An Evaluation of Over-Land Rain Rate Estimates
by the GSMaP and GPROF Algorithms:
The Role of Lower-Frequency Channels

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Abstract

This paper presents an evaluation of over-land rain-rate estimates by both the Global Satellite Mapping of Precipitation (GSMaP) algorithm and the standard (GPROF) algorithm for the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), by comparing them with estimates by the standard algorithm for TRMM Precipitation Radar (PR). This study has the following advantages over previous studies: (1) the errors in rain-rate estimates are decomposed into those caused by rain/no-rain classification and those caused by rain-rate retrieval, (2) the quantitative effects of bright band height (BBH) and land surface physical temperature on retrieval are evaluated; and (3) the role of lower frequency channels (37.0 GHz and lower) for retrieval is investigated.

GSMaP yields monthly average and zonal mean rain-rate estimates close to those estimated by the standard algorithm for PR, as it refers to a database produced with PR data. However, GSMaP and GPROF overestimate (underestimate) rain rates for tall (shallow), stratiform (convective), and evening (morning) rainfall. Dependence on storm height (SH) is unavoidable as long as the algorithm relies on the scattering signal caused by solid precipitation for higher frequency channels (85.5 GHz).

Lower frequency channels are secondarily used in some algorithms to mitigate the above bias characteristics to some degree. In GSMaP Version 4.7, the severe overestimation seen in GSMaP Version 4.5 when SH is higher than 10 km is mitigated by using 37.0 GHz observations as a scattering signal. The following are indicated for stratiform rainfall with a bright band (SRBB). While the rain-rate estimates are negatively dependent on BBH in GSMaP, the use of 21.3 GHz and 10.7 GHz observations resulted in the cancellation of the dependence on the BBH in GPROF. Although lower-frequency observations are subject to variation in land surface physical temperature, no significant effects of land surface physical temperature on the rain-rate estimates were observed in this study. To improve over-land rain-rate estimates, it is important to make the most effective use of lower-frequency observations.
1. Introduction

The Tropical Rainfall Measuring Mission (TRMM) has made a major contribution to the advancement of satellite remote sensing of precipitation by providing regularly available, simultaneous observations with its microwave imager (TMI) and Precipitation Radar (PR). Before the TRMM, rain-rate estimates by microwave imagers were evaluated mainly with ground-based observations in limited areas and times or on coarse scales. The TRMM enables us to evaluate TMI estimates against PR estimates in various areas and periods and on fine scales.

Kummerow et al. (2000) reported the results of an initial evaluation of monthly rain-rate estimates by the standard PR and TMI algorithms (2A25 and 2A12). TMI estimates were generally larger than PR estimates. The early version of their algorithms (V4) indicated that the difference at the equator is 50% over ocean and 10% over land. The modified version (V5) indicated that the difference was reduced to 30% over ocean, but was increased to 26% over land.

Masunaga et al. (2002) compared monthly precipitation water content (PWC) estimates by the standard V5 algorithms. PWC is more directly related to satellite-observable variables than rain rate because PWC does not include the difference in falling velocity assumed by the PR and TMI standard algorithms. Masunaga et al. concluded that a fault in the rain attenuation correction in the standard algorithm for PR leads to the difference between TMI and PR in the tropics.

Furuzawa and Nakamura (2005) compared instantaneous over-land rain-rate estimates in the standard products for V5. Their results clearly indicated that the differences between rain-rate estimates by TMI and those by PR depend on storm height (SH), latitude, season, local time, and convective stratiform classification. This dependency resulted in TMI overestimates for deep, nighttime, or stratiform rain, and TMI underestimates for shallow, daytime, or convective rain. They also reported TMI detection failure at 1000 to 1400 LT (i.e., the first stage of rain system development). Nesbitt et al. (2004) compared the standard products for V5 on a storm, rather than grid, scale. Their study demonstrated that for widespread, stratiform, and deep precipitation systems with ice-scattering signature, instantaneous rain-rates estimated by TMI tended to be overestimated, compared to those by PR.

The standard algorithm for TMI is based on the Goddard Profiling (GPROF) algorithm and has been developed independently of the standard algorithm for PR. As a result, significant discrepancies remain between rain-rate estimates by the standard algorithms for PR and TMI. This discrepancy motivated the Global Satellite Mapping of Precipitation (GSMaP) project to develop a new rain-rate estimation algorithm for TMI (called GSMaP_TMI, but simply denoted as GSMaP hereafter); as much as possible, this algorithm uses the same physical modeling of precipitation as the PR standard algorithm (Okamoto et al. 2005, 2007).

In this study, we compared over-land rain-rate estimates by the GPROF algorithm (the standard algorithm) and the GSMaP algorithm to those made using the PR standard algorithm. These algorithms employ a kind of scattering algorithm (e.g., Spencer et al. 1983) for over-land rain-rate estimation. The emission algorithm (e.g., Wilheit et al. 1977) is not used over land because emission from land surfaces is warm and variable. The scattering algorithm relies on the fact that upward microwave radiation at high frequency (85.5 GHz for TMI) is scattered by solid precipitation particles. Generally, the relationship between ground-level rain rate and observed brightness temperature at high frequency is indirect and depends on the precipitation characteristics and the surrounding environment. Hence, rain-rate estimates by a scattering algorithm are generally considered to be less reliable.

This study attempted to identify causes of the biases in TMI algorithms. According to previous studies (e.g., Furuzawa and Nakamura 2005), variation in SH is one main cause. Some previous studies also focused on land surface conditions. For example, Tian and Peters-Lidard (2007) evaluated high-resolution precipitation products (HRPPs) based on observations by microwave imagers. They found that HRPPs often give a non-zero rain rate in areas partially covered by a lake or artificial water surface, even though ground-based radars indicate no rainfall. Low brightness temperature at the water surface is often mistaken for a signal caused by precipitation. Bauer et al. (2005) evaluated the effects of variations in solid precipitation, liquid precipitation, and land surface emissivity, as well as radiometer noise, on the variation of observed brightness temperature. For winter snowfall in Canada, solid precipitation and land surface emissivity had a large impact on observed brightness temperature. However, for convective summertime rainfall in Florida, solid precipitation had the largest impact, and liquid precipitation had the second largest impact; however, the
effect of land surface emissivity was small.

