

Global Satellite Mapping of Precipitation (GSMaP) for GPM

Algorithm Theoretical Basis Document (ATBD)

Algorithm Ver.9

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1. OVERVIEW

1.1. Background

Development of precipitation map algorithm including microwave radiometer/sounder algorithms has been continued cooperation with the member of Global Satellite Mapping of Precipitation (GSMaP) project (Okamoto et al., 2005; Kubota et al., 2007) in Japan. GSMaP project was sponsored by the Japan Science and Technology Agency (JST) under the Core Research for Evolutional Science and Technology (CREST) framework, and completed its major activity in March 2008. Since April 2008, GSMaP activities have implemented under Japanese Precipitation Measuring Mission (PMM) Science Team, which is joint science team between Tropical Rainfall Measuring Mission (TRMM) and its successor mission, Global Precipitation Measurement (GPM).

Since GSMaP algorithms targeted production of “best” precipitation estimates, they didn’t consider real-time operation and/or data availability. To meet user requirements of such a data in near-real-time, JAXA has developed and operates global rainfall map production system, a prototype for GPM era, in near-real-time since October 2008, and hourly and 0.1-degree resolution binary data and images available via internet (<http://sharaku.eorc.jaxa.jp/GSMaP/>) four hours after observation.

Core algorithms of the system are based on those provided by GSMaP project; microwave radiometer rainfall retrieval algorithm (Aonashi *et al.*, 2009), microwave sounder rainfall retrieval algorithm (Shige *et al.*, 2009), microwave imager/sounder rainfall retrieval algorithm (Kubota *et al.*, 2011), and microwave-infrared (IR) merged algorithm (Ushio *et al.*, 2009).

Major version-up of GSMaP algorithm has been conducted in Sep. 2014 (V03/v6), Jan. 2017 (V04/v7), Dec. 2021 (V05/v8) and Oct. 2026 (V06/v9). The details of GSMaP V03/v6 and V04/v7 algorithm have been reviewed in Kubota et al. (2020) and those of GSMaP V05/v8 have been reviewed in Kubota et al. (2026). In this document, we briefly describe the GSMaP V06/v9 algorithms.

1.2. Principles

GPM-GSMaP algorithm consists of following six main algorithms.

- Microwave imager rainfall retrieval algorithm (MWI algorithm)
- Microwave sounder rainfall retrieval algorithm (MWS algorithm)
- Microwave imager/sounder rainfall retrieval algorithm (MWIS algorithm)
- Microwave Normalization Module (MMN)
- Microwave-IR combined algorithm (MVK algorithm)
- Gauge calibrated rainfall algorithm (MVK_Gauge algorithm)

In developing GPM-GSMaP algorithms, developers should pay attention to following points:

- Develop algorithms based on outcomes from the GSMaP project, which was sponsored by JST under the CREST framework between 2002 and 2007;

- Improve the MWI algorithm, which is being developed as the standard algorithm for precipitation products of the Advanced Microwave Scanning Radiometer 2 (AMSR2) on board the Global Climate Change Mission - Water (GCOM-W) satellite, and apply it to GPM Microwave Imager (GMI) and other microwave imagers on board constellation satellites;
- Develop the MWS algorithm ensuring consistency with the MWI algorithm;
- Improve database of rain rate retrievals using TRMM Precipitation Radar (PR) data, and apply its methodology to Dual-frequency Precipitation Radar (DPR) data;
- Cooperate with the AMSR2 precipitation group in algorithm development and calibration and validation activities; and
- Develop a near-real-time algorithm based on the standard algorithm.

2. INPUT DATA

GPM-GSMaP algorithms uses multi satellite data and ancillary data as inputs. Followings are summary of input data.

2.1. Microwave Imager

Table 1 shows current and/or future conical scanning passive microwave imagers, which will be used as inputs of GPM-GSMaP.

Table 1 Summary of current and planned conical scanning passive microwave imagers
(as of October 2026)

Satellite	Height (km)	Instrument	frequency (GHz)	Data Period	Data Provider
TRMM	402	TMI	10.7, 19.4, 21.3, 37, 85.5	Dec.1997 – Apr. 2015	NASA
Aqua	705	AMSR-E	6.9, 10.7, 18.7, 23.8, 36.5, 50.3, 52.8, 89	Jun. 2002 – Oct. 2011	JAXA
ADEOS-II	802	AMSR	6.9, 10.7, 18.7, 23.8, 36.5, 89	Apr. 2003 - Oct. 2003	JAXA
DMSP-F11	833	SSM/I	19.4, 22.2, 37, 85.5	Dec. 1991 - May 2000	DoD/NOAA
DMSP-F13	833			Dec. 1995 - Nov. 2009	DoD/NOAA
DMSP-F14	833			Dec. 1997 - Aug. 2008	DoD/NOAA
DMSP-F15	833			Dec. 1999 – Sep. 2014	DoD/NOAA
Megha-Tropiques	833	MADRAS	18.7, 23.8, 36.5, 89, 157	Oct. 2012 - Jan. 2013	CNES/ISRO
GCOM-W1	705	AMSR2	6.9, 7.3, 10.7, 18.7, 23.8, 36.5, 50.3, 52.8, 89	Jul. 2013 - present	JAXA
GOSAT-GW	666	AMSR3	6.9, 7.3, 10.25, 10.65, 18.7, 23.8,	Jul. 2026 - present	JAXA

			36.42, 89, 165.5, 183.31±3, 183.31±7		
GPM Core Observatory	442	GMI	10.7, 19.4, 21.3, 37, 85.5, 166, 183.31±3, 183.31±7	Mar. 2014 - present	NASA
WSF-M1	854	MWI	10.85, 18.85, 23.8, 36.75, 37.3, 89	TBD	DoD

2.2. Microwave Sounder

Table 2 shows current and/or future cross-tracking passive microwave sounders, which will be used as inputs of GPM-GSMaP.

