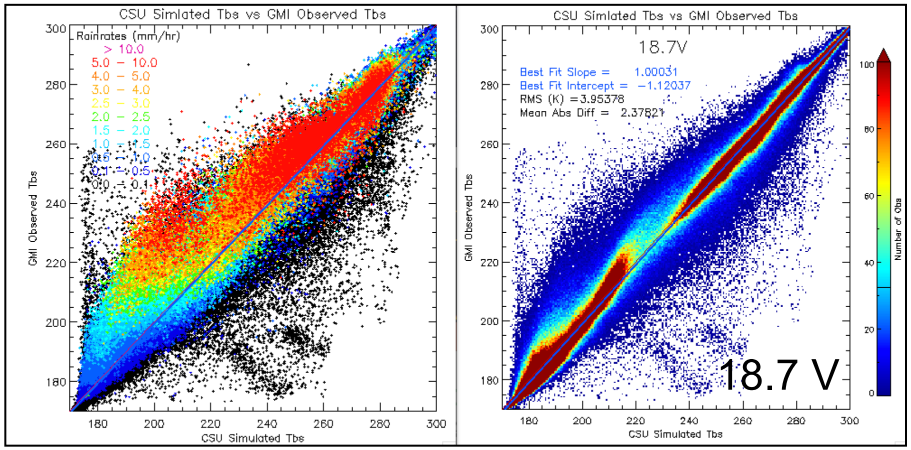
For GMI, training data is constructed CORRA profiles and observed Tb.

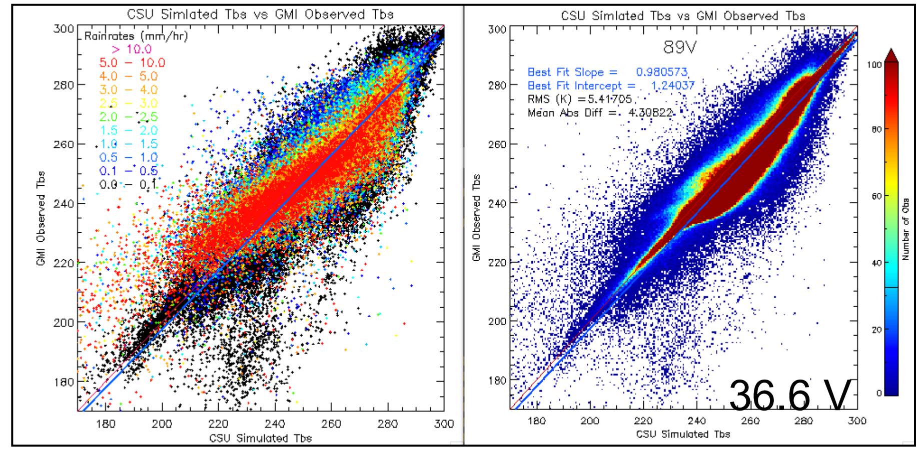
For non-GMI sensors, training data is constructed from CORRA profiles and computed Tb. Implicit assumption is that CORRA produces hydrometeor scenes that fully reproduce GMI observations and thus can be adapted to ~~all~~ similar sensors.

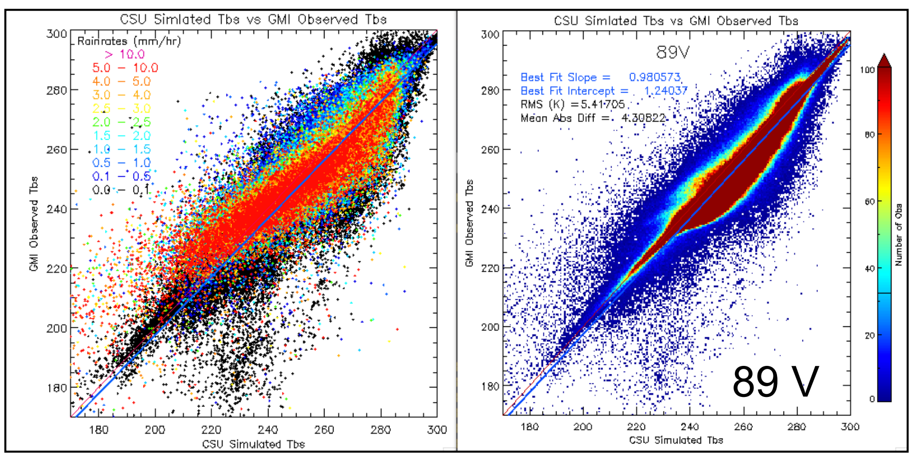
Even if CORRA is perfect, CORRA reverts to reanalysis if no echo is detected. Light rain (<0.2 mm/hr) and snow (except when heavy) are not retrieved. GPROF uses MIRS in light rain and empirical MRMS databases in snow