The remainder of this paper is arranged as follows. Section 2 introduces the rain-rate estimation algorithms used in this study. Section 3 explains the methods of the analysis (i.e., the methods of matching up the PR and TMI products and decomposing the errors in rain-rate estimates). Section 4 provides an overview of the evaluation, and Section 5 offers further evaluation of stratiform rainfall with a bright band (SRBB). Section 6 presents a summary and the conclusions.

2. Data

This section introduces the rain-rate estimation algorithms for PR and TMI used in this study.

2.1 The standard algorithm for PR

The main part of the standard algorithm for PR (2A25) has been well documented by Iguchi et al. (2000) for version 5 (V5) and by Iguchi (2007) and Iguchi et al. (2009) for version 6 (V6). A drop-size-distribution (DSD) model is first assumed according to the result of a rain-type classification algorithm and is modified by a hybrid method of the surface reference technique and the method of Hitschfeld and Bordan (1954). The surface reference technique is part of a sub-algorithm called 2A21 and was documented by Meneghini et al. (2000) for V5 and Meneghini et al. (2004) for V6. The rain-type classification algorithm is part of a sub-algorithm called 2A23 and has been documented by Awaka et al. (1998) for V5 and Awaka et al. (2007) for V6. Here, we used the PR standard product 2A25 in V6, which includes the results of 2A25 and the main results of 2A21 and 2A23.

2.2 The standard algorithm for TMI (GPROF)

GPROF was developed for the Special Sensor Microwave/Imager (SSM/I) (Kummerow et al. 1996). It was then modified and applied as the standard algorithm for TMI (Kummerow et al. 2001) and the Advanced Microwave Scanning Radiometer of the Earth Observing System (AMSR-E) (Wilheit et al. 2003). Hereafter in this paper, GPROF indicates the GPROF algorithm for TMI. GPROF refers to a database of precipitation systems simulated by a cloud-resolving model with corresponding brightness temperature calculated by a radiative transfer model. V5 and V6 are explained below.

a. GPROF V5

Kummerow et al. (2001) provided a good description of V5. Like other rain-rate estimation algorithms, this algorithm consists of two parts: a rain/no-rain classification (RNC) part and a rain-rate retrieval part. The RNC part is used to judge whether a pixel has rain or not. In V5, the RNC calculates a scattering index $SI = TB(21.3\text{V}) - TB(85.5\text{V})$, where $TB$ stands for brightness temperature at the frequency (GHz) and polarization (V for vertical, H for horizontal) indicated in parentheses. When $SI$ is larger than 8K and no snow/desert masks (e.g., Grody 1991) are applied, the pixel is judged to be a rain pixel, and the retrieval part is executed. If the pixel is judged to be a no-rain pixel, the rain-rate estimate becomes zero. In the retrieval part, according to the relationship between $SI$ and the ground-level rain rate ($R_g$) in the database, observed $SI$ is converted to estimated $R_g$.

b. GPROF V6

McCollum and Ferraro (2003) provided the following explanation of V6. The RNC for V6 is basically the same as that for V5. For retrieval, $TB(85.5\text{V})$ is used instead of $SI$. Databases of the relationship between $TB(85.5\text{V})$ and $R_g$ are prepared separately for convective and stratiform rainfall. Observed $TB(85.5\text{V})$ is converted to estimated $R_g$ by referring to each database. The abbreviation $R_g,c$ ($R_g,s$) denotes the estimate when referencing the convective (stratiform) database. To merge the two estimates, a convective/stratiform index (CSI) is introduced as follows:

$$CSI = 0.062 + 0.00887 \times [1.11 \times TB(10.7\text{V}) - 1.23 \times TB(37.0\text{V}) + 0.45 \times TB(85.5\text{V}) - 1.25 \times POL + 0.22 \times NPOL + 1.24 \times STDEV + 0.14 \times PIWD - 84.3], \quad (1)$$

where POL and NPOL are indices derived from brightness temperature with multi-polarization observations, and STDEV and PIWD are indices derived from the texture information (horizontal change of brightness temperature). Merging $R_g,c$ and $R_g,s$ with the weight of CSI produces the final estimate of $R_g$ as

$$R_g = CSI \times R_g,c + (1 - CSI) \times R_g,s. \quad (2)$$

The variables and the values of the coefficients in Eq. (1) are determined so that CSI corresponds best to the convective/stratiform classification by the PR standard algorithm. It is difficult to explain why $TB(10.7\text{V})$ was selected, as it contains little information about precipitation over land. McCollum and Ferraro (2003) offered the explanation that convective rainfall...
is more likely to occur over warmer land surfaces, where $T_B$ (10.7V) is higher.

2.3 GSMaP algorithm for TMI

The GSMaP algorithm is based on an algorithm developed by Aonashi and Liu (2000) and has been improved with the use of PR (Aonashi et al. 2009; Kubota et al. 2007). GSMaP refers to databases prepared daily for a 5° × 5° latitude/longitude grid, whereas the database used by GPROF is fixed in time and space. To prepare the databases for GSMaP, PR-observed vertical profiles of precipitation systems are summarized for different ground-level rain-rate categories and precipitation regimes. The atmospheric profile is taken from the global analysis (GANAL) dataset provided by the Japan Meteorological Agency (JMA). The latest version of GSMaP at the time of preparing this manuscript was version 4.8.4 (V4.8.4). In this study, we investigated versions 4.5 (V4.5) and 4.7 (V4.7).

a. GSMaP V4.5

For the RNC, V4.5 uses a method developed by Seto et al. (2005). This method refers to a database of brightness temperatures under no-rain conditions. The linear regression line between $T_B$ (21.3V) and $T_B$ (85.5V) under no-rain conditions as shown by Eq. (3) is calculated by the least-square error method:

$$T_B (85.5V)_{\text{no-rain}} = a + b \times T_B (21.3V)_{\text{no-rain}},$$

where the subscript no-rain denotes that the brightness temperature is observed under no-rain conditions. In addition to the intercept $a$ and the slope $b$, the standard deviation of the residuals of Eq. (3), denoted as $\sigma_e$, is stored in the database with resolutions of 1° × 1° latitude/longitude and 1 month. If the inequality in Eq. (4) holds, the pixel is judged to be a rain pixel:

$$T_B (85.5V)_e - T_B (85.5V) > k_0 \times \sigma_e,$$

where $T_B (85.5V)_e = a + b \times T_B (21.3V)$.

