J622 **IMPROVING THE QUALITY OF EXTREME PRECIPITATION ESTIMATES USING SATELLITE PASSIVE MICROWAVE RAINFALL RETRIEVALS**

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1. INTRODUCTION AND BACKGROUND

Extreme precipitation events associated with hurricanes, floods, blizzards, droughts and landslides have significant socioeconomic impacts. One of main objectives of the Global Precipitation Measurement (GPM; Hou et al. 2014) mission is to improve the monitoring and prediction of these events. With global rainfall measurements provided in near real time every 3 hours, the GPM mission greatly contributes to the improvement of weather and climate communication and important impact-based decision support services (financial, agricultural, energy, etc.). To ensure full exploitation of GPM temporal and spatial sampling across the globe we must provide consistent and accurate measurements.

Satellite passive microwave rainfall retrievals currently base their land algorithms on an empirical relationship between high frequency brightness temperature depression and rainfall rate (Fig. 1). Errors in retrieved rain rates occur

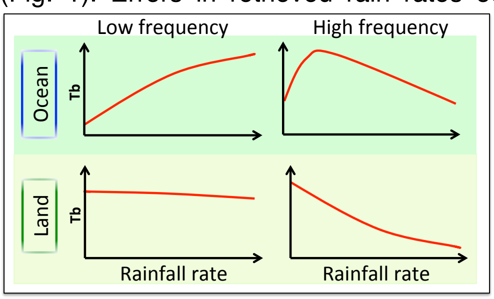

Figure 1. Brightness temperature to rain rate relationship for low and high frequencies over the ocean and land – a schematic.

as soon as the amount of ice present in the clouds is not properly understood. An example of the microwave retrieval underestimating the rainfall rate in warm clouds containing little to no ice aloft is shown in the Fig. 2. On larger scales this sensitivity of the retrieval to changes in the amount of ice relative to rainfall in the cloud results in regional biases of rainfall estimates. For the same reason estimates during extreme precipitation events can be challenging.

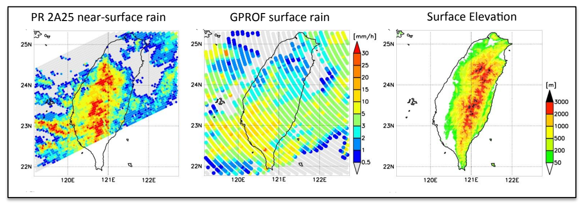

Figure 2. Typhoon Morakot over Taiwan area on 8 August 2009 as seen by TRMM radar (left) and radiometer (middle). Adopted from Taniguchi et al. 2013.

To address these biases we investigate how precipitation regime and the environmental conditions during storms development are linked to this ice vs. rainfall relationship. In this process we look at large-scale environment over the regions with strong biases between TRMM radar and radiometer, and we compare ground radar and gauge observations to the GPM constellation.

2. BAYESIAN *A PRIORI* AND WEIGHTING

The GPM operational passive microwave rainfall retrieval – GPROF2014 (Kummerow et al. 2015), was released after the launch of the GPM core satellite in February 2014. It is a Bayesian retrieval that utilizes ground radar observations to relate observed brightness temperatures (Tbs) to surface rainfall rates. To accomplish this, an *a priori* database was created by coupling NMQ[1] (Zhang et al. 2011) rain rates and corresponding Tbs (for each instrument in the GPM constellation). The "expected" rainfall rate, *E(x)*, is retrieved by:

$$E(\mathbf{x}) = \sum_i \mathbf{x}_i \frac{\exp\{-0.5[\mathbf{y}-\mathrm{H}(\mathbf{x}_i)]^T(\mathbf{O}+\mathbf{S})^{-1}[\mathbf{y}-\mathrm{H}(\mathbf{x}_i)]\}}{A}$$

where $\mathbf{x}_i$ represents all *a priori* database profiles, $\mathbf{y}$ is the observation vector, $\mathrm{H}(\mathbf{x}_i)$ is the simulated observation vector corresponding to profile $\mathbf{x}_i$ with H being the observation operator, **O** and **S** are the observation and model error covariance matrices, respectively, and A is a scalar constant serving as a normalization factor.

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1 National Mosaic and QPE (Quantitative Precipitation Estimate)

An illustration of the information content seen by the Bayesian algorithm over ocean (blue), and land (green) for a given Tb in 1D space (e.g. a single frequency retrieval) is schematically given in Fig. 3.

