Applications of Dynamic Surface Information for Passive Microwave Precipitation Retrieval

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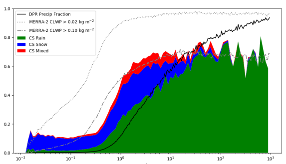
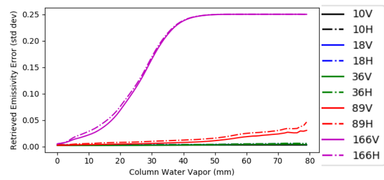
Introduction

Accurate precipitation retrievals over land surfaces continue to be a challenge in the GPM era. Quantitative estimates of rain and snow differ between algorithms in non-systematic ways at both the high and low ends of the rate spectrum. As the retrieval community continues to move toward more physically-based techniques aimed at a better understanding of precipitation processes, it makes sense to approach algorithm development and improvement from a physical perspective as well. Within this framework, the problems can be separated as a function of physical basis. At high rain rates for example, the surface signal is not an issue and the dominant scattering signal is used for retrieval. These relationships are not 1-to-1 however, and understanding these variations could be a valuable tool for constraining and improving retrievals of over-land convection, which tend to be high biased. A separate issue is the consequence of the high surface emissivity compared to the emission signal from light precipitation. Other scattering sources can often be misinterpreted by a Bayesian technique such as GPROF as light precipitation. If the emissivity is known however, the precipitation signal (or lack thereof) can be differentiated with better accuracy. Allowing for dynamic variability in the surface signal and water vapor has the potential therefore to improve spurious light precipitation retrieved from passive microwave sensors. In this work, an emissivity retrieval recently developed at NASA GSFC by Dr. Joe Munchak is coupled with a GPROF-style Bayesian retrieval. The retrieval is run using dynamic information from the emissivity retrieval as a constraint, and compared to a run using the operational model-based constraints. Results indicate that the addition of the dynamic surface information has potential to improve such retrievals for cases of light precipitation over land.

Munchak et al. OE Retrieval: Emissivity, TPW

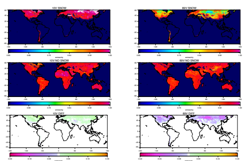




Munchak et al. 2019 (In revision)

For this hybrid-type scheme, the OE retrieval results are taken as a first pass for non-snow covered areas. A threshold on the normalized cost function, which should blow up in the presence of precipitation, is applied and the Bayesian retrieval run for locations exceeding this threshold. Three are tested – 0.1, 0.3, 0.5.

Use to Identify and Eliminate Snow Covered Surfaces



Physical basis: emission signal at low frequency + scattering signal in high frequency

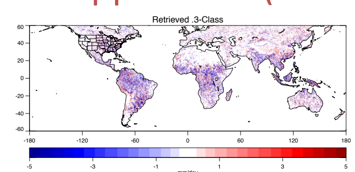
Compare to snow-free emissivity for that location

Utilize emissivity database (1 year, strict cloud clearing with chi-sq) and look at change in both signals from snow-free mean

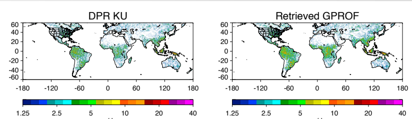
Snowcover if $\Delta 10 - \Delta 89 \geq 0.03$

Positive for emission — Negative for scattering

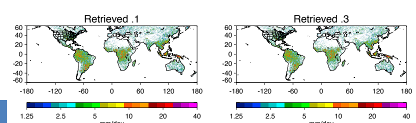
Global Application (Snow Free)



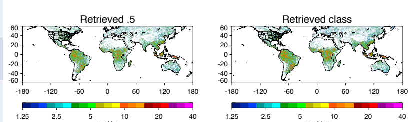
Differences throughout all precipitating areas



1 Yr Global Retrieval



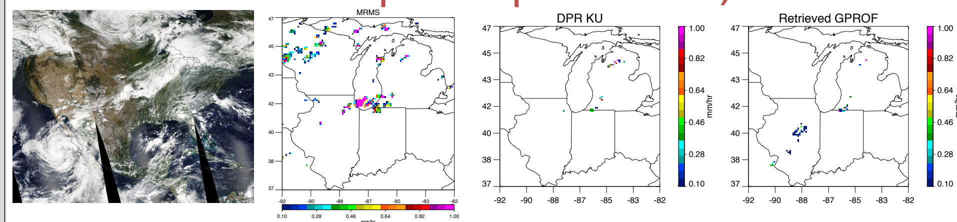
Distribution is basically the same in each case (not affecting the heavier precipitation)