In the above equations, the subscript e denotes that the brightness temperature is an estimate for the assumed no-rain condition, and $k_0$ is a constant parameter in both time and space. When the RNC method is applied to GSMaP, $k_0$ is fixed as 3.5. This RNC method can explain differences in land-surface conditions by changing $a$, $b$, and $\sigma_e$; hence, it does not employ any masks to remove desert or snow-covered areas.

PCT85 is used for the retrieval, where PCT stands for the polarization correction temperature. PCT85 is calculated by brightness temperatures at 85.5 GHz with two polarizations (Spencer et al. 1989).

$$PCT85 = 1.818 \times T_B (85.5V) - 0.818 \times T_B (85.5H).$$

Rain-rate estimates are retrieved from PCT85 using the databases provided by PR and GANAL with the radiative transfer model of Liu (1998).

b. GSMaP V4.7

V4.7 is well documented in Kubota et al. (2007). The RNC for V4.7 is the same as that for V4.5. The retrieval part of V4.7 introduces a melting-layer model, although a convective/stratiform classification scheme is not developed. Therefore, the melting-layer model must be applied for both stratiform and convective rainfall. Another new feature in V4.7 is that 37.0 GHz observations are employed in addition to 85.5 GHz observations. If the estimate derived from PCT85 (Rg85) is smaller than 10 mm h⁻¹, Rg85 is adopted as the estimated Rg. If Rg85 is larger than 20 mm h⁻¹, another estimate (Rg37) is derived from PCT37, defined in Eq. (7) (Lee et al. 2002), and Rg37 is adopted as Rg.

$$PCT37 = 2.18 \times T_B (37.0V) - 1.18 \times T_B (37.0H).$$

If Rg85 is between 10 and 20 mm h⁻¹, Rg is calculated by

$$Rg = Rg85 \times W + Rg37 \times (1 - W),$$

where $W = (20 - Rg85) / 10$.

2.4 Modification of the algorithms

In this study, we did not use the standard product 2A12 (the results of the GPROF algorithm). Instead, we slightly modified the standard algorithm in V6 so that the retrieval part was always executed for all over-land pixels, regardless of the RNC result. The modified algorithm was then applied with the standard product 1B11 (observed brightness temperature). Likewise, the SI-Rg relationship used in the standard algorithm for V5 was applied for all the over-land pixels. Moreover, the original algorithms of GSMaP V4.5 and V4.7 were modified to execute the retrieval part for all the over-land pixels. Section 3 explains why rain-rate estimates were calculated even for
no-rain pixels.

3. Methods

3.1 Match-up data

We prepared match-up data between PR and TMI to evaluate TMI products relative to the PR standard product. In many previous studies comparing PR and TMI, observations were directly converted into grid data. However, in the study by Berg et al. (2006) comparing the PR and TMI standard products over ocean, PR observations were aggregated to a TMI footprint and then converted into grid data with the corresponding TMI observations. This technique effectively minimized mixtures of rain and no-rain data and of different rain types.

The match-up method in this study is basically the same as that in Berg et al. (2006). If the center of a PR pixel was located in a TMI footprint at 85.5 GHz (an ellipse with a short axis of 4.6 km along-scan and a long axis of 7.2 km across-scan), the PR pixel was matched up with the TMI pixel. While Berg et al. (2006) set the footprint size to correspond to 19.3 GHz observations for evaluating over-ocean emission algorithms, we set the footprint size to correspond to 85.5 GHz observations for evaluating over-land scattering algorithms. More details of this match-up method can be found in Seto et al. (2005), which applied the same match-up method as this study. Nearly half (47%) of TMI pixels had two PR pixels matched up, and the others had only one. If only one PR pixel was matched up with a TMI pixel, the PR variables were simply copied to the TMI pixel. If two PR pixels were matched up with a TMI pixel, the variables were aggregated as explained in the following list for PR variables.

1. RNC for PR: If at least one PR pixel matched up with a TMI pixel was judged to be a rain pixel, the RNC for PR at the TMI pixel was set as “rain” (P); otherwise the pixel was set as “no-rain” (p).

2. Ground-level rain-rate estimates for PR: The variable denoted as estimated surface rain rate (e_SurfRain) in the PR standard product was regarded as the ground-level rain-rate estimate for PR (Rg_PR). When two PR pixels were matched up with a TMI pixel, the variables were taken for the aggregation to the TMI pixel.

3. Rain type: A raining PR pixel was classified as convective, stratiform, or other. Rain type was defined for a TMI pixel if the RNC for PR was “rain.” If at least one PR pixel matched up with a TMI pixel was convective or other, the rain type at the TMI pixel was judged to be convective. Otherwise, the TMI pixel was judged to be stratiform. This definition was chosen because the number of convective PR pixels was relatively small compared with the number of stratiform PR pixels. If the combination of convective and stratiform was judged as stratiform, the number of convective TMI pixels became significantly smaller than the number of stratiform TMI pixels.

4. Storm height: Storm height (SH) was defined at a raining PR pixel by the PR standard algorithm. SH was given for a TMI pixel if the RNC for PR was “rain.” When two PR pixels were matched up with a TMI pixel, the SH at the TMI pixel was calculated as the conditional average (excluding no-rain pixels). For example, when a rain PR pixel and a no-rain PR pixel were matched up with a TMI pixel, the SH at the TMI pixel was set as equal to that at the raining PR pixel.

5. Bright band height: The bright band height (BBH) was defined for some part of stratiform rainfall by the PR standard algorithm. At a TMI pixel, BBH was calculated as the conditional average of the BBH of the PR pixels with a bright band matched up with the TMI pixel.

The variables for the TMI products are as follow:

6. RNC for TMI: The RNC for TMI was given by GPROF V6, GSMaP V4.5, and GSMaP V4.7. The symbol “T” indicates that the RNC for TMI is rain, and “t” indicates that the RNC for TMI is no-rain.

7. Ground-level rain-rate estimate of TMI: The ground-level rain-rate estimates of TMI (Rg_TMI) were calculated for all over-land pixels by GPROF V5, GPROF V6, GSMaP V4.5, and GSMaP V4.7. In the TMI standard algorithm, the ground-level rain-rate estimate for GPROF was denoted as “surfaceRain.”

3.2 Decomposition into the RNC error and retrieval error

A matched-up TMI pixel can be categorized according to the variables derived from PR and TMI. For example, TMI pixels can be categorized into four groups according to the combination of RNC for PR and RNC for TMI: PT (RNC for PR is rain, and RNC for TMI is rain), Pt (RNC for PR is rain, but RNC for TMI is no-rain), pT (RNC for PR is no-rain, but RNC
for TMI is rain), and pt (RNC for PR is no-rain, and RNC for TMI is no-rain).