Table 2 Summary of current and planned cross-tracking passive microwave sounders
(as of October 2026)

Satellite	Height (km)	Instrument	frequency (GHz)	Data Period	Data Provider
NOAA-N15	833	AMSU-A/ AMSU-B	23.8-89.1 (AMSU-A), 89.0±0.9, 150.0±0.9, 183.31±1, 183.31±3, 183.31±7 (AMSU-B)	Oct. 1998 – Nov. 2010	NOAA
NOAA-N16	833			Jan. 2001 – Dec. 2007	NOAA
NOAA-N17	833			Aug. 2002 – Nov. 2010	NOAA
NOAA-N18	870	AMSU-A/ MHS	23.8-89.1 (AMSU-A), 89, 157, 183.31±3, 183.31±5, 190.311 (MHS)	May 2005 – Oct. 2018	NOAA
NOAA-N19	870			Apr. 2009 – Jun. 2025	NOAA
MetOp-A	817			May 2007 – Dec. 2019	EUMETSAT
MetOp-B	817			Sep. 2012 - present	EUMETSAT
MetOp-C	817			Sep. 2020 - present	EUMETSAT
NPP	824	ATMS	23.8-88.2, 165.5, 183.31±1, 183.31±1.8, 183.31±3, 188.31±4.5, 188.31±7	Oct. 2011 – Nov. 2026	NOAA
JPSS-1	824	ATMS		to be launched in 2017	NOAA
JPSS-2	833	ATMS		Jul. 2023 – present	NOAA

2.3. Microwave Imager/Sounder

Table 3 shows current and/or future conical scanning passive microwave imager/sounders, which will be used as inputs of GPM-GSMaP.

Table 3 Summary of current and planned conical scanning passive microwave imager/sounders
(as of October 2026)

Satellite	Height (km)	Instrument	frequency (GHz)	Data Period	Data Provider
DMSP-F16	833	SSMIS	19.4, 22.2, 37, 91.7, 60-63, 50-59, 150,	Nov. 2005 - present	NOAA

DMSP-F17	850		183.31±1, 183.31±3, 183.31±7	Mar. 2008 – Nov. 2016	NOAA
DMSP-F18	850			Oct. 2011 – present	NOAA
DMSP-F19	850			Dec. 2014 - Feb. 2016	DoD/NOAA

2.4. Geostationary Satellite IR Imager

Globally-merged full-resolution IR Data, which is merged from the ~11 micron IR channels aboard geostationary satellites (Table 4) in about 4 km grid size, provided by NOAA Climate Prediction Center (CPC), will be used as inputs for MVK algorithm.

Table 4 Summary of geostationary satellites (as of October 2026)

Satellite	Sub-satellite Longitude	Parameter	Data Provider
Himawari-9 (formerly MTSAT-2, MTSat-1R, GMS, Himawari-8)	140E	~11 micron IR channels	JMA
GOES-E (8, 12, 13, now 16)	75W		NOAA
GOES-W (10, 11, 15, 17, 18, now 19)	135W		NOAA
Meteosat-11 (formerly 5, 7, 8, 9, 10)	9.5E		EUMETSAT
Meteosat-9 (formerly 5, 7, 8)	45.5E		EUMETSAT

2.5. Space-borne Precipitation Radar

Data and information from space-borne precipitation radars (Table 5) will be used to develop database and/or precipitation physical models, and not directly.

Table 5 Summary of space-borne precipitation radars (as of October 2026)

Satellite	Height (km)	Instrument	frequency (GHz)	Data Period	Data Provider
TRMM	402	PR	13.8	Dec.1997 – Apr. 2015	JAXA
GPM Core Observatory	442	DPR	13.6, 35.5	Mar. 2014 - present	JAXA

2.6. Atmospheric Condition

Japan Meteorological Agency (JMA) Global Analysis (GANAL) and Forecast data set, which are 6-hourly and 0.5 degree grid box, are used as ancillary data of atmospheric condition for calculating look-up tables, which are referred by MWI and MWS algorithms. ANAL data will be used to process standard products, and FCST data will be used to process near-real-time products. For the past period, the Japanese Reanalysis for Three Quarters of a Century (JRA-3Q) data (6-hourly, model grid (TL319L60)) will be used instead of operational data.

2.7. Sea Surface Temperature

J JMA Merged satellite and in situ data Global Daily Sea Surface Temperatures (MGDSST) data, which is daily and 0.25 degree grid box, will be used as ancillary data of Sea Surface Temperature (SST) for calculating look-up tables, which are referred by MWI and MWS algorithms.

2.8. Rain Gauge

NOAA CPC Unified Gauge-Based Analysis of Global Daily Precipitation data set, which is daily and 0.5 degree grid box, will be used as input to MVK algorithm to calculate gauge-calibrated rainfall.

2.9. Topographic Data

The Shuttle Radar Topography Mission 30-arc second (SRTM30) dataset, which is provided by U.S. Geological Survey (USGS), will be used as information to estimate upward motion in the orographic/nonorographic rainfall classification scheme. Original 30-arc second mesh (about 900 m) and regionally divided data is resampled in 0.05 degree grid box and integrated as global data. See http://dds.cr.usgs.gov/srtm/version2_1/SRTM30/srtm30_documentation.pdf for more detail.