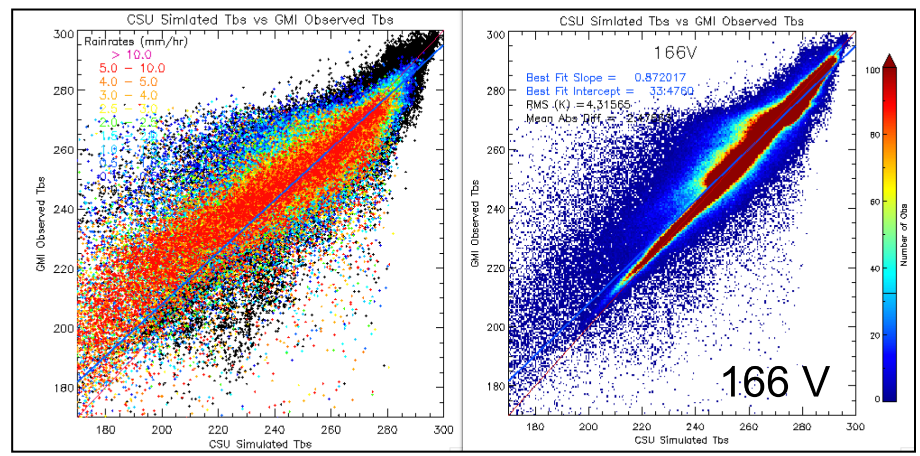
GMI Simulated vs. GMI Observed Tbs
Using COMBINED (Raining) and MIRS (Non-Raining)
October 1 - 10, 2018

