Improving AMSR/AMSR-E Precipitation Algorithm

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Submitted to Journal of the Remote Sensing Society of Japan
– GLI/AMSR special issue (June 30, 2008)
Abstract

This review paper serves for two purposes: describing the algorithm currently used by JAXA to produce precipitation product from AMSR/AMSR-E data and discussing two most important challenges facing passive microwave precipitation algorithm development. The precipitation algorithm used in JAXA today combines emission and scattering signatures, includes a correction for beam-filling problem, and has been validated by surface radar-gauge network data and other satellite retrievals. Because we pieced together all the modifications to the original version of the algorithm in this paper, this article gives the most complete description to the current version of the algorithm, and therefore, can serve as a reference for the precipitation product users to cite. The discussion on the challenges, beam-filling and ice scattering, in passive microwave precipitation retrievals is aimed to more general audiences. While the footprint size of the recent satellite microwave sensors is finer than earlier ones, the beam-filling problem seems still to be one of the most important error sources in current retrieval algorithms. The ice scattering problem is important for retrieving snowfall and precipitation over land since the primary signature for these applications is scattering signal.
1. Introduction

Precipitation is one of the least well-measured atmospheric parameters, especially over the vast oceanic regions on the globe. Two major obstacles contribute to the lack of comprehensive global precipitation measurements. First, there are few surface-based observations over the oceanic areas, which cover about two third of the Earth surface. Second, precipitation is highly variable with both time and space compared to other atmospheric variables, such as temperature and pressure. Although ground-based radars can provide better spatial and temporal coverage than raingauges, well-calibrated radars are only available in limited land regions in developed countries. These problems make satellite remote sensing of precipitation indispensable.

Since microwave emission and scattering signatures are more directly related to precipitating hydrometeors than visible/infrared signatures, microwave radiometry has been increasingly utilized in satellite remote sensing of precipitation. Following Special Sensor Microwave Imager (SSM/I) and Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), the Advanced Microwave Scanning Radiometer (AMSR) and AMSR for EOS (AMSR-E) are probably the third major development in terms of satellite microwave sensors suitable for precipitation monitoring. Compared to its predecessors, AMSR/AMSR-E possesses greater number of channels, finer spatial resolution and broader global coverage.
While many microwave precipitation algorithms have been developed during the past two decades\(^1\)–\(^3\), three of them have been officially selected for the production of AMSR/AMSR-E precipitation - the GPROF\(^4\) has been used by NASA, and the Petty-algorithm\(^5\) and the Liu-algorithm\(^6\) have been used by JAXA. We have been working on improving and validating the Liu-algorithm since 1997. In this article, we describe the Liu-algorithm, summarize its validation results, and discuss the challenges facing microwave precipitation retrievals in general.

The rest of the article is arranged as follows. In section 2, we briefly describe the algorithm and its validation. Research related to addressing the problem caused by inhomogeneity of rain field is discussed in section 3. Problem and solution related to nonspherical ice scattering is addressed in section 4. Finally, a summary is given in section 5.

### 2. The Liu Precipitation Algorithm

The Liu-algorithm\(^6\)\(^7\) combines emission and scattering signatures from water drops and ice particles, has a correction for the error caused by inhomogeneity of the rain field in a satellite pixel, and is less sensitive to the height of freezing level than the emission-based algorithms. The use of the emission signal from liquid hydrometeors picks up the signal from low and moderate precipitation, while the ice-scattering signal (mainly due to the presence of
large ice particles) is sensitive to heavy precipitation. The algorithm can retrieve rainfall over both ocean and land, although slightly different formulations are used for the different surface types. The AMSR/AMSR-E version of this algorithm is built on the SSM/I version with conversions from AMSR/AMSR-E brightness temperatures to SSM/I brightness temperatures.