2.10. High Resolution Ocean/Land Flag

Ocean/Land/Coast flag database will be used in the coast detection scheme. The dataset is produced in 30-arc second mesh, and mainly uses the SRTM Water Body Data provided by the Geospatial-Intelligence Agency (NGA) and NASA for the region south of 60N, and the Global Self-consistent, Hierarchical, High-resolution Shorelines (GSHHS) provided by NOAA's National Geophysical Data Center for the region north of 60N.

3. OUTPUT DATA

3.1. Hourly product

3.1.1. Temporal resolution

Hourly.

3.1.2. Horizontal resolution

0.1 degree latitude/longitude grid.

3.1.3. Coverage

Coverage of output data is from 180W to 180E in longitude and 90S to 90N in latitude. In the V06/v9 algorithm, the rainfall and snowfall estimates are extended to cover the entire latitudinal range from 90S to 90N owing to the use of NEXRA.

3.1.4. Output format

NetCDF4 formats.

3.1.5. Hourly precipitation rate (HourlyPrecipRate)

Hourly rain rate at each pixel. Unit is mm/hour. Missing value is -9999.9.

3.1.6. Satellite information flag (SatelliteInformationFlag)

Information of satellites that observe each pixel within 1-hour. Described in bit.

3.1.7. Observation time flag (ObservationTimeFlag)

Relative time of nearest microwave radiometer (imager/sounder) observation at each pixel, on the basis of start time (XX:00) of observation at XX (UTC).

3.1.8. Gauge-calibrated hourly precipitation rate (HourlyPrecipRateGC)

Hourly rain rate at each pixel, calibrated by using ground-based gauge observation over land. Pixels over the ocean, same values as Hourly precipitation rate are stored. Unit is mm/hour. Missing value is -9999.9.

3.1.9. Gauge quality information (GaugeQualityInformation)

Number of rain gauge used in gauge adjustment at each pixel within one day. Original values in 0.5 degree grid box are stored in corresponding pixels in 0.1 degree grid box in same values. For the near-real-time product, values of 1 or 0 are stored for with or without adjustment.

3.2. Monthly product

3.2.1. Temporal resolution

Monthly.

3.2.2. Horizontal resolution

0.1 degree latitude/longitude grid.

3.2.3. Coverage

Coverage of output data is from 180W to 180E in longitude and 90S to 90N in latitude. In the V06/v9 algorithm, the rainfall and snowfall estimates are extended to cover the entire latitudinal range from 90S to 90N owing to the use of NEXRA.

3.2.4. Output format

NetCDF4 formats.

3.2.5. Monthly mean hourly precipitation rate (MonthlyPrecipRate)

Monthly mean rain rate at each pixel. Unit is mm/hour. Missing value is -9999.9.

3.2.6. Number of observations (ObservationNumber)

Number of observation within one month. Missing value is -9999.

3.2.7. Standard deviation (StandardDeviation)

Standard deviation within one month. Missing value is -9999.9.

3.2.8. Monthly mean gauge calibrated precipitation rate (MonthlyPrecipRateGC)

Monthly rain rate at each pixel, calibrated by using ground-based gauge observation over land. Pixels over the ocean, same values as Hourly precipitation rate are stored. Unit is mm/hour. Missing value is -9999.9.

3.2.9. Gauge quality information (GaugeQualityInformation)

Number of rain gauge used in gauge adjustment at each pixel within one month. Missing value is -9999.

4. ALGORITHM DESCRIPTION

4.1. Microwave Imager Algorithm (GSMaP_MWI)

The GSMaP microwave imager (MWI) algorithm retrieves precipitation rates from microwave brightness temperatures observed by conically scanning microwave imagers, including TMI, GMI, AMSR, AMSR-E, AMSR2, AMSR3, and WSF-M1/MWI. The algorithm is based on the GSMaP MWI framework developed by Aonashi et al. (2009), with successive improvements using TRMM and GPM observations.

The algorithm consists of two components: a forward calculation module and a retrieval module. In the forward calculation module, radiative transfer simulations are performed using atmospheric and surface information from JMA GANAL/JRA-3Q and MGD SST together with precipitation cloud models derived from TRMM and GPM observations. The resulting brightness temperatures are compiled into look-up tables (LUTs). In the retrieval module, observed brightness temperatures are compared with the LUTs to estimate surface precipitation rates. Snowfall retrieval is performed separately under snow-favorable atmospheric conditions.

For rainfall retrieval, precipitation occurrence is first identified and then precipitation intensity is estimated using microwave scattering and, over ocean, emission signals. Orographic precipitation effects are also considered through dedicated precipitation classifications and LUTs. Detailed descriptions of the retrieval framework are available in Aonashi et al. (2009), Shige et al. (2013), Yamamoto and Shige (2015), and Yamamoto et al. (2017).

The major updates introduced in GSMaP V06/v9 are as follows:

- The precipitation detection method for rainfall retrieval was updated from the conventional threshold-based approach to a regression-based method that uses surface emissivity, brightness temperature information, environmental fields, and orographic indices as predictors.
- In the rainfall intensity retrieval, scattering-based precipitation estimates are corrected using a Support Vector Machine (SVM) model incorporating physical indicators related to Convective Precipitation Fraction (CPF) and Frozen Precipitation Depth (FPD).
- The new rainfall retrieval framework was implemented for GMI and AMSR3 observations. For AMSR2 and AMSR3, GMI-equivalent surface emissivity is estimated from synthesized GMI brightness temperatures.
- The snowfall retrieval algorithm was replaced by a machine-learning approach based on

XGBoost. The algorithm was trained using collocated observations from GPM GMI, CloudSat CPR, EarthCARE CPR, and GPM DPR, and retrieves snowfall occurrence and snowfall rate for different surface and atmospheric regimes.