Variables at TMI pixels can be aggregated into grid data on any temporal or spatial scale. In this subsection, Rg_PR and Rg_TMI were treated as unconditionally averaged rain rates. The difference between the two estimates was denoted as $\Delta R_g$, calculated by

$$\Delta R_g = R_g_{\text{TMI}} - R_g_{\text{PR}}. \quad (10)$$

Although $\Delta R_g$ could be caused by both deficiencies in TMI algorithms and deficiencies in the PR standard algorithm, here we assumed that the PR standard algorithm is error-free so as to focus on the evaluation of the TMI algorithms.

As the first step to analyze the causes of $\Delta R_g$, $\Delta R_g$ was decomposed into the error caused by the RNC for TMI ($\Delta R_{\text{RNC}}$) and the error caused by the retrieval of TMI ($\Delta R_{\text{RET}}$). For the decomposition, we assumed a virtual algorithm that employed the RNC for PR and the retrieval of TMI. The rain-rate estimates by the virtual algorithm are denoted as $R_g_{\text{TMIe}}$. By using $R_g_{\text{TMIe}}$, the RNC error ($\Delta R_{\text{RNC}}$) and retrieval error ($\Delta R_{\text{RET}}$) are defined as

$$\Delta R_{\text{RNC}} = R_g_{\text{TMI}} - R_g_{\text{TMIe}}, \quad (11)$$

$$\Delta R_{\text{RET}} = R_g_{\text{TMIe}} - R_g_{\text{PR}}. \quad (12)$$

It is easy to see that

$$\Delta R_g = \Delta R_{\text{RNC}} + \Delta R_{\text{RET}}. \quad (13)$$

Because the pixels categorized as PT and Pt contributed to $R_g_{\text{PR}}$, $R_g_{\text{PR}}$ could be written as

$$R_g_{\text{PR}} = R_g_{\text{PR(PT)}} + R_g_{\text{PR(Pt)}}, \quad (14)$$

where $R_g_{\text{PR(X)}}$ is the contribution of the pixels in category X to $R_g_{\text{PR}}$. Here, $R_g_{\text{PR(X)}}$ can be calculated by dividing the sum of instantaneous $R_g_{\text{PR}}$ for all the category-X pixels by the total number of observations, and $R_g_{\text{PR(PT)}}$ and $R_g_{\text{PR(Pt)}}$ are always equal to zero. Likewise, $R_g_{\text{TMI}}$ and $R_g_{\text{TMIe}}$ can be written as

$$R_g_{\text{TMI}} = R_g_{\text{TMI(PT)}} + R_g_{\text{TMI(Pt)}}, \quad (15)$$

$$R_g_{\text{TMIe}} = R_g_{\text{TMI(PT)}} + R_g_{\text{TMIe(Pt)}}, \quad (16)$$

because $R_g_{\text{TMIe(Pt)}}$ is equal to $R_g_{\text{TMI(PT)}}$. With Eqs. (14) to (16), the RNC error and the retrieval error can be rewritten as

$$\Delta R_{\text{RNC}} = R_g_{\text{TMI(PT)}} - R_g_{\text{TMIe(Pt)}}, \quad (17)$$

$$\Delta R_{\text{RET}} = R_g_{\text{TMI(PT)}} - R_g_{\text{PR(PT)}} + R_g_{\text{TMIe(Pt)}} - R_g_{\text{PR(Pt)}}. \quad (18)$$

RNC is always a compromise between false alarms (pTs) and missing signals (Pts). For example, in the RNC for GSMaP, larger $k_0$ results in fewer false alarms and more missing signals. In contrast, smaller $k_0$ results in fewer missing signals and more false alarms. Thus, $\Delta R_{\text{RNC}}$ becomes negative for the former case and positive for the latter case. Additionally, $\Delta R_{\text{RNC}}$ is used to judge the balance between false alarms and missing rainfall, not the accuracy of the RNC. Seto et al. (2005) evaluated the accuracy of the RNC with such indices as the ratio of true detection with the weight of rain amount (RTDA) and the ratio of false alarm occurrence (RFAO). If the RNC of TMI perfectly agrees with the RNC of PR, $\Delta R_{\text{RNC}}$ becomes zero, but the reverse is not always true. The interpretation of $\Delta R_{\text{RET}}$ is straightforward: positive (negative) $\Delta R_{\text{RET}}$ indicates overestimation (underestimation) in $R_g_{\text{TMIe}}$ against $R_g_{\text{PR}}$. Zero $\Delta R_{\text{RET}}$ indicates that $R_g_{\text{TMIe}}$ is the same as $R_g_{\text{PR}}$.

As the value of $R_g_{\text{TMIe(Pt)}}$ could not be obtained from the standard products, it was necessary to modify and rerun the TMI algorithms, as introduced in Section 2.4. Without $R_g_{\text{TMIe(Pt)}}$, the simpler decomposition could be considered as follows:

$$\Delta R_{\text{RNC,test}} = R_g_{\text{TMI(PT)}} - R_g_{\text{PR(Pt)}}, \quad (19)$$

$$\Delta R_{\text{RET,test}} = R_g_{\text{TMI(PT)}} - R_g_{\text{PR(PT)}}. \quad (20)$$

If $R_g_{\text{TMIe(Pt)}}$ is equal to $R_g_{\text{PR(Pt)}}$, the two decompositions give the same results. The advantage of $\Delta R_{\text{RET}}$ over $\Delta R_{\text{RET,test}}$ is that $\Delta R_{\text{RET}}$ is independent of the RNC for TMI, because $R_g_{\text{TMIe}}$ and $R_g_{\text{PR}}$ are compared for all the rain pixels judged by the RNC for PR. However, $\Delta R_{\text{RET,test}}$ depends on the RNC for TMI because the comparisons are conducted for only the pixels judged as rain by both the RNC for PR and the RNC for TMI. For example, if the RNC for TMI judges all pixels as no-rain, $\Delta R_{\text{RET,test}}$ is always zero even if a very poor retrieval algorithm is employed. Hence, we adopted the elaborated and rigorous method of decomposition cal-
Fig. 1. Global maps of (a) the retrieval error for GPROF V6, (b) the RNC error for GPROF V6, (c) the retrieval error for GSMaP V4.7, and (d) the RNC error for GSMaP V4.7.
culated in Eqs. (17) and (18). It is important to note that the RNC error is not independent of the retrieval algorithm in Eqs. (17) and (19).

