Dynamic Emissivity Estimates to Support Physical Retrievals for GPM

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Introduction

Passive microwave precipitation retrieval over land surfaces continues to be a challenging problem. Because of the radiometrically warm surface compared to the absorption signal from precipitation-sized hydrometeors, physically-based method such as those employed successfully over the ocean in the TRMM era are more problematic, particularly for lower rain rates where the scattering from ice particles is not significant. Because of this, previous retrieval schemes have employed more empirical methods over land surfaces. In the GPM era, the Goddard Profiling Algorithm (GPROF) utilizes the coincident active/passive core satellite observations in creation of a database for Bayesian retrieval over land in the same procedure as that over ocean. While the move toward more physically-based retrieval is important for data assimilation applications as well as furthering understanding of precipitation processes, problems in observing and interpreting hydrometeor signal over land in the passive microwave continue to be an important area of research.

To aid in this effort, dynamic information about the land surface is collected and attached to GPM observations for retrieval experiments. Through improved understanding of the dynamics of the surface signal it is hoped that the precipitation signal be more successfully differentiated and retrieved in a physically-based scheme.

Motivation

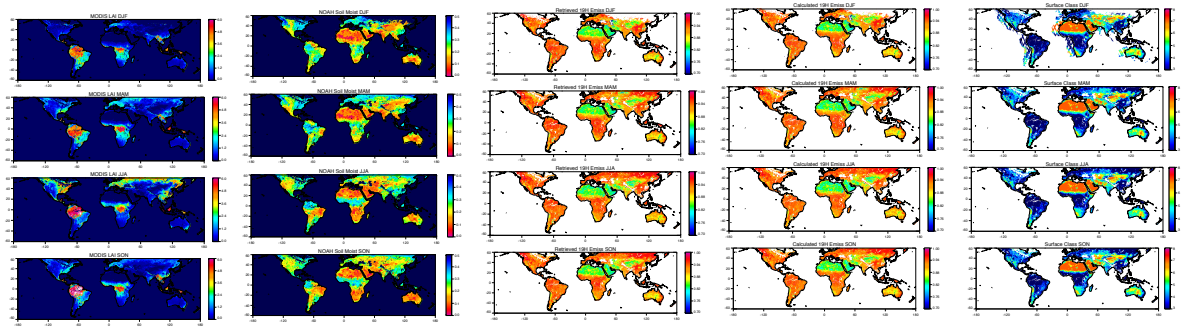
Calculations from 1 year of retrievals over non-snow land surfaces (Ku rain rate over GMI footprint area):

0-1 mm/hr: 73% of raining footprints
: mean ku: .30, mean GPROF: .49 (+63%)
1-5 mm/hr: 23% of raining footprints
: mean ku: 2.1, mean GPROF: 2.3 (+8%)
5-10 mm/hr: 3% of raining footprints
: mean ku: .6.72, mean GPROF: 5.39 (-20%)
10+ mm/hr: 1% of raining footprints
: mean ku: 19.67, mean GPROF: 7.62 (-61%)

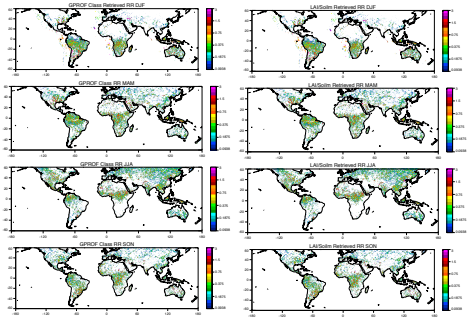
The retrieval shows significant overestimation at light rain rates, underestimation at heavy rain rates. Similar results are reported by Kidd et al. (QJRMS 2017) and Petkovik et al. (JHM 2017)

Database and Retrieval

The GPM GPROF retrieval algorithm database includes one year of combined DPR-GMI observations and retrievals which can be used in combination with radiative transfer for application to other constellation members in a consistent retrieval framework. This database contains a wealth of information for examination of connections between observables and other ancillary data fields. In order to examine the relationship between observed Tb, radar rain rate, and surface characteristics, the database is enhanced with several ancillary datasets. The enhancement is also done for the 1 year period after the database for retrieval testing. Output from the NCEP Noah land surface model (forced using MERRA-2) is attached to each GPM observation along with leaf area index (LAI) retrieved from the MODIS instruments aboard NASA EOS Aqua and Terra satellites.