Further details of the V06/v9 rainfall and snowfall retrieval algorithms are described in Appendix.

4.2. Microwave Sounder Algorithm (GSMaP_MWS)

The GSMaP over-ocean rainfall retrieval algorithm for microwave sounders (MWS) was developed by Shige et al. (2009) based on the GSMaP algorithm for microwave imagers (MWI). This algorithm combines an emission-based estimate from brightness temperature (Tb) at 23 GHz and a scattering-based estimate from Tb at 89 GHz. Precipitation inhomogeneities are also taken into account. Improvements of rain/no-rain classification method over coast and mitigation of underestimation in mountainous areas (Shige et al., 2013, Taniguchi et al., 2013) have been done.

The GSMaP over-land rainfall retrieval algorithm for MWS is a scattering algorithm that mainly relies on Tb data at 89 GHz and its rain/no-rain classification method has been developed utilizing Tb data at 150 GHz and 180 GHz (Kida et al. 2012).

In the MWS algorithm, LUT is fitted by a five degree polynomial function of incident angle number. The MWS algorithm saves coefficients of the regression function. The LUT is reconstructed from the regression coefficients in the retrieval algorithm for MWS.

4.3. Microwave Imager/Sounder Algorithm (GSMaP_MWIS)

The GSMaP rainfall retrieval algorithm for microwave imager/sounders (MWIS) was developed by Kubota et al. (2011) based on the GSMaP algorithm for microwave imagers (MWI). SSMIS does not have 10 GHz channels same as SSM/I, the algorithm combines emission-based estimates using TB polarization differences at 19 GHz, in addition to emission-based estimates using TB at 19 GHz vertical polarization and scattering-based estimates using TB at 89 GHz, over the ocean. Precipitation inhomogeneities are also taken into account. See Kubota et al. (2011) for more details.

In this version, we conducted sensitivity experiments on the weights used for this combination and adjusted them to optimal values. Furthermore, we re-evaluated correction coefficients regarding precipitation non-uniformity and brightness temperature adjustments for high-frequency bands, aligning with updates to input brightness temperature data.

The GSMaP over-land rainfall retrieval algorithm for MWIS was developed based on the GSMaP algorithm for microwave imagers (MWI).

4.4. Microwave Normalization Module (MMN)

There are discrepancies among PMW rain estimates due to differences in sensor characteristics and retrieval algorithms. To reduce these discrepancies in rainfall estimates among PMW sensors, the V05/v8 algorithm implemented the Method of Microwave Rainfall Normalization (MMN) module.

The details are described in Yamamoto and Kubota (2022).

In V06/v9, the normalization method has been modified based on Bouwer et al. (2004). The precipitation rate is normalized using the following equations;

$$\mu_f = \frac{\mu_{OBS}}{\mu_{SRE}}, \quad \tau_f = \frac{\tau_{OBS}}{\tau_{SRE}} \quad (5)$$

The subscript “OBS” denotes the reference sensor (i.e., GPM/GMI or TRMM/TMI), while the subscript “SRE” denotes the other PMW sensors. SRE_0 means the original rainfall rate and SRE_{cor} is the normalized precipitation rate. The normalization is calculated for normalization table for each surface type. However, for the coast areas, the normalization table for land is used. Further details are mentioned in Yoshida et al. (2026).

4.5. Microwave-IR Merged Algorithm (GSMaP_MVK)

GSMaP_MVK is a product that integrates passive microwave radiometer data with infrared radiometer data in order to have high temporal (1 hour) and spatial (0.1 degree) resolution global precipitation estimates. The product (GSMaP_MVK) is produced based on a Kalman filter model that refines the precipitation rate propagated based on the atmospheric moving vector derived from two successive IR images. The basic framework of the algorithm can be found in Ushio et al. (2009).

The GSMaP_MVK algorithm includes a cloud-type classification and precipitation-rate correction method based on a self-organizing map. Cloud systems are classified using characteristics derived from geostationary infrared observations, and the precipitation rate is adjusted according to the classified cloud type.

From this version, we newly implemented a polar PMW-IR algorithm utilizing the JAXA Real-time Weather Prediction system (NEXRA), based on the NICAM-LETKF, and the Japanese Reanalysis for Three Quarters of a Century (JRA-3Q) due to large zenith angles and radiometric effects, limiting most PMW-IR products to within 60 degrees in latitude from IR observation. Instead of IR data, column water vapor information from these datasets is used to calculate moving vectors and noise tables for the Kalman filter. Furthermore, we developed a new method to integrate precipitation estimates from IR and NEXRA.