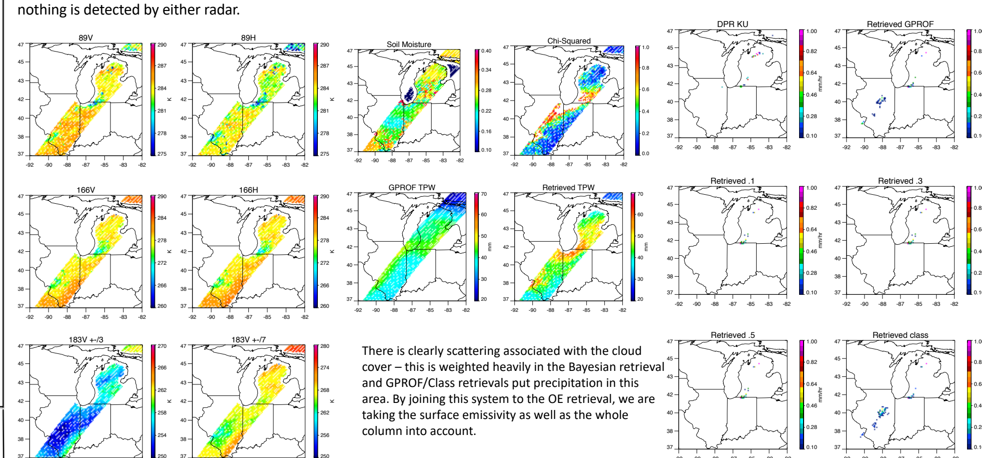
1 Yr Global Statistics: Retrieval/Ku Radar

	Chi-sq .1	Chi-sq .3	Chi-sq .5	Class
Correlation	0.47	0.47	0.47	0.47
Bias	0.044	0.038	0.035	0.045
RMSE	1.04	1.04	1.04	1.07
POFD	0.29	0.15	0.08	0.29
POD	0.91	0.84	0.75	0.90

Retrieval Example: September 8, 2015



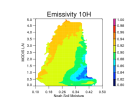
A typical midlatitude cyclone is present across central North America. MODIS observation in the visible show extended cloud cover in the upper Midwest. Precipitation validation data shows rain south of Lake Michigan with surrounding scattered precipitation. The GPM Ku radar swath is south of the heavier precipitation but captures the rain east of the lake. GPROF detects precipitation in these areas as well, but adds light rain in Illinois, where nothing is detected by either radar.



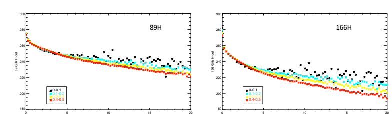
There is clearly scattering associated with the cloud cover – this is weighted heavily in the Bayesian retrieval and GPROF/Class retrievals put precipitation in this area. By joining this system to the OE retrieval, we are taking the surface emissivity as well as the whole column into account.

Looking ahead to improving retrievals for heavier precipitation: how/what surface conditions affect the character of the boundary layer and associated scattering signals?

Soil Moisture



Soil moisture strongly correlated to the surface signal – perhaps also cloud top scattering and related meteorology/microphysics to better represent precipitation?



Conclusions

A hybrid scheme is investigated combining a non-raining optimal estimation retrieval for rain-free areas over land surfaces and a Bayesian precipitation algorithm in areas where the OE cost function indicates no solution when non-raining conditions are assumed. Multiple cutoffs are compared. Results indicate that combination of such techniques can improve upon the pure Bayesian retrieval by using the dynamic information to eliminate the spurious light precipitation often retrieved by such schemes. Global statistics indicate that the error parameter threshold significantly decreases false alarms with respect to the GMI Ku radar. Future algorithms could be enhanced by utilizing this type of physically-based OE-Bayesian hybrid technique, and could be further improved by implementing a retrieval for light precipitation below the DPR threshold in "gray areas" where the OE error parameter is elevated. Such a technique has the potential to more fully utilize the information content available from the passive sensors regarding hydrometeors in the column.