2.1 Over-Ocean Algorithm

In the latest version, the combination function of brightness temperatures ($T_B$s) is defined by Liu et al. 8) as follows:

$$\varphi = (1 - \frac{D}{D_0}) + 2(1 - \frac{PCT}{PCT_0}),$$  \hspace{1cm} (1)

where $D$ is the depolarization of brightness temperatures, $T_{B19V}-T_{B19H}$, at 19 GHz and $D_0$ is $D$ at the threshold of rain onset; $PCT$ is the polarization corrected brightness temperature defined by Spencer et al. 9): $PCT = 1.818T_{B89V} - 0.818T_{B89H}$, and $PCT_0$ is $PCT$ at the threshold of rain onset. In all expressions in this paper, brightness temperature is denoted by $T_{B\nu\rho}$, where $\nu$ indicates frequency in GHz and $\rho$ is either $V$ or $H$ to indicate vertical or horizontal polarization. $PCT$ and $D$ for AMSR/AMSR-E channels are then converted to SSM/I $PCT$ and $D$ by the following equations:

$$PCT_{SSM/I} = 4.7 + 0.986PCT_{AMSR}$$
$$D_{SSM/I} = -0.1 + 0.849D_{AMSR} + 0.0017D_{AMSR}^2.$$  \hspace{1cm} (2)

These equations are derived by radiative transfer simulations for various atmospheric and surface conditions to adjust the slight differences in observing frequencies and view angles between SSM/I and AMSR/AMSR-E. Then rainrates are calculated based on the equations
originally derived from SSM/I channels. \( D_0 \) and \( PCT_0 \) are determined monthly for every 3° (latitude) \( \times \) 6° (longitude) box based on 37 GHz depolarization ratio and sea surface temperature, and are stored as a look-up table. This rain threshold look-up table can be improved in the future based on multi-year simultaneous observations of TRMM Precipitation Radar (PR) and TMI.

The relationship between \( \varphi \) in (1) and rainrate is determined by radiative transfer simulations with consideration of the rain field inhomogeneity, and can be expressed by

\[
R = \alpha \varphi^\beta, \tag{3}
\]

where \( \alpha \) and \( \beta \) are spatial scale-dependent coefficients. The dependence of \( \alpha \) and \( \beta \) on spatial scale is due to the spatial dependence of the beam-filling effect. For SSM/I in which the spatial resolution of 19 GHz is \( \sim 50 \) km, \( \alpha = 10.6 \) and \( \beta = 1.621 \) when freezing level height is at 4 km or higher. For AMSR/AMSR-E and TMI, the spatial resolution for 19 GHz is about half of that in SSM/I. The values for \( \alpha \) and \( \beta \) are determined by an empirical equation based on radiative transfer model simulation as \( \alpha = 8.25 \) and \( \beta = 1.88 \) for a freezing level of 4 km or higher. The spatial dependence of \( \alpha \) and \( \beta \) is further discussed in section 2.3. In addition, the values of \( \alpha \) and \( \beta \) also vary with the rain layer height, which we use freezing level height to represent. Based on radiative transfer model simulations, it is determined that \( \alpha \) needs to be multiplied by the following proportional factor, \( \alpha_{\text{fac}} \):
\[
\alpha_{frc} = \begin{cases} 
1.60 - 0.303Z_{frz} + 0.0369Z_{frz}^2 & \text{if } Z_{frz} < 4\, \text{km} \\
1.0 & \text{if } Z_{frz} \geq 4\, \text{km}
\end{cases},
\]

where \(Z_{frz}\) is freezing level height in km. The final \(\alpha\) value will be the \(\alpha\) value determined by spatial scale dependence multiplied by the above freezing level height correction factor.

Finally, the value of \(\beta\) will be determined by equation given later in section 2.3. Test results show that these coefficients produce satisfactory rain rates when compared to surface radar-raingauge network and Global Precipitation Climatology Project (GPCP) data\(^\text{10}\).