4.6. Gauge-calibrated rainfall algorithm (GSMaP_Gauge)

GSMaP_Gauge is a product that adjust the GSMaP_MVK estimate with global gauge analysis (CPC Unified Gauge-Based Analysis of Global Daily Precipitation) supplied by NOAA. The product also has the same spatial and temporal resolution with GSMaP_MVK and GSMaP_NRT, which is 0.1 degree and 1 hour. The adjustment is applied to the estimation only over land, and the rain rate over ocean, GSMaP_Gauge and GSMaP_Gauge_NRT, are same as that from GSMaP_MVK and GSMaP_NRT for near real time version, respectively. The rain rate of GSMaP_Gauge is calculated based on the optimal theory which adjusts the GSMaP_Gauge hourly rain rate so that the sum of the 24 hour GSMaP_Gauge rain rate is roughly same as the gauge measurement (Ushio *et al.*, 2013). For

even distribution of the spatial weighting of rain-gauge observations, an additional spatial regularization using a cosine tapering function was introduced in V06/v9 algorithm to smoothly distribute the gauge-adjustment factor around gauge locations over land. This approach suppresses unrealistic discontinuities and localized extremes by ensuring a gradual transition of gauge-adjustment factor between neighboring regions. During the final process of gauge calibration, an IR-cutoff method is applied. This method cancels precipitation estimation in areas with warm IR brightness temperatures and low water vapor content. Consequently, rainfall amounts may differ between the gauge-calibrated and non-calibrated products, even at rain-gauge stations where no rainfall is recorded.

4.7. Near-real-time Algorithm (GSMaP_NRT)

Near-real-time algorithm is based on standard algorithm, but some simplification in the processing are implemented to keep operability and data latency in near-real-time. Major differences between near-real-time and standard processing are as follows.

- JMA forecast data is used as atmospheric information
- Latest available MGD SST data is used as SST information
- Only temporarily forward cloud movement is used in microwave-IR merged module
- Only the error parameters are used to adjust the GSMaP_NRT estimation in gauge adjustment module

5. MODULES

5.1. Overview

Figure 1 is algorithm flow of GPM-GSMaP.

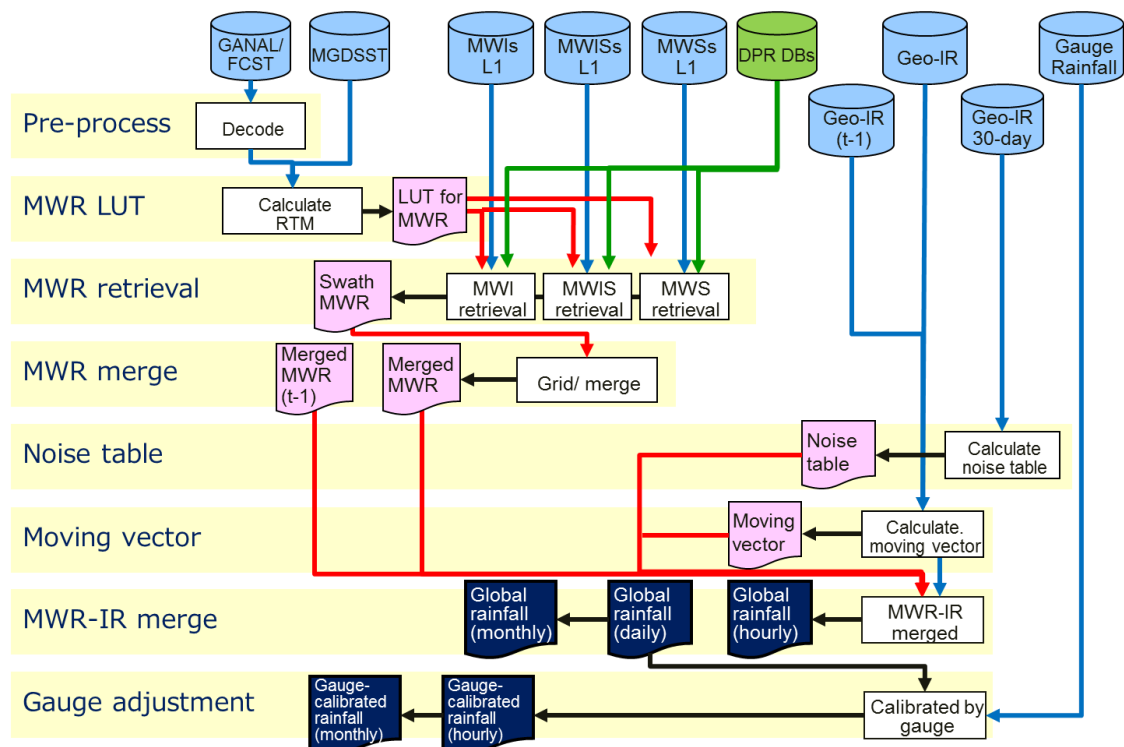


Figure 1 Algorithm flow of GPM-GSMaP

5.2. Major modules

Followings are major modules constructed the GPM-GSMaP algorithm.

- Pre-processing module
- Microwave radiometer (MWI, MWS, MWIS) look-up table module
- Microwave radiometer retrieval module
- Microwave radiometer merging module
- Noise table processing module
- Cloud moving vector calculation module
- Microwave-IR merging module
- Gauge adjustment module

6. VALIDATION

6.1. Validation Plan

Precipitation has wide fluctuation in temporal and horizontal variation, and one of the most difficult geophysical parameters to compare directly to ground observations. Basically, validation of precipitation uses current operational ground-based radar and rain gauge networks, but comparison with space-borne precipitation radar is critical in terms of accuracy and homogeneity of ground truth data. Also, simultaneous observation of cloud physics of solid precipitation and microwave radiometer is needed to evaluate scatter algorithm, we plan to coordinate with the validation plan and campaign experiments for the GPM Dual-frequency Precipitation Radar.

6.2. Comparison with Space-borne Precipitation Radar

The Global Rainfall Map and/or each microwave radiometer retrieval will be routinely compared with space-borne radars, such as TRMM/PR and GPM/DPR.

6.3. Comparison with Ground-based Data

The Global Rainfall Map and/or each microwave radiometer retrieval will be compared with JMA AMeDAS (rain gauge), Radar-AMeDAS (gauge-calibrated ground-based radar analysis (merged and gridded data) over Japan), and ground-based radar.

