A Microwave-Based Hydrometeor Profile Retrieval Algorithm Using a Variational Technique

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1. INTRODUCTION

This study presents the results of a microwave-based algorithm which attempts to perform the retrieval of hydrometeor parameters in a profile form. The hydrometeors in question are both phases of the precipitating rain (liquid and frozen). The algorithm is called the Microwave Integrated Retrieval System (MiRS) which uses microwave radiances from AMSU and MHS sensors onboard NOAA-18, NOAA-19, Metop-A and DMSP-F16 SSMIS. It is running operationally at NOAA/NESDIS for a number of atmospheric, land and cryospheric products as well as for the integrated ice water path and surface rainfall rate. The retrieval is performed in a reduced space to ensure inversion stability, using Empirical Orthogonal functions (EOF). The assessment of the results is performed by using TRMM/TMI-PR profiles to ensure that vertical cross sections (global and regional) are consistent. Given the footprint sizes difference, the time synchronization issues, and the nature of the phenomena being sensed (rapid transformation/motion of the hydrometeors) it is shown that collocation is a major challenge. A discussion will summarize the final results that will be obtained in this on-going study.

2. ALGORITHM APPROACH

MiRS is a One-Dimensional Variational inversion scheme (1DVAR) that employs the Community Radiative Transfer Model (CRTM) as the forward and adjoint operators. It solves simultaneously for the surface and the atmospheric parameters including hydrometeors. The iterative process of the 1DVAR inversion scheme employed in this study aims at minimizing the following cost function, similar to the variational radiance data assimilation employed in Numerical Weather Prediction (NWP) models:

$$J(X)=\left[\frac{1}{2}\left(X-X_0\right)^T\times B^{-1}\times\left(X-X_0\right)\right]+\left[\frac{1}{2}\left(Y^m-Y(X)\right)^T\times E^{-1}\times\left(Y^m-Y(X)\right)\right]$$

Where X_0 and B are the mean vector (background) and covariance matrix of X, the state vector to be retrieved, respectively. E is the measurement and/or modeling error covariance matrix. The first term on the right J_b represents the penalty in departing from the background value (a-priori information) and the second right term J_r represents the penalty in departing from the measurements Y^m. Solving for this equation assumes we have a forward operator Y that can simulate radiances similar to the measurements without bias and with statistics well captured within E. To address the ill-posed nature of the problem, the retrieval is performed in a reduced space. Empirically Orthogonal Functions (EOFs) are computed for the covariance matrix to diagonalize it.

3. PHYSICAL CONSTRAINTS

The retrieval of rainfall rate from space, along with any other hydrometeor parameter, is notoriously an ill-posed problem. This is because the brightness temperature measurements, depending on the sensing frequency, are a mixture of multiple signals coming from the rain itself, the ice, the suspended non-precipitating cloud droplets, the surface temperature, the surface emissivity, the atmospheric temperature and degree of humidity. The rain and ice signals themselves do not necessarily depend only on the rain or ice amounts. They also depend to various degrees on the particle size assumed, the vertical distribution, the shape, the size distribution and the density, among other things. So handling this challenge has a direct impact on what gets retrieved. Different geophysical data could generate equivalent radiometric signal/measurements, leading to potentially large errors in the rain parameters retrieval. In order to properly address the ill-posed nature of the rain retrieval, it is necessary to physically constrain the solution as much as possible. Physical algorithms offer ways to do just that. This study suggests the use of a One-Dimensional Variational algorithm (1DVAR) because this technique offers several ways to constrain the solution, all of them physical. The following constraints could be mentioned:

- (1) 1DVAR algorithms rely on constraint covariance matrices (composed of variances and correlations between the parameters) that force the different parameters to vary within *reason* during the physical retrieval. This has the added advantage of allowing to *extract* rain-related information from sounding channels for instance since the temperature has clearly a correlation with the presence of rain or ice.
- (2) The other powerful constraint in the 1DVAR algorithm is its reliance on a physical radiative transfer model that simulates brightness temperatures but also Jacobians. Starting from a first guess, the 1DVAR alters the solution until it fits the measured brightness temperatures. When the retrieval alters all parameters simultaneously, it relies on physical Jacobians (derived in CRTM using Tangent Linear and Adjoint techniques) to tell it which parameter should be altered, given the measurements in all channels. It can therefore physically distinguish the signal coming from ice, from rain, from the surface and from skin temperature, etc. This offers a powerful way to

retrieve rain while at the same time accounting for secondary effects impacting the measurements, including the emissivity and the skin temperature.

- (3) The additional physical constraint in the 1DVAR system relates to finding a solution that fits the measurements. This is a physical constraint by definition since the measurements are assumed to respond to physical phenomena that the sensor detects. The non-uniqueness is certainly an issue, but the fact that we couple this constraint with the previous constraints mentioned above, allows a generally physically consistent solution to be obtained. The added advantage is that the convergence metric (or degree of fitting of the measurements) offers a powerful mean for quality controlling the retrieval. It is clear for these reasons that the physical retrievals offer a significant advantage when compared to the regression-based approaches. This 1DVAR methodology has been applied recently and offers significant promise (Boukabara et al, 2007).

4. ASSESSMENT

The assessment of the hydrometeor profile inversion using MiRS is done essentially by checking the horizontal fields at different layers as well as checking vertical cross sections of MiRS retrievals of liquid and frozen rain profiles. They will be assessed on a qualitative basis as well as on a quantitative basis by comparing them to TRMM/TMI-PR derived profiles.