### 2.2 Over-Land Algorithm

The land portion of our algorithm uses 19 and 89 GHz brightness temperatures (either horizontal or vertical polarization, since, over land, the difference between horizontal and vertical brightness temperatures is very small). The rainrate is expressed by

\[
R = c(\Delta T_B - \Delta T_{B0}),
\]

where \(c=0.2\) is a coefficient derived from radiative transfer model simulations assuming an averaged vertical profile of hydrometeors; \(\Delta T_B = T_{B19} - T_{B89}\). Again, we first convert \(\Delta T_B\) for AMSR/AMSR-E to \(\Delta T_B\) for SSM/I by

\[
\Delta T_{B\text{ SSM/I}} = -0.6 + 0.9558\Delta T_{B\text{ AMSR}}.
\]

Then the rainfall algorithm originally developed for SSM/I is used. \(\Delta T_{B0}\) is \(\Delta T_B\) at the threshold of rain onset that is determined monthly for every 3° (latitude) x 6° (longitude) box.
based on Liu and Curry\textsuperscript{6) and is saved as a look-up table.

\textbf{2.3 Spatial Scale Dependence}

Results of earlier studies\textsuperscript{6,9)} showed that the beam-filling effect tends to make the R-T\textsubscript{B} relation closer to “linear” than that indicated by radiative transfer models when assuming a plane-parallel rain layer. Liu and Curry\textsuperscript{6)} have explained this behavior of the R-T\textsubscript{B} relation using sub-pixel rainrate variability. The determination of \( \alpha \) and \( \beta \) in this algorithm is based on this consideration. First, we assume the parameter \( \beta \) in (3) varies with spatial scale, \( x \) (in km), as

\[
\beta = \beta_\infty - A[1 - \exp(-Bx^\kappa)],
\]

where \( \beta_\infty = 2.792 \) is \( \beta \) for a 4 km deep plain-parallel rain layer determined by our radiative transfer simulations. \( \kappa = 0.7 \) is an adjustable parameter used to vary the strength of scale dependence. The values of \( A \) and \( B \) are determined as follows. First, when scale, \( x \), becomes infinite large, \( \beta \) is 1, implying that for infinitely large spatial resolution the R-T\textsubscript{B} relation is linear (note the argument mentioned earlier). Then, it is determined that \( A = \beta_\infty - 1 \). The constant \( B \) is then determined by applying (7) to our SSM/I algorithm used in Liu and Curry\textsuperscript{7)}, which gives \( \beta_{SSM} = 10.6 \) for a scale of 50 km with 4 km deep rain layer.

In the study of Liu and Curry\textsuperscript{6)}, it is also found that when rainrate is as high as 50 mm h\textsuperscript{-1}, the ratio between observed T\textsubscript{B} and plane-parallel model generated T\textsubscript{B} is close to 1.
Based on this argument, we determine $\alpha$ by letting

$$\left( \frac{R_{50}}{\alpha_{\text{AMSR}}} \right)^{\frac{1}{\beta_{\text{AMSR}}}} = \left( \frac{R_{50}}{\alpha_{\text{SSMI}}} \right)^{\frac{1}{\beta_{\text{SSMI}}}},$$

where $R_{50}=50$ mm/h. The same equation is used after adjusting $\alpha$ for freezing level height [cf. (4)], in which case,

$$\left( \frac{R_{50}}{\alpha_4} \right)^{\frac{1}{\beta_4}} = \left( \frac{R_{50}}{\alpha} \right)^{\frac{1}{\beta}},$$

where $\alpha_4$ and $\beta_4$ are the $\alpha$ and $\beta$ values derived for 4 km deep rain layer. Figure 1 shows the $\varphi$-$R$ relations derived from the aforementioned approach for different spatial resolutions. For very high resolution, we may believe the rainfall within the radiometer’s field of view (FOV) is homogenous; therefore, plain-parallel model results apply. For very low resolution, the $\varphi$-$R$ relation is assumed to be linear. Actual satellite measurements (e.g., AMSR/AMSR-E, TMI, SSM/I) will have a $\varphi$-$R$ relation curve between the two extremes.

The above treatment for beam-filling correction is empirical in nature. An improved treatment for this problem based on statistical model of sub-pixel inhomogeneity of rainrates derived from TRMM PR is discussed in section 3, and can be implemented in the future.