Also, in collaboration with the GPM Ground Validation team, the Global Rainfall Map will be validated and evaluated its accuracy in global scale, by using ground-based observation data in various climate zones outside Japan, such as East Asia, over the ocean, etc.

6.4. Collaboration with GCOM-W1/AMS2

Validation of GSMaP_MWI algorithm will collaborate with validation activities of the GCOM-W/AMS2 project. GCOM-W project routinely produces match-up dataset of AMSR2 observations with space-borne precipitation radar or ground-based rain gauge and radar data, and compares them. Those results will be uploaded to the GCOM-W/AMS2 Validation web site (in operation since 2012),

6.5. Collaboration with International Precipitation Working Group

The team will join international precipitation inter-comparison activities led by the International Precipitation Working Group (IPWG) co-hosted by the Coordination Group of Meteorological Satellites (CGMS) and World Meteorological Organisation (WMO), to contribute coherent validation of precipitation products. Kyoto University, in collaboration with the JAXA/GPM research project, is currently operating Japanese IPWG validation web site for inter-comparison of multi-satellite precipitation products (http://www-ipwg.kugi.kyoto-u.ac.jp/IPWG/sat_val_Japan.html). The team will coordinate with this activity to implement comparison and monitoring time-series of the Global Rainfall Map and/or each microwave radiometer retrieval with JMA Radar-AMeDAS rainfall analysis in hourly and daily basis.

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Microwave Imager Algorithm

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APPENDIX

Detail of Microwave Imager Algorithm (GSMaP_MWI)

Rain Retrieval Algorithm

GSMaP microwave imager (MWI) algorithm retrieves global precipitation rates from satellite microwave imager (TMI, GMI, AMSR, AMSRE, AMSR2, AMSR3, and WSF-M1/MWI) bright temperatures (TBs). To develop this algorithm, we improved that of Aonashi *et al.* (2009) by introducing the orographic rain adjustment method etc.

The basic idea of the MWI algorithm is to find precipitation rates that give radiative transfer model (RTM)-calculated TBs that best fit with TMI TBs. The MWI algorithm employs polarization corrected temperatures (PCTs) at higher frequencies (37 and 85 GHz for TMI) over land and coast, TBs with vertical polarization at lower frequencies (10, 19, and 37 GHz for TMI) in addition to the higher frequency PCTs over ocean. (For SSM/I, this algorithm employs TB polarization differences at 19 GHz instead of TBs at 10GHz. See Section 4.3).

The MWI algorithm consists of the forward calculation part to calculate the LUTs, and the retrieval part to estimate precipitation rates from the observed TBs using the LUTs. Before performing precipitation retrievals from satellite observations, a precipitation type identification algorithm (Sims and Liu, 2015) is applied to each satellite pixel to determine whether the atmospheric condition at the time and location of the satellite observation is more favorable for rain or snow precipitation based on available surface and atmospheric temperature and moisture data (JMA reanalysis GANAL). If the condition is more favorable for rain, rainfall retrieval is performed. Otherwise, snowfall retrieval is performed.

The following subsections are described as the GSMaP rain retrieval algorithm (V06) for GMI, AMSR2, and AMSR3.

The major improvements implemented in this algorithm, compared to the previous version (V05), are as follows:

1. Update of the precipitation detection method: The precipitation detection method in the retrieval module has been updated to an approach which utilizes surface emissivity (E_s), and other parameters as inputs.
2. Correction of scattering-based precipitation intensity retrieval: In the precipitation intensity retrieval section that utilizes scattering signals, the retrieved precipitation values are now corrected using a Support Vector Machine (SVM), incorporating physical variables related to the Convective Precipitation Fraction (CPF) and Frozen Precipitation Depth (FPD).

Data and radiative transfer model

Outline

The GMI is a microwave imager (MWI) onboard the GPM satellite, featuring 13 channels across

eight frequencies: 10, 18, 23, 36, 89, 166, 183 ± 3 , and 183 ± 7 GHz (Draper et al., 2015). The GMI performs conical scanning, with Earth-incidence angles of 52.8° for frequencies of 89 GHz and below, and 49.2° for frequencies of 166 GHz and above. We utilized L1B Version 05 brightness temperature (TB) data.

AMSR-2 is a microwave imager onboard GCOM-W that observes TBs with vertical and horizontal polarizations at the following frequencies: 6.925, 7.3, 10.65, 18.7, 23.8, 36.42, and 89.0 GHz. By employing a large antenna with a diameter of 2 meters, AMSR-2 achieves improved spatial resolution for each channel in the microwave window region (Imaoka et al., 2010).

AMSR-3 is a microwave imager onboard the GOSAT-GW satellite that observes TBs for the following frequencies: 6.925, 7.3, 10.25, 10.65, 18.7, 23.8, 36.42, 89.0, 165.5, 183.3 ± 3 , and 183.3 ± 7 GHz. Among these, the 23.8, 165.5, 183.3 ± 3 , and 183.3 ± 7 GHz channels observe vertical polarization only, while the other channels observe both horizontal and vertical polarizations. Equipped with a large 2-meter diameter antenna, AMSR-3 achieves improved spatial resolution across all microwave channels (Inaoka et al, 2026).

Radiative transfer model (RTM)

We used the RTM program of Liu (2004). This program computed the TBc for the plane-parallel atmosphere by four-stream approximation. In this study, all the precipitation particles were assumed to be spherical, and the absorption and scattering coefficients as well as phase functions were computed from the Mie theory.