All Surface Types and Global





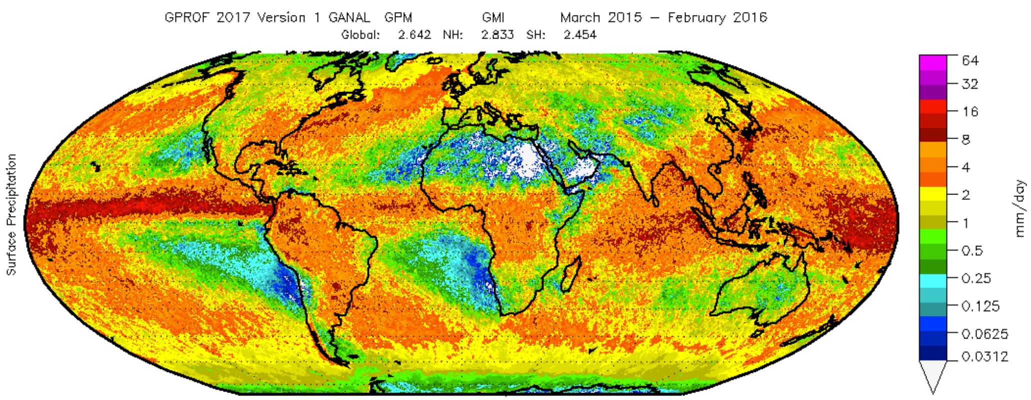




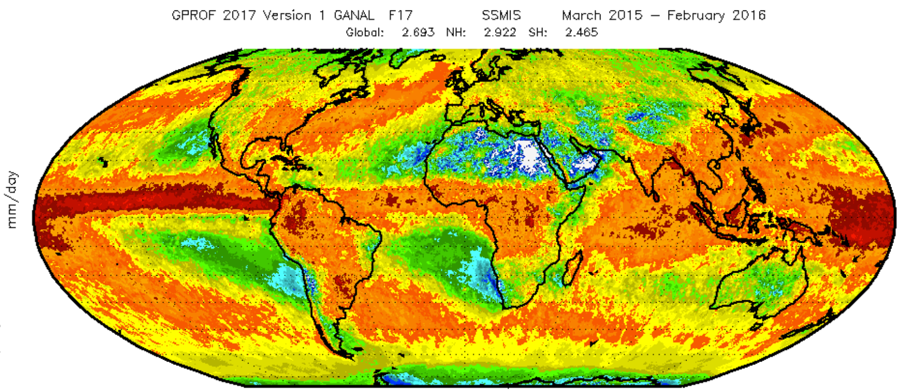
Uses MIRS emissivities over sea-ice surfaces

