

The Motivation

Shortcomings in the Cloud Resolving Model Databases

[Kummerow, C., W. Berg, J. Thomas-Stahle, and H. Masunaga, 2006: Quantifying global uncertainties in a simple microwave rainfall algorithm, *J. Atmos. and Oceanic Tech.*, 23, 23–37] showed that the lack of "Representativeness" was the largest source of uncertainty in Bayesian rainfall estimates using CRM Model databases.

Representativeness errors will persist until global high resolution CRM simulations are carried out that capture the distribution of all cloud types in different meteorological regimes as observed in nature.

PR/TMI Rainfall Biases

Careful examination of biases between V6 of TRMM radar and radiometer rainfall products showed a strong correlation with total water vapor in each scene [Berg, W., T. L'Ecuyer, and C. Kummerow, 2006: Rainfall climate regimes: The relationship of regional TRMM rainfall biases to the environment, *J. Appl. Meteor. & Climatol.*, 45, 434-454.] A bias removal based upon water vapor shows only small residual differences as shown in the bottom panel of Figure 1. This suggested that water vapor, although accounted for in the retrievals, has a secondary effect on either the radiometer, radar or both products. These differences must be understood before rainfall trends associated with in warmer climates (more water vapor) can be trusted.

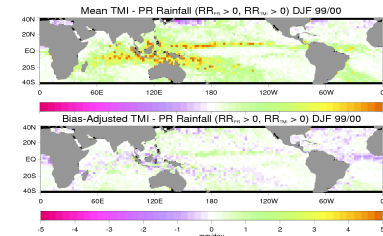


Fig. 1. Regional discrepancies between TRMM radiometer (TMI) and Radar (PR). Top panel shows original discrepancies. Bottom panel shows residual after bias adjustment based upon scene water vapor.

Further analysis of rainfall vertical structure as a function of total water vapor is shown in Figure 2. The progression of shallow rain clouds to deeper systems as a function of total precipitable water is clearly illustrated in this figure.

Particularly evident is the relative increase in deep convective systems with very cold cloud tops and deep echo structures in high water vapor environments. These differences in cloud morphology, when not properly accounted for in retrieval algorithms, can easily lead to apparent trends in surface precipitation when the trend is merely in the cloud physics.

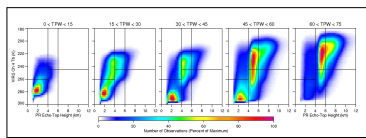


Fig. 2. Histograms of TRMM radar echo top height versus cloud top temperature as determined from TRMM's IR sensor (VIRS).

The Approach

GPROF2010 relies on observed rainfall structures from a combined PR & TMI retrieval with some Cloud Resolving Model information instead of using only CRM output. Using one year of observations generates 16 million profiles spanning all SST and TPW categories seen by TRMM. The database is constructed in an iterative manner that begins with the radiometer-only solution where no rain is found by the radar and the radar-only solution where it is raining. This solution is used to create a complete geophysical scene description, which is subsequently used to compute T_b that are then compared to the T_b observations. If discrepancies exist, the method iterates on the raining cloud structures until the rain profiles lead to the observed radar reflectivities and microwave T_b . Because non-raining pixels are present in the database, no screening for rain free pixels is needed.

