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Evaluation of precipitation detection over various surfaces from passive microwave imagers and sounders

S. Joseph Munchak [a,b,*], Gail Skofronick-Jackson [a]

[a] Mesoscale Atmospheric Processes Laboratory, Code 612, NASA Goddard Space Flight Center, 8800 Greenbelt Rd., Greenbelt, MD, USA 20771
[b] Earth System Science Interdisciplinary Center, University of Maryland, College Park, MD, USA

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ABSTRACT

During the middle part of this decade, a wide variety of passive microwave imagers and sounders will be unified in the Global Precipitation Measurement (GPM) mission to provide a common basis for frequent (3 h) global precipitation monitoring. The ability of these sensors to detect precipitation by discerning it from non-precipitating background depends upon the channels available and characteristics of the surface and atmosphere. This study quantifies the minimum detectable precipitation rate and fraction of precipitation detected for four representative instruments (TMI, GMI, AMSU-A, and AMSU-B) that will be part of the GPM constellation. Observations for these instruments were constructed from equivalent channels on the SSMIS instrument on DMSP satellites F16 and F17 and matched to precipitation data from NOAA's National Mosaic and QPE (NMQ) during 2009 over the continuous United States. A variational optimal estimation retrieval of non-precipitation surface and atmosphere parameters was used to determine the consistency between the observed brightness temperatures and these parameters, with high cost function values shown to be related to precipitation.

The minimum detectable precipitation rate, defined as the lowest rate for which probability of detection exceeds 50%, and the detected fraction of precipitation are reported for each sensor, surface type (ocean, coast, bare land, snow cover) and precipitation type (rain, mix, snow). The best sensors over ocean and bare land were GMI (0.22 mm h^{-1} minimum threshold and 90% of precipitation detected) and AMSU (0.26 mm h^{-1} minimum threshold and 81% of precipitation detected), respectively. Over coasts (0.74 mm h^{-1} threshold and 12% detected) and snow-covered surfaces (0.44 mm h^{-1} threshold and 23% detected), AMSU again performed best but with much lower detection skill, whereas TMI had no skill over these surfaces. The sounders (particularly over water) benefited from the use of re-analysis data (vs. climatology) to set the *a priori* atmospheric state and all instruments benefited from the use of a conditional snow cover emissivity database over land. It is recommended that real-time sources of these data be used in the operational GPM precipitation algorithms.

1. Introduction

Passive microwave remote sensing of precipitation from space has advanced tremendously in the past three decades with regard to both number and capabilities of instruments in operation. The "golden age" of passive microwave precipitation is anticipated to begin in 2014 with the launch of the Global Precipitation Measurement (GPM) core satellite on a mission to unify precipitation estimates from a constellation of sensors.

Early systems such as the Electrically Scanned Microwave Radiometer (ESMR; Allison et al. (1974)) and Scanning Multi-channel Microwave Radiometer (SMMR; (Gloersen and Hardis,

* Corresponding author at: Mesoscale Atmospheric Processes Laboratory, Code 612, NASA Goddard Space Flight Center, 8800 Greenbelt Rd., Greenbelt, MD, USA 20771. Tel.: +1 301 286 2392; fax: +1 301 614 5492.
E-mail address: s.j.munchak@nasa.gov (S.J. Munchak).

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1978)) and corresponding retrieval algorithms (e.g., Wilheit et al. (1977), Prabhakara et al. (1986)) primarily focused on the retrieval of rainfall over oceans due to the clear contrast between the radiometrically cold background of the low-emissivity ocean surface and radiometrically warm emission from falling rain at low frequencies (below 50 GHz). The introduction of the Special Sensor Microwave/Imager (SSM/I; Hollinger et al. (1990)), with vertically and horizontally polarized channels at 89 GHz in addition to the lower frequencies on SMMR allowed for detection of precipitation with the detection of brightness temperature (Tb) depressions due to the scattering produced by large, precipitation sized ice particles (e.g., Wu and Weinman (1984), Spencer (1986)). Although the relationship between the amount of ice scattering and surface precipitation rate is dependent on the vertical structure of the precipitation profile (Kummerow and Weinman, 1988) and ice microphysics (Petty and Huang, 2010), it has nevertheless remained the primary source of information regarding precipitation over land surfaces due to their high, variable, and inhomogeneous emissivity.