One year of GPM data

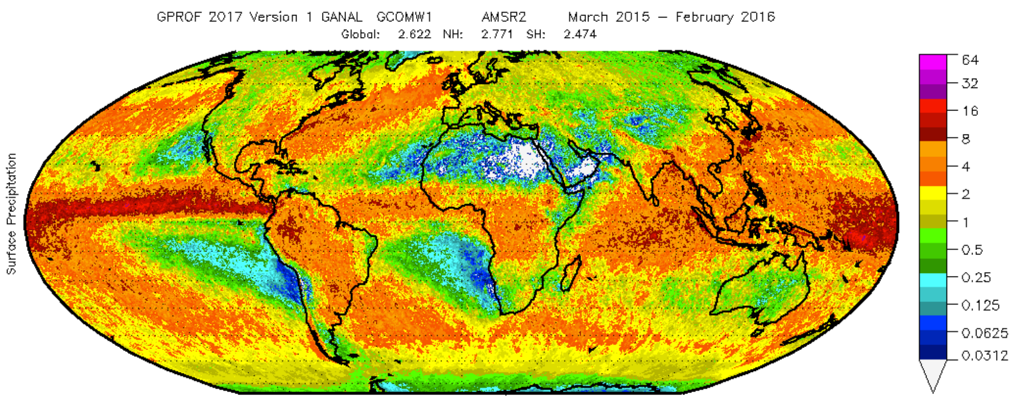
GMI



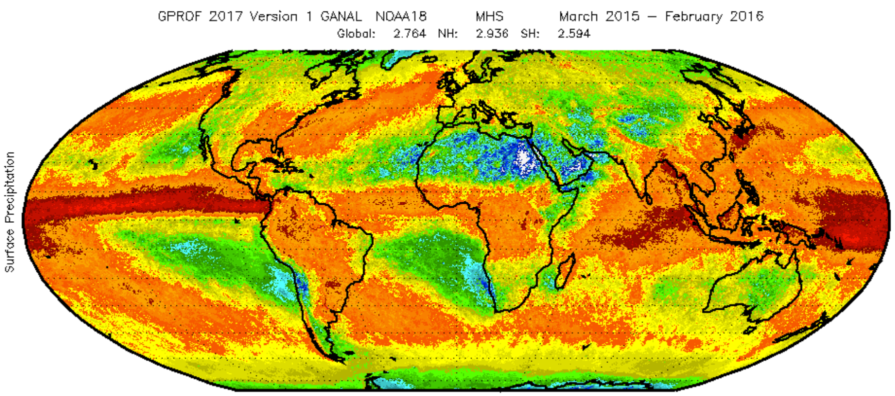
SSMIS



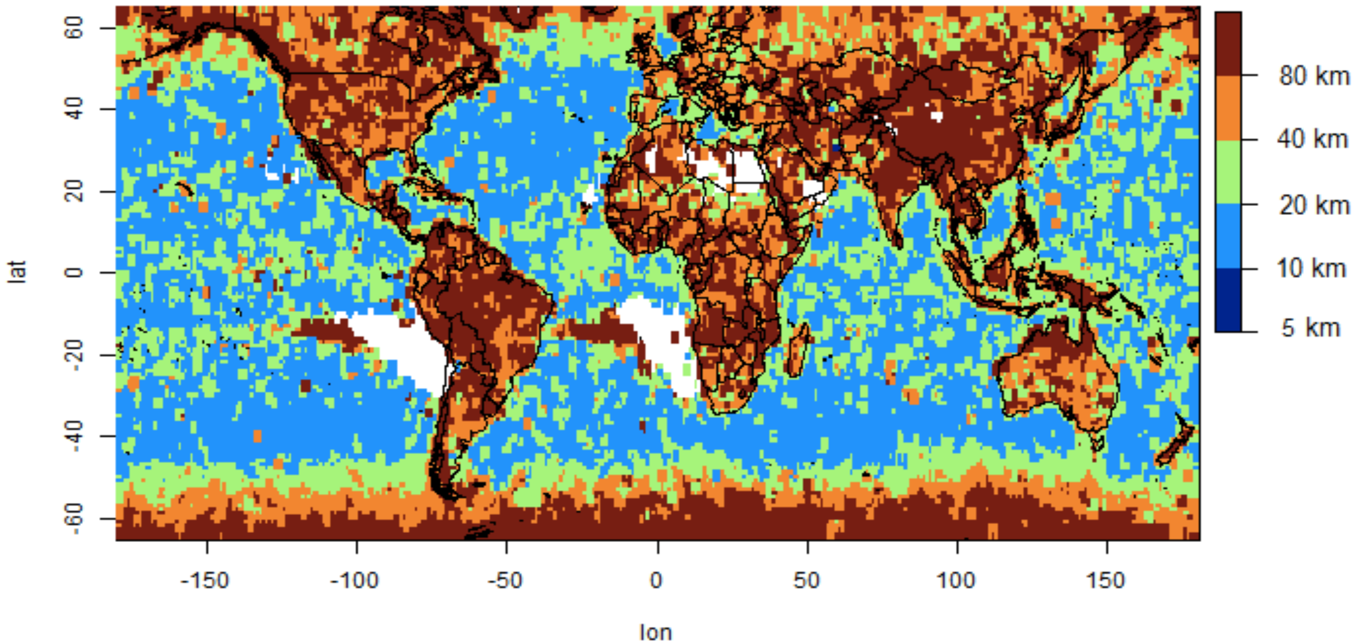
AMSR2



MHS