2.4 Validation

Validations by comparing retrievals with other measurements (ground-based or
space-borne) can identify problems of the retrieval algorithms. The comparison results of our algorithm with AMeDAS analysis are shown in Figs. 2 and 3 below. In Fig.2, the areal and monthly-averaged rainrates and the correlation coefficients between our retrieval and that of AMeDAS are shown for the entire year of 2003. Both AMSR and AMSR-E data are used in the comparison. Over ocean, the two averaged rainrates closely followed each other; the correlation coefficient is around 0.6 throughout the year. Over land, while the two rainrates follow the same trend, there are some visible differences, particularly in early spring (April) when the correlation coefficient falls to 0.2. This result indicates that there are rooms for improvement to over-land component of the algorithm. Figure 3 shows the spatial distribution for each month. It is seen that the AMSR/AMSRS-E retrievals by our algorithm agree well with AMeDAS rainrates in both averages and spatial patterns. The largest differences between AMSR/AMSRS-E and AMeDAS occur during January to April (also smaller correlation coefficients).

Another validation was carried by comparing our retrievals with GPCP rainfall on a global scale. The GPCP product is a combination of surface gauge records, and satellite infrared and microwave retrievals. The product provides monthly rainfall amount at 2.5°x2.5° grids. As shown in Fig.4, the comparison is reasonably good except for some points where GPCP show virtually no rain while AMSR/AMSRS-E rainrate is large. These points are from near-polar regions where our algorithm failed to mask sea ice surface. The relative bias is less
than 10% and the correlation coefficient is around 0.7 to 0.8.

In summary, the above validation shows that the current algorithm produces rainrates consistent with both surface radar-raingauge network and other satellite based products. The comparison is particularly favorable at oceanic areas with correlation coefficients constantly greater than 0.6. Over polar and some land areas, improvement of the algorithm is still needed.

3. On Problem Related To Rain Field Inhomogeneity

In the following two sections, we discuss two challenges facing passive microwave rainfall retrieval in general, not specific to a particular algorithm. The first challenge is related to the inhomogeneity of rain field within a satellite sensor’s FOV, and the second is related to the scattering by ice particles.

To illustrate the problem associated with rain field inhomogeneity, let us first show results from a study using TRMM data. Figure 5 shows the difference of TMI minus PR derived rainrates as a function of rainrates and rain type (convective fraction, ConvF) using 5-year global data\(^{11}\). Both retrievals are from standard TRMM version 6 products\(^{12,13}\). At low rainrates, particularly for low ConvF clouds, TMI overestimates rainrates compared to PR. However, TMI becomes underestimation as rainrates and ConvF increase. At the extreme,
when rainrates are over 25 mm h\(^{-1}\) and ConvF is close to 1 (pure convective), the difference goes as high as -20 mm h\(^{-1}\). As we know that the rain field inhomogeneity is greater for clouds associated with higher rainrates and larger convective fraction, the large underestimation by TMI suggests a problem related to rain inhomogeneity in the TMI algorithm.

The problem can be further illustrated by a comparison of observed rainrate – brightness temperature relation vs. radiative transfer model simulated one when assuming plane-parallel rain layer. Figure 6 shows a result by Varma et al.\(^{14}\) using TRMM TMI T\(_{Bs}\), PR near surface rainrates, and simulation by a radiative transfer model. It is seen that without considering sub-pixel inhomogeneity the radiative transfer model cannot correctly predict observed rainrate – brightness temperature relation even on average (red vs. green line in the figure).

To improve precipitation retrieval by statistically taking the inhomogeneity into consideration, we surveyed the global distribution of the sub-pixel variability of rainrates using TRMM PR data\(^{15}\). The horizontal distribution of rainrates within an area of 0.25° x 0.25°, approximately, 30 km x 30 km, has been studied over the global tropics using three years (Dec. 1997 – Nov. 2000) of TRMM PR data. In the data analysis, the 0.25° x 0.25° rainy “pixels” are categorized by rain type (convective or stratiform), rain intensity (light, moderate or heavy), surface type (land or ocean) and latitudinal location (tropics or extratropics). Two attributes are used to characterize the small-scale rainrate variability: fractional rain cover, or FRC, and conditional
rainrate probability density function, or PDF. It is found that FRC is closely related to the areal averaged rainrate, $R_{av}$, and the greatest cause in varying the FRC – $R_{av}$ relation is rain type (Fig.7). Given the same $R_{av}$, FRC for stratiform rain is larger than FRC for convective rain. FRC increases with $R_{av}$ to 100% at $R_{av} \sim 3$ mm h$^{-1}$ for stratiform rain and $\sim 10$ mm h$^{-1}$ for convective rain. For a convective rain event, even the averaged rainrate over a $0.25^\circ \times 0.25^\circ$ area is as high as 5 mm h$^{-1}$, 30% of that area may still be rain-free. This figure vividly illustrates how variable the horizontal rain field could be.