While these instruments and algorithms generally perform well for moderate to heavy rainfall during the warm season (Ebert et al., 2007), cold-season precipitation, i.e., light rain and snowfall in particular, remains challenging (Iturbide-Sanchez et al., 2011) due to the weaker scattering signal and higher contribution from the earth surface (Skofronick-Jackson and Johnson, 2011), the emissivity of which may be complicated by the presence of snow or ice on the ground (Hewison and English, 1999). Frequencies higher than 100 GHz are particularly useful for falling snow because of increasingly effective scattering with frequency and reduced opacity of the atmosphere from water vapor in cold and dry environments (Bennartz and Bauer, 2003). An early attempt to retrieve falling snow (Liu and Curry, 1997) used the 92 and 150 GHz channels on the Special Sensor Microwave/Temperature-2 (SSM/T2) sounder in combination with temperature profiles from the ECMWF forecast model to detect snowfall over the north Atlantic using empirically-determined Tb thresholds. Empirical methods have since expanded to use the water vapor channels on Advanced Microwave Sounding Unit-B (AMSU-B) and Microwave Humidity Sounder (MHS) instruments to effectively mask the surface (Chen and Staelin (2003), Kongoli et al. (2003), Surussavadee and Staelin (2009)), improving detection skill. These algorithms generally use brightness temperature thresholds to detect precipitation and empirical regression or neural networks to determine intensity within the precipitation mask.

Physically-based methods, in contrast, use radiative transfer models to simulate brightness temperatures (Tbs) from Bayesian databases of observed (Noh et al. (2006, 2009), Kummerow et al. (2011)) and modeled (Skofronick-Jackson et al. (2004); Kim et al. (2008)), or variationally-adjusted (Bauer et al. (2005), Boukabara et al. (2011)) precipitation profiles. These methods ensure physical consistency between observed Tbs and retrieved precipitation, but require accurate models of ice particle scattering (e.g., (Liu (2004), Kim (2006), Kim et al. (2007), Petty and Huang (2010)) and emissivity of snow and ice-covered surfaces (e.g., Hewison and English (1999), Weng et al. (2001)), which are not as mature as their counterparts regarding liquid precipitation and ocean surfaces.

The purpose of this study is to establish the minimum precipitation rate that can be reliably detected over various surface types and with various channel combinations that will be available on satellites in the GPM constellation. Because the Bayesian retrieval databases for GPM are still under development, we instead employ a variational approach that combines physical and empirical models, described in Section 2 to identify precipitation using a null hypothesis test. The Special Sensor Microwave Imager/Sounder (SSMIS) is used as a proxy for various GPM-era sensors and evaluated over the continental United States using the National Mosaic and Quantitative Precipitation Estimates (NMQ; Zhang et al. (2011)). These data sets are also described in Section 2 and results given in Section 3. A summary and the concluding remarks are given in Section 4.

2. Method

This section describes the retrieval theory and data set-specific implementation details used to delineate precipitation in this study. An example retrieval is also provided to familiarize the reader with the output of the optimal estimation method applied to this remote sensing problem.

2.1. General retrieval theory

A variational (optimal estimation; Rodgers (2000)) retrieval of non-precipitation surface and atmospheric parameters via the inversion of a non-scattering radiative transfer model (Elsaesser and Kummerow, 2008) has been adapted for the data sets used in this study. Essentially, we test a null hypothesis that an observed set of brightness temperatures **y** is consistent with a reasonable set of surface and clear-air atmospheric parameters **x** not including liquid or frozen precipitation. This screening method is conceptually identical to that of Bytheway and Kummerow (2010) and Boukabara et al. (2011) as well as earlier versions of the Bayesian GPROF algorithm (Kummerow et al., 2001) (more recent versions (Kummerow et al., 2011) include non-precipitating profiles in the Bayesian database, eliminating the need for an explicit screening step).

The retrieval minimizes a cost function:

$$\Phi = (x-x_a)^T S_a^{-1}(x-x_a) + (y-f(x))^T S_y^{-1}(y-f(x)), \tag{1}$$

where $\mathbf{x}_a$ is the *a priori* state vector, $\mathbf{S}_a$ is the state covariance matrix, f is the forward (radiative transfer) model, and $\mathbf{S}_y$ is the observation covariance matrix. The contents and formulation of $\mathbf{y}$, $\mathbf{x}_a$, f, $\mathbf{S}_a$, and $\mathbf{S}_y$ depend on the input and ancillary data sets; further details are provided in Section 2.2 Common aspects of all retrievals are the use of Rosenkrantz (1998) and Rosenkrantz (1999) for absorption of atmospheric gases (with improvements (Tretyakov et al., 2003) to the water vapor lines at 22 and 183 GHz) and the use of FASTEM4 (Liu et al., 2011) for emissivity over water surfaces.

The cost function (1) is minimized iteratively, starting from $\mathbf{x}_a$, using the Gauss–Newton method to find the value of $\mathbf{x}$ where the gradient of Φ with respect to $\mathbf{x}$ is zero. This requires the calculation of the Jacobian matrix $\mathbf{K}$ at each iterative step n by calculating the derivative of each observation (y_i) with respect to each state element (x_j):

$$K_{ij} = \frac{\partial y_i}{\partial x_j}. \tag{2}$$