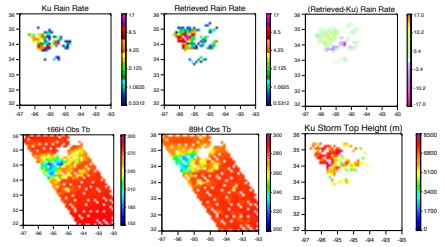


The Bayesian retrieval scheme utilized in operational GPROF is adapted for experimentation. Following modification to include the dynamic surface information, the retrieval can be easily indexed by any relevant parameters (for example LAI and soil moisture as shown far right) and compared to the GPROF surface class retrievals. One year of retrievals are performed for all non-snow covered land surfaces globally.



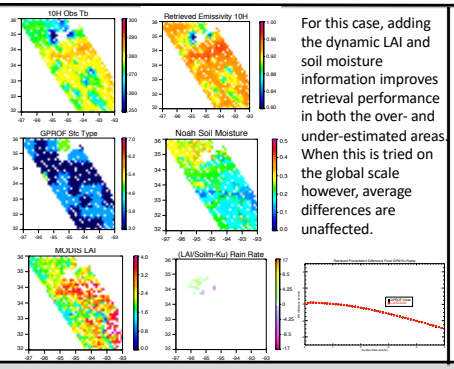
Case Study

The retrieval is examined for an instantaneous precipitation case in the Southern Great Plains (SGP) area of the Kansas-Oklahoma border.



Retrieved rain rate here basically looks like the 89 GHz scattering signal. The area of greatest scattering retrieves the highest rain rates, which are not seen by the DPR. Where the DPR sees the highest RR, the retrieval significantly underestimates.

Clearly this is more complicated than a straight scattering-rain rate relationship!



For this case, adding the dynamic LAI and soil moisture information improves retrieval performance in both the over- and under-estimated areas. When this is tried on the global scale however, average differences are unaffected.

Applications

You et al. 2018 use the dynamic surface signal, as manifested by the change in Tb calculated using constellation overpasses, to retrieve the precipitation. This work further illustrates the information available to passive microwave retrieval schemes in the instantaneous surface signal.

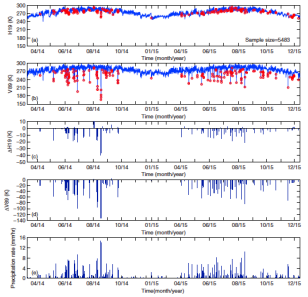


Figure 2. Time series from March 2014 to December 2015 the 0.5° grid box of (100.5°–101°W, 41.5°–42° N) for (a) H19, (b) V89, (c) ΔH19, (d) ΔV89, and (e) precipitation rate. The red circles in panels (a) and (b) represent the precipitation observations identified by Y19 – V89 greater than 8 K.

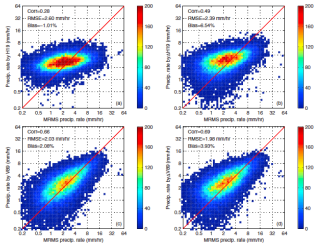


Figure 10. Scatter plots between surface radar observed precipitation rate (reference) and (a) retrieved precipitation rate from H19; (b) retrieved precipitation rate from ΔH19; (c) retrieved precipitation rate from V89; and (d) retrieved precipitation rate from ΔV89. RMS = root-mean-square; MRMS = Multi-Radar/Multi-Sensor System.

Conclusions

A global database has been assembled and is available to algorithm developers containing dynamic surface information associated with GPM observations for a 2 year period, including the GPROF operational database year and an additional year for retrieval testing. The retrieval itself has been adapted to incorporate this information, and retrievals tested for a case study and full year comparing bin indexing using the standard GPROF classes and LAI/soil moisture information. Full year, average global statistics show that the TELSEM land classes adequately represent the surface characteristics at this scale, however there is some suggestion that integrating dynamic surface information in the algorithm may improve results at the instantaneous "snapshot" scale. The surface signal is further demonstrated to have empirical retrieval uses as illustrated by You et al. 2018.

A case study comparison shows that incorporating dynamic surface information as an index for the Bayesian scheme improves estimation in both the lower and higher rain rate areas, suggesting that along with better categorizing the instantaneous surface conditions, these quantities may also hold information about the character of the precipitation as manifested by the scattering signal. When the dynamic stratification is examined on the global average level however, no improvement is apparent, and the retrieval continues to overestimate at low rain rates and underestimate at high rain rates.

While promising, these results suggest more information is needed to accurately retrieve precipitation over land in a Bayesian scheme. The database presented here, along with improvements in channel weighting and incorporating better use of the surface signal, contains a wealth of information that can be used to achieve this goal.