Figure 8 shows the conditional PDFs of rainrates derived from the 3 years of TRMM PR data for 3 categories of FOV averaged rain intensities: light rain ($< 2.5$ mm h$^{-1}$), moderate rain ($2.5 – 10$ mm h$^{-1}$) and heavy rain ($> 10$ mm h$^{-1}$). Convective rain PDFs are broader over all rain intensity ranges, but particularly evident when the FOV averaged rainrates are light or moderate. For convective rain over land (lines with hollow symbols), the PDFs of rainrate do not show a difference between the tropics and extratropics regardless of the intensity of rain. However, the land-ocean difference in convective rainrate PDFs is particularly evident for the light and heavy rain categories. For stratiform rain in the light rain category, the four PDFs of rainrate do not show much difference among them. Although the difference among them increases as rainfall intensity increases, the land-ocean difference continues to dominate the variability of the PDFs. The influence of latitudinal location on the pattern of rainrate PDFs is greater for heavy rain than for light rain.
By analyzing the TRMM PR data, it is found that the FRC and the conditional PDF of sub-pixel rainrates may be parameterized by the following equations:

\[
FRC(R_{av}) = 1 - a \exp(b R_{av}),
\]

and

\[
PDF(x, R_{av}) = \sum_{i=1}^{2} \frac{2}{b_i} \exp \left[ -0.5 \left( \frac{x - x_i}{b_i} \right)^2 \right],
\]

where \(R_{av}\) is the pixel-averaged rainrate; \(x = \ln(R)\) is the natural log of a given rainrate \(R\); \(a, b, x_i, b_i\) are coefficients and can be parameterized as a function of \(R_{av}\) based on surface and/or TRMM radar data. These parameters are listed in Varma and Liu\(^{15}\).

Once the FRC and the conditional PDF of sub-pixel rainrates for a given pixel averaged rainrate \(R_{av}\) are statistically established, we may express the satellite observed pixel-averaged brightness temperature \(T_B\) based on an “independent column approximation” approach as follows:

\[
T_B(R_{av}) = [1 - FRC(R_{av})]T_B(0) + FRC(R_{av}) \int R_{av} \cdot \int PDF[\ln(R), PDF(R) dR / R ,
\]

where \(T_B(R)\) is the brightness temperature calculated from a plane-parallel radiative transfer model for sub-pixel rainrate \(R\). The brightness temperature vs. rainrate relationship derived using the above approach is also shown in Fig.6 (cyan line with diamonds). It is seen that by incorporating the statistical model of sub-pixel rainrate variability, the \(T_B\) bias in the \(T_B\)-\(R_{av}\) relation is largely eliminated (compared to observation averages). Therefore, it is possible to
mitigate the beam-filling problem by incorporating a statistical model for sub-pixel rainrate distribution when calculating the pixel-averaged (satellite observed) brightness temperatures.

This method of incorporating sub-pixel rainrate distribution into radiative transfer models is the so-called “independent column approximation” approach. As rightfully pointed out by Petty\textsuperscript{16}, the satellite received brightness temperature can also vary substantially depending on the three-dimensional nature of the rain cells. Whether and how we are able to incorporate the three-dimensional information into the radiative transfer calculations are also an open issue need to be studied.