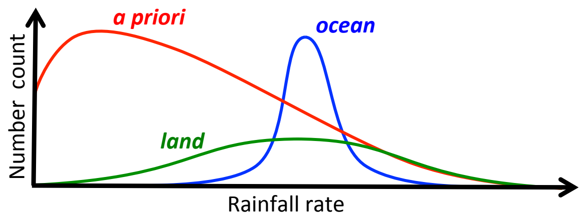

Figure 3. A schematic of rain rate PDF in the *a priori*, and weights PDFs over the ocean and land for typical observed vector.

Two primary sources of bias can be identified, especially over land where information content provided by observation vector is low: 1) smoothing of extreme *a priori* database values due to a larger population of lower rain rates in the database, and 2) smoothing over a broad range of database elements due to inability of the *a priori* to offer a close match to the observation vector.

3. LINKS BETWEEN THE ENVIRONMENT AND REGIONAL BIASES

To test what influence the large-scale environment may have on the ice-to-rain ratio we characterize storm-preceding environment using common variables such as humidity and CAPE. Figure 4 shows the effect of the environmental humidity on the mean PR dBZ profile averaged over 1° x 1° raining scenes over land. A “dry aloft” environment is characterized by stronger reflectivity above the freezing level implying higher amounts of ice. This further implies that the existing GPROF *a priori* database is not ideal for rain rates in all environmental conditions. A number of ECMWF ERA-Interim variables are used to test their potential in predicting environmental link to ice-to-rain relationship. Results show that up to 30% of the regional biases between TRMM active and passive sensors over Africa and Amazon can be explained using this knowledge of large-scale environment.

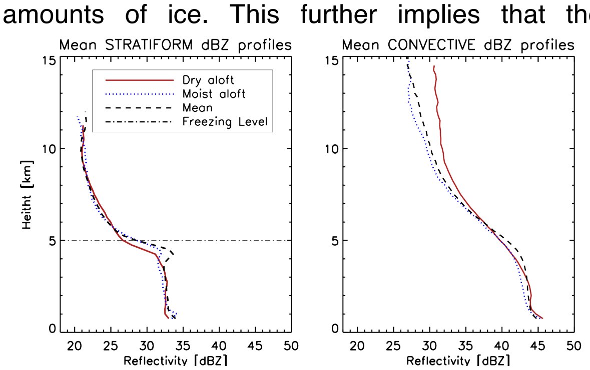

Figure 4. Mean dBZ profile as a function of large-scale environment.

4. THE BALKAN FLOOD EVENT

Two 3-day precipitation events over the Balkan region in southeast Europe are compared with a goal to gain better understanding of rainfall estimates during extreme precipitation events. The first, non-flood, event (May 1st – 3rd 2014) was a typical spring precipitation event, while the second event (May 14th – 16th 2014) caused historical flooding with record rainfall accumulations over a 6° x 5° area. The events were characterized by different precipitation intensity and large-scale environment. Ratios between estimates made by GPM constellation, and ground radar and gauge networks are highly correlated with precipitation regime and level of the systems organization (table 1).

	Day	GPM bias	Precipitation regime
Flood event	14th	-2.5*	Strong well-organized
	15th	-2.7*	Strong well-organized
	16th	-2.3*	Strong well-organized
	14th - 16th	***-2.5***	***Extreme***
Non-flood event	1st	-0.95*	Scattered convection
	2nd	-0.90*	Scattered convection
	3rd	-1.80*	Average well-organized
	1st - 3rd	***-1.20***	***Typical***

Table 1. Quantitative comparison of rainfall accumulation estimates given by gauges and satellite constellation. * denotes an estimate.

5. LINKS BETWEEN THE DATABASE STRUCTURE AND OBSERVED BIASES

We use GPM constellation overpasses during the Balkan flood event to address contributions of the two bias sources using the ground radar and gauge network as a reference. Using the existing GPROF *a priori* database we derive the observational vectors that correspond to the ground observations. Using them in a “synthetic” retrieval we find that up to 75% of the systematic biases observed during the Balkan flood event are due to structural differences in microphysics between the *a priori* database and observed systems.

6. CONCLUSIONS

Understanding the relationship between the environment and ice-to-rain ratio is the key for eliminating systematic errors in passive microwave satellite measurements. There are strong indications that the large-scale biases between TMI and PR observations are linked to storm's microphysical structure and organization.

Regional variation in the ratio between ice scattering signal and surface rainfall is correlated with environmental conditions during the development of precipitating systems. Relating the environment to ice-to-rain ratio improves the information content and understanding of observed rainfall signatures. Using this knowledge to better constrain the *a priori* information would allow for up to 75% reduction in satellite systematic biases.

7. REFERENCES**

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