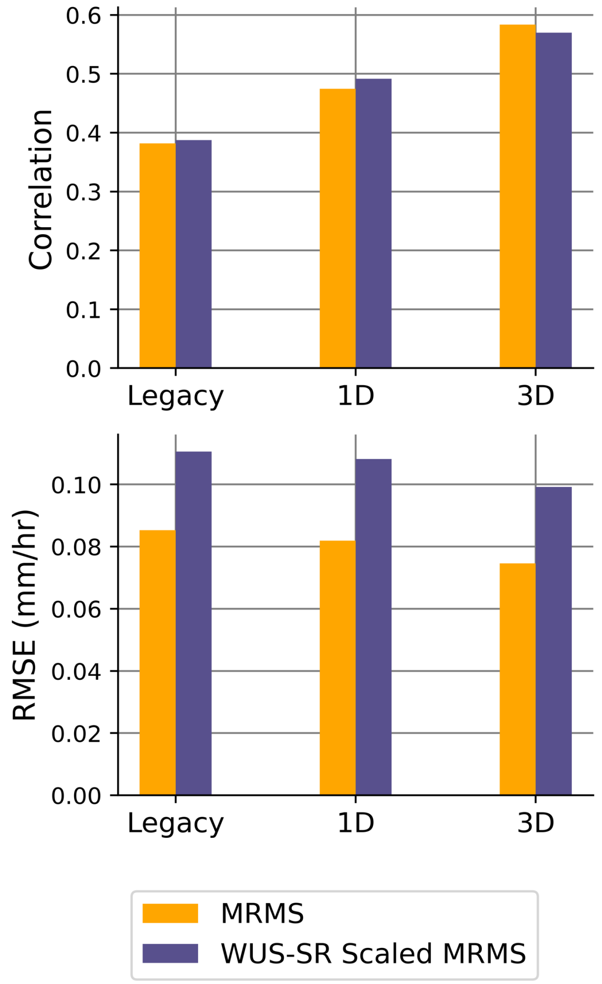


The effective resolution of GMI GPROF



Clement Guilloteau
UC Irvine

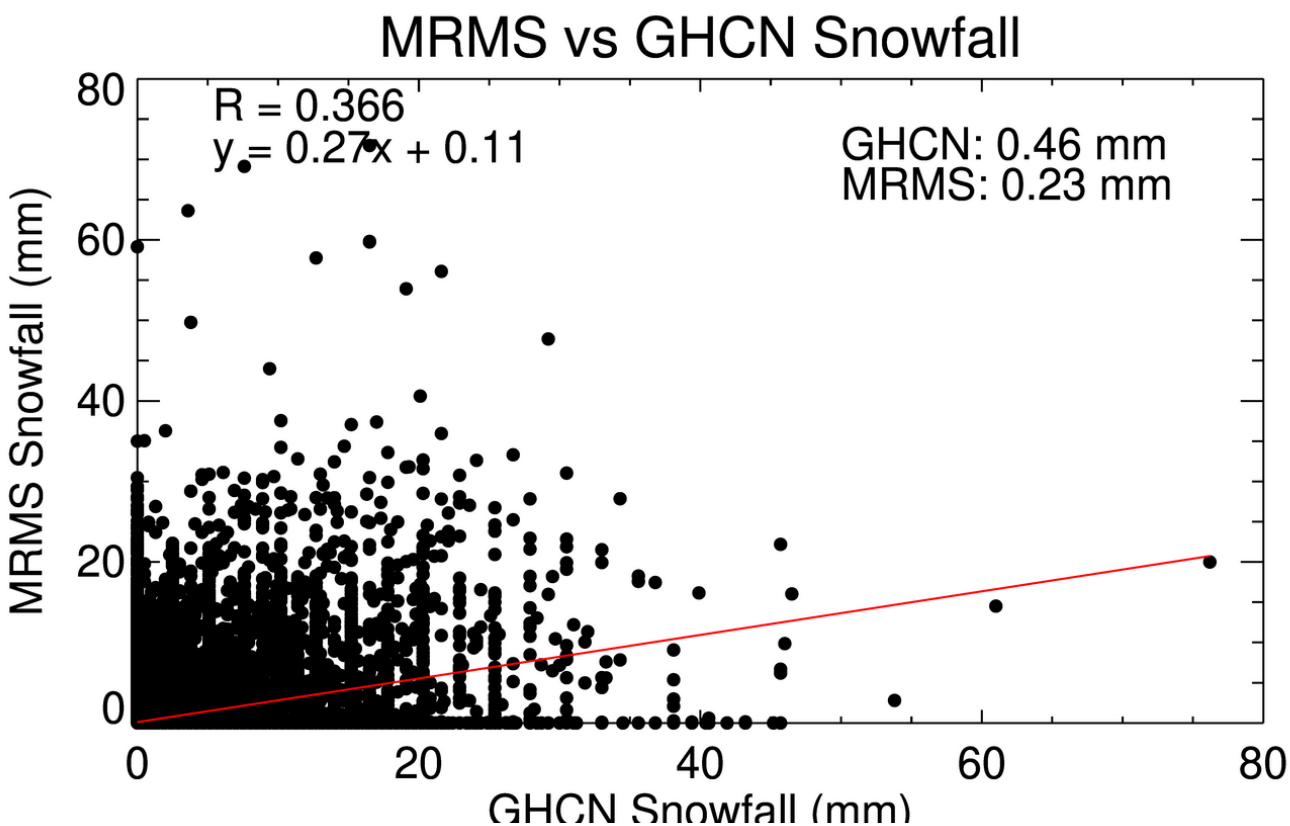
A Machine Learning Algorithm
Trained on MRMS for snow