4. On Scattering by Nonspherical Ice Particles

Scattering signature by cloud and precipitating ice particles becomes measurable as radiometer’s frequencies become high. In the case of AMSR/AMSR-E, satellite received radiances at 89 GHz, probably even at 37 GHz depending on the ice loading of the atmosphere, are often reduced by the ice scattering. This scattering signature is particularly important for retrieving snowfall and precipitation (both rainfall and snowfall) over land, since ice scattering is the primary signal available for the retrieval algorithms under these situations. Even under situations where ice scattering is not the primary signature, as long as radiances at scattering-sensitive channels (89, 37 GHz) are included, a retrieval algorithm still
suffers from any inaccurate treatment of ice scattering. Therefore, it is necessary to have the ice scattering being treated correctly in the radiative transfer models. However, due to the nonspherical nature of ice particles, computing their single scattering properties in radiative transfer models has never been a trivial task. For the convenience of computation, two types of approximations are often used by investigators. One is to approximate an ice particle by a solid sphere with the same mass (hereafter called solid-sphere approximation). Another (hereafter called soft-sphere approximation) is to approximate it by a loose sphere with the same mass but a diameter being the same as the particle’s maximum dimension. The sphere is considered as a mixture of ice and air whose effective dielectric constant can be derived by mixing rules published in the literature. Using discrete-dipole approximation (DDA) modeling\textsuperscript{17}, Liu\textsuperscript{18} showed that neither of the above approximation methods is adequate. Figure 9 shows the differences among the radiative transfer model simulated brightness temperatures at 89 GHz when using three different methods to compute the single-scattering properties of snowflakes: solid-sphere approximation, soft-sphere approximation, and DDA. If the solid-sphere assumption is used, the simulated brightness temperatures are too low, while if the soft-sphere assumption is used, the simulated brightness temperatures are too high. The differences among the brightness temperatures calculated by the three different methods are so large that any meaningful radiative transfer modeling of cloud ice particles/snowflakes at microwave frequencies must take into their nonsphericity into account. Therefore, it is
important to compute the single-scattering parameters (absorption and scattering cross sections and phase function) using accurate methods (e.g., DDA) to take the nonsphericity effect into account, rather than just simply assuming solid- or soft-spheres.

To find a better handling of the nonspherical ice particles’ scattering problem, we have studied the single-scattering properties for 11 types of ice particles: long-, short-, block-columns, thin-, thick-plates, 3-, 4-, 5-, 6-bullet rosettes, sector and dendrite snowflakes as shown in Fig.10. These particles are constructed in such a way that their area ratio and effective density decreases with maximum dimension following the recently published results by Heymsfield et al.\textsuperscript{19} and Heymsfield and Miloshevich\textsuperscript{20}. DDA calculations have been performed for these particles with their maximum dimension varying from 50 μm to 12 mm, covering most of the possible size range of cloud ice and snowflakes, and frequencies varying from 15 to 340 GHz. Based on the calculation results, we proposed an approximation scheme for calculating the single-scattering properties of nonspherical ice and snow particles at microwave frequencies\textsuperscript{17}. The approximation allows us to compute the single-scattering properties of ice particles fast and with good accuracy. At heart of the approximation is to substitute the single-scattering properties of a nonspherical ice particle by those of an equal-mass sphere, which can be calculated by Mie theory, with an effective dielectric constant derived by mixing ice and air using Maxwell-Garnet formula. The diameter of such an equal-mass sphere, $d$, is bigger than the diameter of the solid-sphere, $d_0$, but smaller than
the particle’s maximum dimension, $d_{\text{max}}$. Defining a softness parameter, $SP=(d-d_0)/(d_{\text{max}}-d_0)$, it is found that the best-fit equal-mass sphere has a $SP$ value of 0.2~0.5 for calculating the scattering efficiency factor, depending on frequency and particle shape. At 150 GHz, the best-fit softness parameter is found to be $\sim 1/3$ when averaging over all particle shapes. For calculating the asymmetry parameter, the DDA modeling results show that the best-fit softness parameter is close to 0 (i.e., the same as the solid-sphere) for frequencies high than 150 GHz while it is about 0.3 for 85.5 GHz.