GANAL and MGDSST

The algorithm incorporates physical variables of atmosphere and surface conditions except for sea surface temperatures from the Japan Meteorological Agency (JMA) Global Analysis (GANAL). Sea surface temperatures are derived from JMA's Merged satellite and in situ data Global Daily Sea Surface Temperatures in the global ocean (MGDSST) data.

AutoSNOW

This study utilized AutoSNOW, a daily global snow and ice flag from the National Snow and Ice Data Center (NSIDC) in the United States, as an indicator for snow cover and sea ice.

surface emissivity (E_s)

The precipitation area detection method developed in this study inputs the GMI surface emissivity (E_s). Therefore, GMI E_s was obtained using the following procedure:
1) For AMSR2 and AMSR3, synthesize GMI TB from the MWI TBs.
2) Estimate E_s from GMI TB using the method of Turk et al. (2014).

To synthesize GMI TB from AMSR2 TB, we utilized GMI-AMSR2 match-up data (with an observation time difference of within 300 seconds) from June 2014 to May 2016. Using this dataset, we developed a linear regression model for GMI TB that takes AMSR2 TB, surface temperature (T_s), and the fraction of water (FOW)—calculated using the method of Mega and Shige (2016)—as inputs.

To synthesize GMI TB from AMSR3 TB, we developed a linear regression model for GMI TB using GMI–AMSR3 matchup data from August to December 2025 (with an observation time difference within 600 seconds), where AMSR3 TB, T_s , and FOW were used as inputs.

Next, from the synthesized GMI 18–89 GHz vertically and horizontally polarized TB, the vertically and horizontally polarized TB at 18–89 GHz was estimated using the EPC method of Turk et al. (2014) (hereafter referred to as EsEPC).

Rainfall algorithm description

Outline

The algorithm consists of a priori information for the atmosphere, surface conditions, and precipitation clouds, a forward calculation module, and a retrieval module (Figure 2).

In the forward calculation module, look-up tables (LUTs) of MWR TBc are calculated for the surface precipitation rate using a priori information. The retrieval module obtains the surface precipitation rate that gives the TBc value that best matches TBo.

The algorithm is applied to locations where the surface temperature is 0C or higher and that are free of snow cover and sea ice.

Improvements over the conventional algorithm

The conventional precipitation area detection method (hereafter referred to as conventional method) underestimates precipitation areas over land and coastal regions compared to GPM Dual-frequency Precipitation Radar (DPR) observations. In particular, it frequently misses precipitation events in areas with high frequencies of orographic precipitation, such as the Western Ghats. Conversely, over the ocean, the conventional method overestimates precipitation areas compared to DPR observations. In this study, we first analyzed the effects of surface conditions and environmental fields on the probability density functions (PDFs) of GMI EsEPC and the ratio of TB to T_s (TB/ T_s) in both precipitating and non-precipitating areas. The results revealed that while EsEPC and TB/ T_s vary significantly in coastal regions, they exhibit a high correlation with the FOW of each GMI pixel. Furthermore, calculating the difference (dEs) between EsEPC and the estimated non-precipitating value (Es0) for each FOW showed that the standard deviation (STD) of dEs larger in precipitating areas than in non-precipitating areas.

The conventional method misses DPR-detected precipitating areas with small scattering signals (referred to as "Miss"), which frequently occur in regions with high frequencies of orographic precipitation. Therefore, we investigated the characteristics of orographic precipitation indices (Shige and Kummerow, 2016, Yamamoto et al, 2017) when such Miss events occur. The results demonstrated that Miss events have a peak probability of occurrence along the coast, and that the low-level relative humidity (RH) is concentrated at 90% or higher.

Based on these findings, we developed a new precipitation area detection method that regresses the DPR rain flag. This method uses surface conditions, environmental fields, and orographic precipitation indices as inputs, in addition to EsEPC and TB/ T_s . The global domain was divided into regions, and separate regression models were constructed for land/coastal areas and oceanic areas

within each region. Note that the target areas were limited to regions without snow cover and sea ice using NSIDC AutoSNOW. For the AMSR3 routine processing, a regression model based on a linear algorithm was constructed.

Additionally, in the precipitation intensity retrieval section that utilizes scattering signals within the retrieval module, the retrieved precipitation values were corrected using SVM, incorporating physical variables related to CPF and FPD.

Algorithm Configuration

A priori information

As Figure 3 schematically illustrates, the RTM calculation requires information on atmospheric variables (temperature, relative humidity, Freezing Level Height (FLH), Cloud Liquid Water Content (CLWC), etc), surface conditions (surface temperature, sea surface wind speed), and precipitation-related variables (precipitation profiles, precipitating particle size distribution, refractivity of frozen and mixed-phased particles, horizontal inhomogeneity of precipitation, etc.).

In this study, the FPD was estimated by the forward calculation module based on a priori information. The precipitation cloud model was then varied by precipitation type and the FPD. Inhomogeneity of precipitation and CPF were estimated in the retrieval module.

Atmospheric and surface variables

We adopted atmospheric temperature, FLH, and surface temperature over land and coast from JMA GANAL. We adopted sea surface temperature from JMA MGD SST. The LUTs were calculated for every 5x5 degree point in the latitude-longitude coordinates. Thus, we incorporated the above variables on the 5x5 degree points into the RTM calculation. As for relative humidity and CLWC, we assumed the same constant values, 100 % and 0.5 kg m⁻².