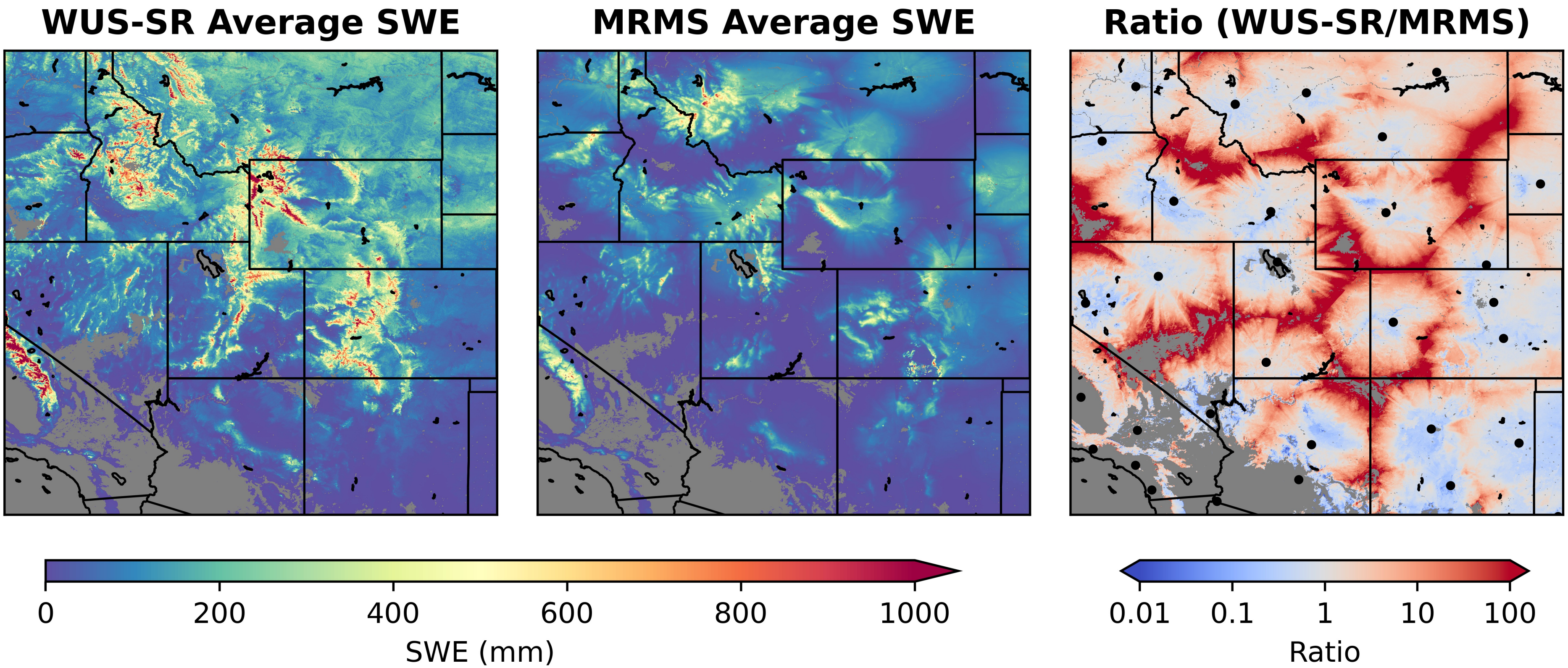
Retrieval statistics for GPROF, GPROF-NN 1D, GPROF-NN 3D for the Western US.

MRMS and WUS-SR Scaled MRMS

MRMS vs in-situ snowfall



MRMS and GHCN daily snowfall matchups for the Dakotas. Correlation is 0.37. Average MRMS daily snowfall is half of GHCN. Many points where MRMS reports 0mm snowfall and GHCN has >0mm snowfall.



Snow accumulation for WY2017 - 2021

Research Needs

- Parametric Algorithms are quite mature and probably need little development.

- Prior/training data – CORRA, MIRS, Snow etc. Having a ”curated” database or training data that can predict Tbs for all new sensors is essential for parametric retrievals, and the key to an “Enterprise” solution that does not change with constellation makeup. This is a STAR activity rather than a satellite need.