In addition, a lookup table based on these DDA results has been generated\textsuperscript{21),} which contains the absorption and scattering cross-sections, phase function and asymmetry parameter of columns, plates, 3 to 6-bullet rosettes, sector and dendrite snowflakes for frequencies from 10 to 340 GHz, temperature from 0 to -40°C, and particle effective radius from 10 to 1000 $\mu$m. The lookup table and its reading program have been archived through the following website: \url{http://cirrus.met.fsu.edu/research/scatdb.html}. A radiative transfer model, in which the above lookup table is to be implemented, is currently under development.

5. Summary

This review paper serves for two purposes: describing the algorithm currently used by JAXA to produce precipitation product (i.e., the Liu algorithm) and discussing two most
important challenges facing passive microwave precipitation algorithm developers. First, the Liu precipitation algorithm is described, which was developed by the author and currently is used by JAXA to retrieve global precipitation from AMSR/AMSR-E observations. The algorithm combines emission and scattering signatures, includes a correction for beam-filling problem, and has been validated by surface radar-raingauge network data and other satellite retrievals. Validations showed that the current algorithm produces rainrates consistent with both surface radar-raingauge network and GPCP monthly precipitation product. The comparison is particularly favorable at oceanic areas with correlation coefficients constantly greater than 0.6. Over polar and some land areas, improvement of the algorithm is still needed. Because in this paper we pieced together all the modifications to the original version of the algorithm, this article gives the most complete description to the current version of the algorithm, and therefore, can serve as a reference for the precipitation product users to cite.

The discussion on the challenges in passive microwave precipitation retrievals is aimed to more general audiences who are not necessarily users of the JAXA precipitation products. The beam-filling and ice scattering problems discussed here apply to all passive microwave precipitation algorithms regardless their designing strategy. While the footprint size of the recent satellite microwave sensors such as TMI and AMSR/AMSR-E is finer than earlier ones, the beam-filling problem seems still to be one of the most important error sources in current retrieval algorithms. To mitigate this error, characterizing the horizontal
Rainrate variability and including its statistics in the retrieval algorithms are needed. In this article, we discussed one way how the mitigation can be done. Future research in this area to develop more robust methods is recommended. Another challenge discussed in this article is the scattering properties by nonspherical ice particles. This problem is important for retrieving snowfall and precipitation over land since the primary signature for these applications is scattering signal. We showed that an improper treatment of the ice scattering in the radiative transfer models could cause an error in brightness temperatures by tens of Kelvin. In order to correctly handle the scattering by ice particles, we need to first figure out the characteristic particle shapes under different weather conditions. Using accurate scattering computation methods, such as DDA, we can develop a database of scattering properties by these characteristic ice particles. This database, in turn, may be used in radiative transfer models for algorithm development. A preliminary version of such a database has been constructed by the author\textsuperscript{21}.

**Acknowledgements**

This research has been supported by JAXA ADOES II program.
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Biography

Guosheng Liu received his M.S. in 1986 and Ph. D in 1990 in Atmospheric Science from Nagoya University, Japan. His research interests are radiative transfer and satellite remote sensing of clouds and precipitation. Since 1990, he has held several positions at Pennsylvania State University, University of Colorado and Florida State University. Presently, he is a professor at Department of Meteorology, Florida State University.
Figure Captions

**Fig. 1** Relations between $\varphi$ and rainrate for different spatial resolutions.

**Fig. 2** Comparison of monthly-averaged rainrates between our AMSR/AMSR-E retrievals and those of AMeDAS for the year of 2003 for (a) over ocean and (b) over land area. The covering area is the same as that covered by the AMeDAS in Fig.3.

**Fig. 3** Monthly averaged rain maps from AMSR/AMSR-E retrievals and from the AMeDAS for the year of 2003.

**Fig. 4** Comparison of AMSR/AMSR-E retrievals with GPCP products over 2.5°×2.5° boxes for February and July of 2003.

**Fig. 5** The difference (color pixels) in mm h$^{-1}$ between TMI- minus PR-derived rainrate as a function of PR rainrate and convective fraction (ConvF). Contours represent occurrence frequency of rain pixels in % at the intervals of 0.005, 0.01, 0.1, 0.5, 1, 2, 4, 6, 8, 10. Adapted from Seo et al.\(^{11}\).