4. Results

TMI products by GPROF and GSMaP were evaluated against the PR standard product for three years (from 1998 to 2000). Unless otherwise noted, the following results were derived from all available observations during this three-year period. For example, the monthly rainfall in July was calculated from the data for July 1998, July 1999, and July 2000.

4.1 Overview of the RNC error and retrieval error

This section presents overviews of the RNC error and the retrieval error for GPROF V6 and GSMaP V4.7. The RNC error for GPROF V5 could not be calculated, as the RNC for TMI for GPROF V5 was not reproduced for this study. However, it was assumed that similar results would be obtained with GPROF V6 because the RNC algorithm for V5 is basically the same as that for V6. Furthermore, the results for GSMaP V4.5 are omitted here because the RNC error in GSMaP V4.5 was similar to that in GSMaP V4.7. Figure 1 depicts three-year averaged RNC errors and retrieval errors as global maps (resolution: 1° × 1° latitude/longitude). Figure 2 presents the zonal and seasonal variations (resolution: 1° latitude and 1 month) of the errors. In these two figures, the errors are indicated as the unconditional average in millimeters per month.

GPROF V6 generally yielded positive retrieval errors and negative RNC errors. The total error was positive because the absolute value of the retrieval error exceeded that of the RNC error. A positive retrieval error as large as 100 mm month\(^{-1}\) was observed over tropical rain forests in such areas as the Amazon, the Congo, and Indonesia. The Sahel of Africa and the area surrounding the Tibetan Plateau also indicated a significant positive retrieval error (Fig. 1a). Focusing on seasonal and zonal variations, a large positive retrieval error was observed in latitudes below 20°N/S in the summer hemisphere (Fig. 2a).

A significant negative RNC error was found in latitudes over 30°N/S, the Sahel, the Sahara Desert, the interior of Australia, northern Amazonia, Indonesia, and eastern China (Fig. 1b). A severe negative RNC error was found between 10° and 15°N latitudes in the summer hemisphere and in latitudes over 30°N/S in the winter hemisphere (Fig. 2b). Monthly global maps (figures not shown) indicated that such severe underestimation occurred in the Sahel in

![Fig. 2. Zonal and seasonal variations in (a) the retrieval error for GPROF V6, (b) the RNC error for GPROF V6, (c) the retrieval error for GSMaP V4.7, and (d) the RNC error for GSMaP V4.7. The solid contour line corresponds to the zero value. The dotted contour lines denote an interval of 50 (10) mm month\(^{-1}\) for the retrieval (RNC) error.](image)
summer and on the Tibetan Plateau in winter. Because of desert and snow masks, most precipitation over desert and snow-covered surfaces is undetected in GPROF. As an exception, a positive RNC error was observed in the southern part of the Sahel at 10°N in winter, due to an insufficient desert mask.

GSMaP V4.7 generally yielded smaller biases in terms of both retrieval error and RNC error. This result was not surprising, considering that the PR standard product was used to develop the database to which the GSMaP algorithms referred. Still, some biases were observed. Around the equator, the retrieval error was negative in northern Amazonia and Indonesia but positive in Africa (Fig. 1c), whereas the zonal mean did not indicate significant bias (Fig. 2c). The difference in SH could partially explain this regional difference (Kubota et al. 2007). A significant positive retrieval error was observed in the Sahel in summer. The RNC error was generally very close to zero (Figs. 1d and 2d). It was somewhat surprising that the fixed $k_0$ (3.5) could yield such small biases in various regions and seasons, indicating that the tradeoff of false alarm and missing rain went well. Careful investigation revealed negative bias in the region surrounding the Tibetan Plateau and positive bias in tropical summer with a relatively large amount of rainfall. To compensate for the regional difference, different settings of $k_0$ by seasons and regions are necessary.

4.2 Basic features of retrieval error

Retrieval error could be calculated for all four algorithms. Here, the dependences of the retrieval error on latitude (zonal mean), local time (diurnal variation), and SH are indicated separately for stratiform and convective rainfall.

a. Zonal mean

In Fig. 3, the zonal mean of retrieval error is indicated as an unconditional average in millimeters per month. For stratiform rainfall (Fig. 3a), the retrieval error was positive at all latitudes and for all algorithms. GPROF algorithms yielded larger positive retrieval errors than GSMaP algorithms. The retrieval error tended to become smaller at higher latitudes, with the exception of GSMaP V4.5 over 30°N/S. For convective rainfall (Fig. 3b), the retrieval error was generally negative, but was positive at 10° to 15°N, except for GSMaP V4.7. GPROF algorithms indicated a retrieval error close to zero at all latitudes, whereas GSMaP algorithms exhibited severe underestimation around the equator.

Compared with GPROF V5, the retrieval error for stratiform rainfall was slightly reduced in GPROF V6, while the retrieval error for convective rainfall did not change. This result may have been partially due to the fact that GPROF V6 employed a convective/stratiform classification scheme (c/s scheme), even though further improvement of the c/s scheme is necessary. In contrast, compared with GSMaP V4.5, the absolute value of the retrieval error for both stratiform rainfall and convective rainfall became large in GSMaP V4.7, which incorporated a melting-layer model without a c/s scheme. An urgent task for GSMaP algorithm improvement is to develop a c/s scheme.

b. Diurnal variation

In Fig. 4, the diurnal variation in retrieval error is
presented as a conditional average in millimeters per hour (mm h\(^{-1}\)). For stratiform rainfall (Fig. 4a), the retrieval error was always positive and larger at night than during the day. GPROF V5, GPROF V6, and GSMaP V4.5 exhibited peak positive bias around 1800 LT, while the peak time was unclear for GSMaP V4.7. The range of diurnal variation was 1 mm h\(^{-1}\) or smaller. For convective rainfall (Fig. 4b), the diurnal variation was clearly observed with a range of 2 to 3 mm h\(^{-1}\). Compared with stratiform rainfall, the time of maximum was more clearly observed between 1800 and 1900 LT. The time of minimum for the GPROF algorithms was between 0900 and 1000 LT, and that for the GSMaP algorithms was between 1200 and 1300 LT.