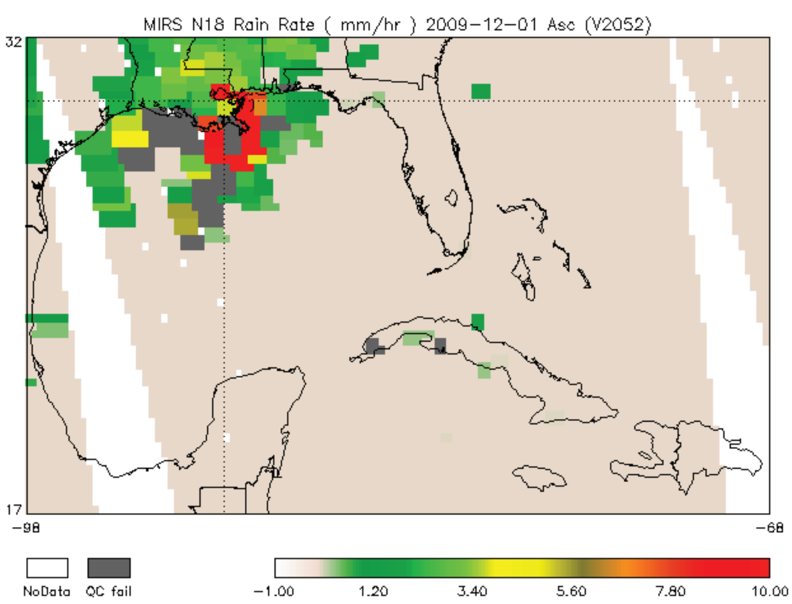

Figure 1. *Horizontal field of surface rainfall rate over the Gulf of Mexico corresponding to December 1st 2009, as derived by the MiRS algorithm using data from NOAA-18 AMSU and MHS sensors.*

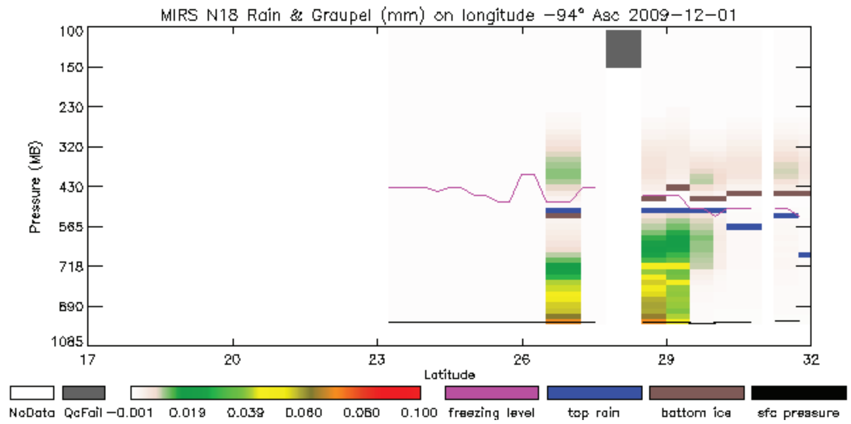

Figure 2. *An example of a vertical cross-section of the liquid rain profile as derived by the MiRS algorithm using data from NOAA-18 AMSU and MHS sensors. Data correspond to December 1st 2009 and to a section at longitude 94 West.*

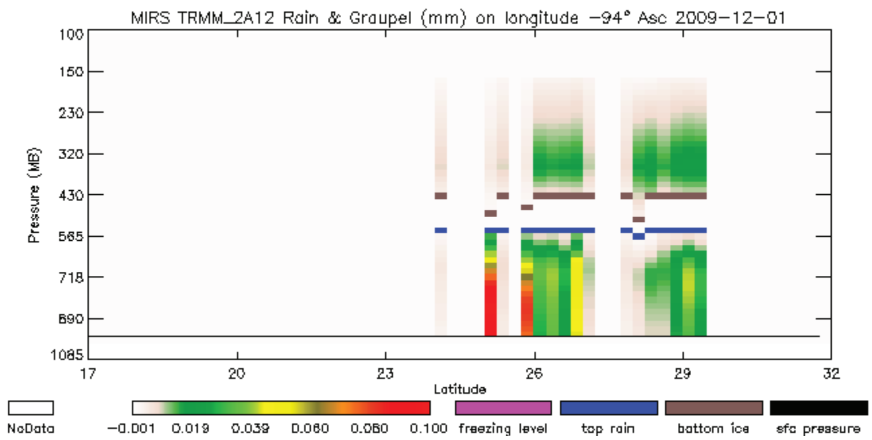

Figure 3. ***An example of a vertical cross-section of the liquid rain profile as determined from TRMM/TMI-PR.. Data correspond to December 1st 2009 and to a section at longitude 94 West. The time difference however between MiRS retrievals shown previously and these TRMM-based estimates is not small.***.

5. SUMMARY/DISCUSSION

A physically-based algorithm has been developed to retrieve hydrometeor profiles in liquid and frozen forms. It is strictly a remote sensing algorithm relying on radiance signatures, with no additional information from NWP data or any coupling with cloud-resolving models. It performs the retrieval in a consistent fashion ensuring that temperature, moisture, surface parameters along with rain and ice profiles are all retrieved simultaneously. This allows the final solution to be consistent with the measurements within the noise level (convergence). When non-convergence occurs, it allows a powerful quality-control tool to screen out the difficult cases. Assessment of this hydrometeor profiling capability is performed using TRMM TMI-PR based profiles. The collocation criteria are shown to play an important role in interpreting the results.

6. REFERENCES

[1] S.-A. Boukabara, F. Weng and Q. Liu, "Passive Microwave Remote Sensing of Extreme Weather Events Using NOAA-18 AMSUA and MHS," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 7, pp. 2228-2246, Jul 2007.