Sensor Needs

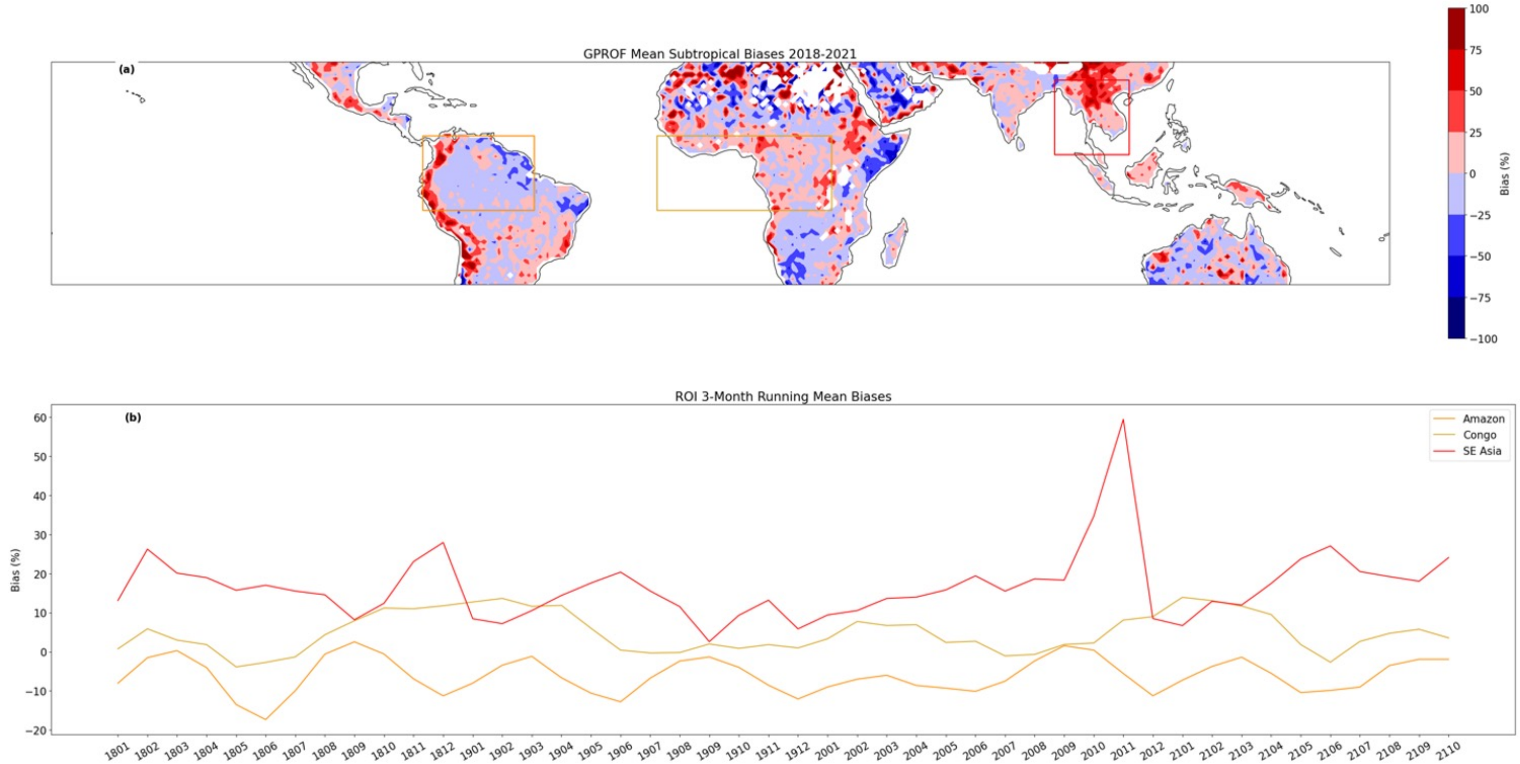
- If precipitation is changing, will need radar/radiometer pairs for training data in the future. JAXA? Can use current GPM under static climate assumptions.

- Sensors as simple as MHS (89, 165, 183 GHz) are demonstrably better than IR for precipitation. Large FOV not a demonstrable disadvantage at this time. Merged products can speak better to advantage of increased sampling.

- Lower frequency help increase effective resolution over water but not land.

- Higher frequency (ν > 183 GHz) may be an advantage for snow but not demonstrated on any systematic basis.

Validation and Ancillary Data



While all decent algorithms are unbiased relative to training data, regional biases exist. They make validation difficult. Biases result from an algorithm's inability to distinguish scenes with similar observations but different surface rainfall rates. We will need ancillary data to distinguish. What to include is probably the only active area of algorithm research.