c. Dependence on SH

Figure 5 illustrates the dependence of the retrieval error on SH as a conditional average in millimeters per hour. For stratiform rainfall (Fig. 5a), dependence on SH was not observed when SH was below 6 km, but positive dependence was clearly observed and the retrieval error had large positive values when SH was higher than 6 km. This was qualitatively true for all the algorithms, but some quantitative differences existed among them. The retrieval error in GPROF V5 indicated stronger positive dependence than that in GPROF V6. Severe overestimation occurred with GSMaP V4.5 when SH was over 10 km, but not with GSMaP V4.7. This improvement was attributed to the addition of PCT37 in GSMaP V4.7 (Kubota et al. 2007). For convective rainfall (Fig. 5b), dependence on SH was negative when SH was below 6 km but positive when SH was above 6 km. The retrieval error of GPROF V5 and V6 had a positive value when SH was above 8 km and a negative value when SH was
between 3 and 8 km. Severe overestimation in GSMaP V4.5 also occurred for convective rainfall. With GSMaP V4.7, a positive retrieval error occurred only when SH was above 10 km.

The dependences of TMI estimates on latitude, season, local time, SH, and rain type (convective/stratiform) have been analyzed in previous studies (e.g., Masunaga et al. 2002; Nesbitt et al. 2004; Furuzawa and Nakamura 2005) for GPROF V5. Results of this study are consistent with the dependence in GPROF V5 and demonstrated that the same qualitative dependences are also found in GPROF V6. In GSMaP V4.5 and V4.7, the dependences on latitude and season became smaller; however, the dependences on local time, SH, and rain type still remained.

5. Evaluation of SRBB

This section investigates the causes of retrieval error, focusing on the width of the solid precipitation layer and the land surface physical temperature; the role of lower-frequency channels on the retrieval is also discussed. Analysis was limited to SRBB, which provided a good estimate of the width of the solid precipitation layer. Although the effects of SH discussed in Section 5.1 could be studied for the other types of rainfall, we limited our analysis to SRBB for consistency.

Figures depicting the zonal mean (Fig. 3), diurnal variation (Fig. 4), and dependence of the retrieval error on SH (Fig. 5) are prepared for stratiform and convective rainfall, as well as for SRBB (Fig. 6). The zonal mean of the retrieval error for SRBB (Fig. 6a) was qualitatively the same as that for stratiform rainfall (Fig. 3a), but the slight increase of the retrieval error above 30°N/S is not presented in Fig. 6a. The diurnal variation of the retrieval error for SRBB (Fig. 6b) could be explained in the same way as for Fig. 4a. The dependence on SH for SRBB (Fig. 6c) was nearly the same as that for stratiform rainfall (Fig. 5a), except for the relatively large positive retrieval error in GPROF V5 and GSMaP V4.7.

5.1 Effect of SH

As indicated in Fig. 6c, the retrieval error was independent of SH for stratiform rainfall when SH was below 6 km; however, the retrieval error was positively dependent on SH when SH was above 6 km. To investigate this relationship between retrieval error and SH, SRBB was categorized by SH and Rg_PR. For SH, ten categories were set: one category under 2 km, eight categories between 2 and 10 km with a step of 1 km, and one category over 10 km. For Rg_PR, nine categories were set: <0.1, 0.1–0.5, 0.5–1, 1–2, 2–5, 5–10, 10–20, 20–50, and >50 mm h⁻¹.

Fig. 6. (a) Zonal mean of the retrieval error, (b) diurnal variations of the retrieval error, and (c) dependence of the retrieval error on storm height for SRBB.
Fig. 7. A sensitivity analysis of SRBB to Rg_PR (horizontal axis) and SH (vertical axis); (a) The gray scale is drawn as a 2D histogram for the number ratio of occurrences to the total in a general logarithm scale. The solid line and squares indicate the average of Rg_PR for each SH category. In the other sub-figures, contours and gray scale denote (b) TB (85.5V), (c) TB (37.0V), (d) Rg_TMIe by GSMaP V4.5, (e) Rg_TMIe by GSMaP V4.7, (f) Rg_TMIe by GPROF V5, (g) Rg_TMIe by GPROF V6, (h) ΔRg_RET by GSMaP V4.5, and (i) ΔRg_RET=0 by the four algorithms. The average of Rg_PR is presented in (h) and (i) as well as in (a).
When SH is below 6 km, the curve of average Rg_PR (the same as in Fig. 7a) overlapped with that in Fig. 7h. The curve indicating the average of Rg_PR dependent on SH and negatively dependent on Rg_PR cases in the reference database of the algorithm. Partially due to the small number of precipitation was below 10 km in GPROF V5 might have been explained if the ground-level liquid rain rate and the upper-level solid rain rate were positively correlated. Figure 7c was drawn for TB (37.0V). The dependence on SH is not clear, and the dependence on Rg_PR is apparently negative, although the sensitivity is less than that for TB (85.5V).

For all the algorithms, Rg_TMIe was positively dependent on both SH and Rg_PR, and slight quantitative difference was found among the algorithms. In GSMaP V4.5, Rg_TMIe had strong dependence on SH and weak dependence on Rg_PR, especially when SH was above 10 km (Fig. 7d). In GSMaP V4.7, the strong dependence on SH was moderated; moreover, dependence on Rg_PR became clear (Fig. 7e). In GPROF V5, dependence on SH was strong when SH was below 10 km (Fig. 7f). In GPROF V6, strong dependence on SH was moderated except for heavy and high precipitation (Fig. 7g). Among the four algorithms, only GSMaP V4.7 successfully avoided severely strong dependence on SH when SH was above 10 km, due to the employment of 37.0 GHz observations. Relatively strong dependence on SH when SH was below 10 km in GPROF V5 might have been partially due to the small number of precipitation cases in the reference database of the algorithm.

In GSMaP V4.5, the retrieval error was positively dependent on SH and negatively dependent on Rg_PR (Fig. 7h). The curve indicating the average of Rg_PR (the same as in Fig. 7a) overlapped with that in Fig. 7h. When SH is below 6 km, the curve of average Rg_PR is upward sloping (i.e., Rg_PR and SH were positively correlated) and is close to the contours of ΔRg_RET=0. When SH was above 6 km, the curve of average Rg_PR became independent of SH and was located in the region of ΔRg_RET>0. These results corresponded with the finding that the retrieval error was almost zero when SH was below 6 km but was positively dependent on SH when SH was above 6 km (Fig. 6c). Figure 7i presents contours of ΔRg_RET=0 for the four algorithms with the curve of average Rg_PR. The contours of ΔRg_RET=0 for GSMaP V4.7 and GPROF V6 were similar to that for GSMaP V4.5. For GPROF V5, the contour of ΔRg_RET=0 was not upward sloping when SH was less than 4 km, but largely demonstrated characteristics similar to those of the contour for GSMaP V4.5. Therefore, we could observe the independence of the retrieval error from SH when SH was below 6 km and the positive dependence of the retrieval error on SH when SH was above 6 km in all four algorithms.