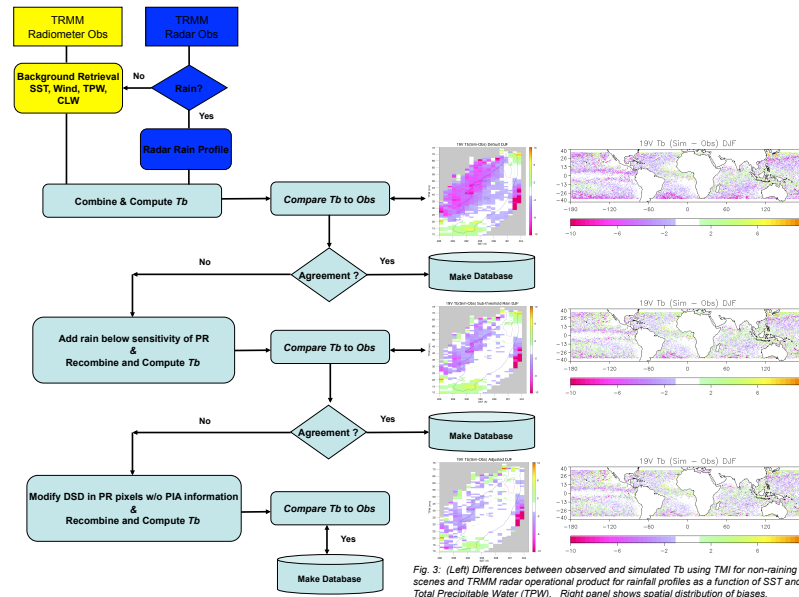
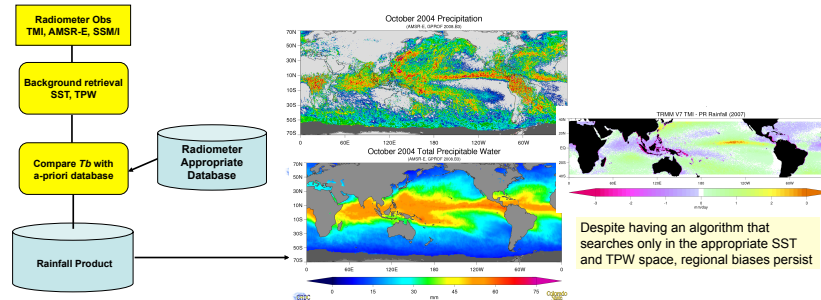


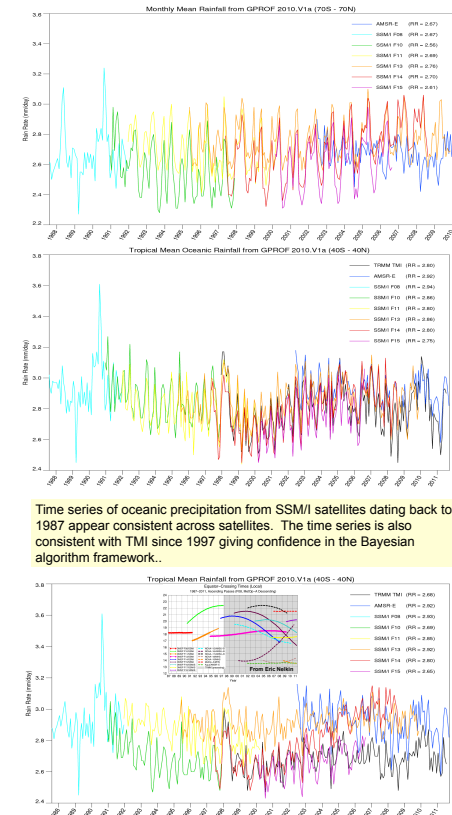
Fig. 3. (Left) Differences between observed and simulated T_b using TMI for non-raining scenes and TRMM radar operational product for rainfall profiles as a function of SST and Total Precipitable Water (TPW). Right panel shows spatial distribution of biases.

The *a-priori* database consists of geophysical parameters at the resolution of the TRMM PR (i.e. 4 km). T_b s are computed and averaged to any sensor for which retrievals are to be performed. There are no free parameters that can be adjusted for individual sensors. The retrieval itself is only a slight modification of the Bayesian scheme used in GPROF2004 to account for the different structure of the *a-priori* database, including the stratification by SST and TPW. Once TPW and SST are assigned, the database is searched in appropriate SST and TPW space for matches with observed T_b using Bayesian methodology.



Despite having an algorithm that searches only in the appropriate SST and TPW space, regional biases persist

The Results



Time series of oceanic precipitation from SSM/I satellites dating back to 1987 appear consistent across satellites. The time series is also consistent with TMI since 1997 giving confidence in the Bayesian algorithm framework.

Time series over land appear much less robust but most of the differences can be ascribed to diurnal sampling. Screening differences due to diurnal temperature differences also play a role.

Gridded products are available from Web page at CSU.

<http://rain.atmos.colostate.edu>

Algorithm Status	
Tropical Oceanic	
TMI	Operational
AMSR-E	Operational
SSM/I F10	Operational
SSM/I F11	Operational
SSM/I F12	Operational
SSM/I F13	Operational
SSM/I F14	Operational
SSM/I F15	Operational

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