**Fig. 6** Relations between brightness temperature at 19 GHz and surface rainrates. dots: individual pixels of TRMM observations of TMI $T_B$ and PR near-surface rainrate; Red line: averaged for TRMM observations; Green line: radiative transfer model results assuming uniform rainrates with satellite pixels; Cyan line: radiative transfer model results when incorporating a statistical model of sub-pixel rainrate variability. Adapted from Varma et al.\(^{14}\).
**Fig.7** Fractional rain cover (FRC) versus window average rainrate ($R_{av}$) derived from 3 years (Dec. 1997 – Nov. 2000) of TRMM PR data. The “pixel” size is 0.25°x0.25°, typical of low frequency microwave radiometers’ FOV. Regions: tropics - 20°S-20°N, Extratropics – north of 20°N or south of 20°S. Adapted from Varma and Liu$^{15}$.

**Fig.8** Conditional PDFs of rainrates separated by surface type (land and ocean), rain type (convective and stratiform), latitudinal location (tropical and extratropical) and rainrate category (light, moderate and heavy). Derived from 3 years (Dec. 1997 – Nov. 2000) of TRMM data. Adapted from Varma and Liu$^{15}$.

**Fig.9** Radiative transfer model simulated brightness temperatures at 89 GHz as a function of ice water path based on three different ways to compute the ice particles’ single-scattering properties, i.e., solid- sphere: approximating an ice particle by a solid ice sphere with same mass but smaller diameter; soft-sphere: approximating an ice particle by a low density sphere with the same mass and a diameter being equal to the particle’s maximum dimension; DDA-nonspherical: using DDA model to compute single-scattering properties of the nonspherical ice particles.

**Fig.10** The eleven particle shapes used for representing ice and snow particles in the DDA simulations. Adapted from Liu$^{21}$.
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Fig. 4 Comparison of AMSR/AMSR-E retrievals with GPCP products over 2.5° x 2.5° boxes for February and July of 2003.
Fig. 5  The difference (color pixels) in mm h⁻¹ between TMI- minus PR-derived rainrate as a function of PR rainrate and convective fraction (ConvF). Contours represent occurrence frequency of rain pixels in % at the intervals of 0.005, 0.01, 0.1, 0.5, 1, 2, 4, 6, 8, 10. Adapted from Seo et al.¹¹).
Fig. 6 Relations between brightness temperature at 19 GHz and surface rainrates. Dots: individual pixels of TRMM observations of TMI T\textsubscript{B} and PR near-surface rainrate; Red line: averaged for TRMM observations; Green line: radiative transfer model results assuming uniform rainrates with satellite pixels; Cyan line: radiative transfer model results when incorporating a statistical model of sub-pixel rainrate variability. Adapted from Varma et al. 14.
Fig. 7 Fractional rain cover (FRC) versus window average rainrate ($R_{av}$) derived from 3 years (Dec. 1997 – Nov. 2000) of TRMM PR data. The “pixel” size is 0.25°x0.25°, typical of low frequency microwave radiometers’ FOV. Regions: tropics - 20°S-20°N, Extratropics – north of 20°N or south of 20°S. Adapted from Varma and Liu.\textsuperscript{15}
Fig. 8  Conditional PDFs of rainrates separated by surface type (land and ocean), rain type (convective and stratiform), latitudinal location (tropical and extratropical) and rainrate category (light, moderate and heavy). Derived from 3 years (Dec. 1997 – Nov. 2000) of TRMM data. Adapted from Varma and Liu\textsuperscript{15}. 
Fig. 9 Radiative transfer model simulated brightness temperatures at 89 GHz as a function of ice water path based on three different ways to compute the ice particles’ single-scattering properties, i.e., solid-sphere: approximating an ice particle by a solid ice sphere with the same mass but smaller diameter; soft-sphere: approximating an ice particle by a low density sphere with the same mass and a diameter being equal to the particle’s maximum dimension; DDA-nonspherical: using DDA model to compute single-scattering properties of the nonspherical ice particles.
Fig. 10 The eleven particle shapes used for representing ice and snow particles in the DDA simulations. Adapted from Liu.\textsuperscript{21}