5.2 Effect of BBH

Given that scattering is caused mostly by solid precipitation, the width of the solid precipitation layer (WSL) should be more relevant than SH in explaining retrieval error. For SRBB, WSL could be defined as the difference between SH and BBH because BBH is available from the PR algorithm 2A23. Here, SRBB was categorized by SH and BBH (Fig. 8). Ten categories were set for SH, in the same way as for Fig. 7. Nine categories were set for BBH: one category under 1.5 km, seven categories between 1.5 and 5.0 km with a step of 0.5 km, and one category over 5.0 km.

Figure 8a indicates the number of occurrences as a two-dimensional histogram. A large number of observations revealed WSL between 0 and 5 km. Figure 8b illustrates TB (85.5 V), the contours of which were upward sloping and generally corresponded to constant WSL lines when WSL was between 0 and 5 km. This figure clearly illustrates that WSL, rather than SH or BBH, is directly related to TB (85.5 V), and that TB (85.5 V) is positively dependent on BBH. Here, Rg_TMIe by GSMaP V4.5 also corresponded to WSL (Fig. 8c), and the dependence of Rg_TMIe on BBH was negative. For GSMaP V4.7, a slight discrepancy existed between the contours of Rg_TMIe and the constant WSL lines; however, negative dependence on BBH could be observed (Fig. 8d). For the GPROF V5 and GPROF V6 algorithms, Rg_TMIe was almost independent of BBH when BBH was less than 4 km (Figs. 8e and 8f). It is important to note that no con-
Fig. 8. Sensitivity analysis of SRBB to BBH (horizontal axis) and SH (vertical axis). (a) 2D histogram for the number ratio of occurrences to the total in a general logarithm scale. In the other sub-figures, contours and gray scales denote (b) TB (85.5V), (c) Rg_TMle by GSMaP V4.5, (d) Rg_TMle by GSMaP V4.7, (e) Rg_TMle by GPROF V5, (f) Rg_TMle by GPROF V6, (g) TB (21.3V), (h) TB (10.7V), and (i) PCT37. The dotted lines in each sub-figure are constant WSL lines from 0 to 5 km with an interval of 1 km.
tours for Rg_TMIe=1 mm h\(^{-1}\) appear in these two figures.

The lower sensitivity of Rg_TMIe to BBH in the GPROF algorithms was the result of the use of lower-frequency brightness temperatures. GPROF V5 employed TB (21.3V) to calculate SI. Both TB (21.3V) and TB (85.5V) were positively dependent on BBH (Fig. 8g). Thus, SI had less dependence on BBH than TB (85.5V); consequently, Rg_TMIe was less dependent on BBH. The change in WSL caused the positive dependence of TB (85.5V) on BBH. However, this was not true for TB (21.3V), which was almost independent of SH (Fig. 8g). Instead, changes in land surface physical temperature probably caused the positive dependence of TB (21.3V) on BBH. If the lapse rate were constant, higher BBH would be accompanied by a warmer land surface, which leads to warmer TB (21.3V). However, when BBH is above 4 km, TB (21.3V) is not related to BBH, and Rg_TMIe is negatively dependent on BBH.

Fig. 9. Same as Fig. 7, but the vertical axis is WSL instead of SH.
As with TB (21.3V), TB (10.7V) is almost independent of SH and is positively dependent on BBH, except when BBH is above 4 km (Fig. 8h). This positive dependence of TB (10.7V) on BBH could explain the independence of Rg_TMIe from BBH in GPROF V6 as follows. According to Eq. (1), CSI is larger for higher TB (10.7V) and is positively dependent on BBH. This relationship suggests that Rg_TMIe by GPROF V6 is positively dependent on BBH, but that this effect is actually cancelled by the positive dependence of TB (85.5V) on BBH through the change of WSL.

Rg_TMIe in GSMaP V4.7 is affected by PCT37, which is negatively dependent on SH and positively dependent on BBH; however, PCT37 could not be adequately determined with WSL alone (Fig. 8i). For example, we considered the following two cases with WSL of 3 km. In the first case, SH is 6 km and BBH is 3 km. In the second case, SH is 7 km and BBH is 4 km. For both cases, TB (85.5V) is almost the same (Fig. 8b), as is PCT85 (figures not shown); however, PCT37 is higher for the second case. This result could be explained if we assume that PCT37 is affected by the land surface physical temperature and by scattering at the solid precipitation layer, since the higher BBH suggests a higher land surface physical temperature for the second case. In GSMaP V4.7, the effects of PCT37 on Rg_TMIe mainly appear when SH is high. The positive dependence of PCT37 on BBH through the land surface physical temperature might slightly reduce the dependence of Rg_TMIe on BBH.

Figure 9 is the same as Fig. 7, but the vertical axis is WSL instead of SH. WSL and Rg_PR are positively correlated when WSL is less than 3 km, but Rg_PR is independent of WSL when WSL is more than 3 km (Fig. 9a). The negative dependence of TB (85.5V) and TB (37.0V) on WSL is clearly demonstrated in Figs. 9b and 9c. For all four algorithms, Rg_TMIe is positively correlated to WSL (Figs. 9d, 9e, 9f, and 9g). The curve indicating the average of Rg_PR lies in the region of positive retrieval error for GSMaP V4.5 (Fig. 9h) and the other three algorithms (Fig. 9i), especially when WSL exceeds 3 km. These results suggest that the retrieval error increases with WSL. From Fig. 9, we could confirm that WSL is a good parameter to explain the retrieval error.

5.3 Effect of land surface physical temperature on retrieval

The previous discussion strongly suggests the effects of land surface physical temperature on lower-frequency observations. This section discusses the effects of land surface physical temperature on higher-frequency observations and retrieval. For that purpose, we investigated the diurnal variations of observed brightness temperature and retrieval results by letting land surface physical temperature change and by fixing, as much as possible, other conditions affecting the retrieval.

SRBB was categorized by Rg_PR and WSL. Six categories were set for WSL between 0 and 6 km with a step of 1 km. For all six categories, Rg_PR was set between 2.0 and 5.0 mm h⁻¹, because a large amount of data belonged to this Rg_PR category (Fig. 9a). For confirmation, the diurnal variations of Rg_PR, SH, and BBH are presented in Figs. 10a, 10b, and 10c. While Rg_PR lies between 2.0 and 5.0 mm h⁻¹, it displayed a slight decrease in the afternoon, especially for wider WSL categories. SH and BBH exhibited slight diurnal variation with a range of less than 300 m, which corresponded to the temperature change of less than 1.8 K (calculated by assuming a lapse rate of 6 K km⁻¹). Although the diurnal variations in Rg_PR, SH, and BBH were small, it was necessary to keep them in mind for carefully analyzing the diurnal variations in observed brightness temperature and retrieval results.

The diurnal variation in TB (85.5V) was small for all six categories, whereas TB (85.5V) under the no-rain condition exhibited clear diurnal variation (Fig. 10d). A slight increase in the afternoon was observed, but it corresponded with the decrease in Rg_PR. The change of land surface physical temperature affected TB (85.5V) under the no-rain condition, but not under rain conditions. This result was reasonable because emission from the land surface was masked by liquid precipitation with Rg_PR of 2 to 5 mm h⁻¹ at 85.5 GHz.

Although TB (10.7V), TB (21.3V), and TB (37.0V) did exhibit diurnal variations under rain conditions, the range of these variations was smaller than that under the no-rain condition, and the phase (local time at maximum TB) was slightly different between rain and no-rain cases (Figs. 10e, 10f, and 10g). This gap could be explained as emission from the land surface being partly masked by liquid precipitation and water vapor even at lower frequencies. It was also reasonable to consider that TB (21.3V) exhibited smaller diurnal variation than TB (10.7V) and TB (37.0V) because 21.3 GHz is located in the absorption band of water vapor. Diurnal variations of TB (10.7V) and TB (21.3V)
under rain conditions did not differ significantly for different WSL classes. As discussed in Section 5.2, TB (37.0V) was significantly affected by WSL, but the phase of diurnal variation of TB (37.0V) was not significantly different among different WSL classes. These results on the diurnal variation of observed brightness temperature basically agreed with a sensitivity study using a plane-parallel radiative transfer
As only 85.5 GHz observations were used in GSMaP V4.5, $R_{g\_TMIe}$ exhibited no significant diurnal variation. Thus, no direct effect of land surface physical temperature was found (Fig. 10h). As lower-frequency observations were employed in other algorithms, the retrieval might have been affected by the land surface physical temperature. A slight decrease of $R_{g\_TMIe}$ in GSMaP V4.7 was indicated in the afternoon (Fig. 10i), possibly due to relatively strong dependence of $TB$ (37.0V) on land surface physical temperature. In GPROF V5, no significant diurnal variations were observed in $R_{g\_TMIe}$ because $TB$ (21.3V) is less sensitive to land surface physical temperature (Fig. 10j). In GPROF V6, $R_{g\_TMIe}$ exhibited a slight increase at the WSL of 4 to 6 km in the afternoon, probably due to the use of $TB$ (10.7V) to calculate CSI (Fig. 10k).

We conducted the same analysis for light rain ($R_{g\_PR}$ between 0.5 and 1.0 mm h$^{-1}$) and heavy rain ($R_{g\_PR}$ between 5.0 and 10.0 mm h$^{-1}$). No large diurnal variations in $TB$ (85.5V) or $R_{g\_TMIe}$ were observed in either case (figures not shown), as well as in Fig. 10. Overall, we could conclude that land surface physical temperature did not significantly affect retrieval for SRBB.

6. Summary and conclusions

This study evaluated multiple over-land rain-rate estimation algorithms for TMI against the PR standard algorithm V6 and analyzed biases in TMI rain-rate estimation algorithms. The study may be summarized as follows.

1. TMI and PR data were matched up on a TMI footprint before being aggregated into grid data to minimize mixtures of rain and no-rain pixels and different rain types.

2. The error was decomposed into RNC error and retrieval error by considering a virtual algorithm employing the RNC for PR and the retrieval of TMI. The retrieval error could be defined as being absolutely independent of the RNC for TMI.

3. On a monthly and 1° grid scale, GSMaP yielded rain-rate estimates close to those estimated by the PR standard algorithm, in terms of both RNC error and retrieval error, whereas GPROF generally yielded negative RNC error and positive retrieval error. However, this result did not guarantee the superiority of GSMaP, because GSMaP referred to a database produced with PR data.

4. The dependence of the retrieval error on latitude, local time, and SH was qualitatively similar for the GPROF and GSMaP algorithms, as both were based on a scattering algorithm.

5. No positive dependence of retrieval error on SH was observed for any algorithm when SH was below 6 km, corresponding to a positive correlation between $R_{g\_PR}$ and SH.

6. Severe overestimation when SH was above 10 km could be mitigated by using 37.0 GHz observations as a scattering channel (GSMaP V4.7).

The following results are limited to SRBB.

7. WSL, not SH, is relevant in explaining the bias in the scattering algorithm, because scattering was caused mainly by the solid precipitation layer.

8. The dependence of $TB$ (85.5V) on BBH was positive, but the dependence of $R_{g\_TMIe}$ on BBH could be largely avoided by using lower-frequency observations (GPROF V5, GPROF V6).

9. No significant effects of land surface physical temperature on retrieval were found.

Our study provides some conclusions about the effects of BBH and land surface physical temperature (items 7, 8, and 9), partly due to improvements in the analysis method by items 1 and 2. However, the conclusions (items 7, 8, and 9) are limited to SRBB. The effects of freezing height and land surface physical temperature on the retrieval of convective and stratiform rainfall with no bright band must also be investigated to obtain a more thorough understanding.

This study clarified the role of lower-frequency observations in over-land rain-rate retrieval, as indicated by items 6 and 8. In GPROF, $TB$ (10.7V) and $TB$ (21.3V) mitigated the variation in BBH, but these effects may not have been intended by the algorithm developers because $TB$ (10.7V) in GPROF V6 was originally introduced to estimate CSI. Future algorithm development should involve efforts to make the most effective use of lower-frequency observations.

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