Precipitation type

We constructed statistical precipitation profile models using the Tropical Rainfall Measuring Mission (TRMM) observation. To this end, first, we classified TRMM Precipitation Radar (PR) data into 14 types (8 over land, 6 over ocean) by the ratio between PR precipitation rates and TRMM Lightning Imaging Sensor (LIS) flash rates (Takayabu 2008).

Coastal zones within 200 km of the coastline exhibit precipitation characteristics distinct from those of inland and open-ocean regions (Ogino et al., 2016). Therefore, within the coastal grid boxes, this study defined coastal-ocean and coastal-land precipitation types that correspond to the six oceanic precipitation types.

Frozen precipitation depth (FPD)

Similar to previous studies (Shige and Kummerow, 2016), this study examined the correlation between FPD and GANAL physical variable. The results show that FPD correlates relatively well with physical variables such as atmospheric instability and relative humidity (RH). FPD also correlates with surface precipitation rate, since stronger precipitation tends to be taller. Based on this, this study

obtained an index of FPD (FPD_ENV) for given surface precipitation rate from GANAL's mid-lower tropospheric temperature lapse rate and RH.

Precipitation profile

Precipitation profiles vary in high correlation with FPD. Convective precipitation has stronger frozen precipitation than stratiform precipitation, which also shows greater variability with FPD.

For each precipitation type, this study obtained the statistical mean and standard deviation of precipitation profiles for convective and stratiform precipitation using DPR data. We also calculated correlation between the DPR precipitation rate at each level and the FPD. However, for the coast, the number of samples was small, so both coastal land and sea data were used to create statistics for the coastal precipitation profiles.

In low temperature regions, the precipitation profiles near the surface became too shallow. To avoid this, FLH-weighted averages of the conventional precipitation profiles and the WAKASA2003 profiles were used in the region where the FLH was below 1500 m.

Particle size distribution

For rain drop size distribution, we constructed statistical models for each precipitation type using the globally-available TRMM PR observations (Kozu et al. 2009). To this end, first, we assumed the gamma distribution of rain drop size:

$$N(D) = N_0 D^\mu \exp(-\lambda D) \quad (1)$$

where N is the number concentration for particles with diameter D , $\mu=3$, N_0 and λ are parameters to be determined. For convective precipitation, we calibrated N_0 and λ using the attenuation corrected factors derived from the PR data. For stratiform precipitation, we used the standard values of N_0 and λ of PR 2A25 version 6. Then, we averaged the above values for each precipitation type to produce the statistical models of rain drop size distribution.

On the other hand, conventional models were used for frozen and mixed-phase particle size distribution that could not be estimated from the TRMM observation. For frozen particle size distribution, we applied the Harimaya (1977)'s distribution to both convective and stratiform precipitation. Particle size distribution for mixed-phase stratiform precipitation (between FLH minus 1 km and FLH) was parameterized in terms of atmospheric temperature (Nishituji et al. 1983), while we neglected mixed-phase convective precipitation.

Density of frozen and mixed-phase precipitation particles

We estimated frozen precipitation particle densities for convective and stratiform precipitation using DPR Ku radar observed reflective factor (Z_m) versus the difference between -Ku and Ka radar reflective factors (DFR). The estimated frozen precipitation particle density averaged over 2015-2018 increased with altitude difference from FLH.

Based on this, we searched by try and error for the optimal value of frozen precipitation density for FPD_ENV, such that the zonal mean of the precipitation bias for the over-land MWR retrievals for July 2014 is close to zero. The results show that the optimum values of frozen precipitation density are (0.65-0.80) for convective and (0.50-0.65) for stratiform at 89 GHz.

Density of mixed-phase stratiform particles was parameterized in terms of atmospheric temperature (Nishituji et al. 1983).

Convective precipitation fraction (CPF)

Following previous studies, this study calculated correlations between the DPR CPF and various physical variables. The results showed high correlations with the index of FPD (FPDpix) obtained from GANAL and MWR retrievals, inhomogeneity of precipitation estimated from MWR, polarization difference of TB89, and surface temperature. Based on this, an index of CPF (CPFpix) was estimated from the above physical variables.

Forward calculation

Preprocessing

From GANAL and MGSST, atmospheric and surface variable data were created for every 5x5 degree point in the latitude-longitude coordinates. Based on a priori information, FPD_ENV for each precipitation rate was calculated from the GANAL data. Then, the precipitation profile and the density of frozen precipitation were varied by precipitation type and FPD_ENV.

RTM calculation

First, we calculated the convective and stratiform LUTs for horizontally homogeneous precipitation by incorporating the above atmospheric, surface, and precipitation-related variables into the RTM program of Liu (2004) for every 5x5 degree point in the latitude-longitude coordinates.

Then, we derived the convective and stratiform LUTs with various horizontal precipitation inhomogeneities by the approximation of Aonashi and Liu (2000). This approximation converted TBc for homogeneous precipitation (TB^h) into those for inhomogeneous precipitation (TB^i), assuming the lognormal distribution of precipitation:

$$TB^i = \int \frac{1}{\sqrt{2\pi}\xi} \exp\left[-\frac{1}{2\xi^2}(\ln(pr) - \overline{\ln(pr)})^2\right] TB^h d\ln(pr), \quad (2)$$

where $\ln(pr)$ is the natural logarithm of precipitation, and $\overline{\ln(pr)}$ and ξ is the average and the standard deviation of $\ln(pr)$, respectively.

The LUTs used in the retrieval module were weighted averages of the above convective and stratiform LUTs. The weights were determined by the statistical frequency distribution of DPR convective and stratiform precipitation for each precipitation types and surface precipitation rates.

Retrieval

The retrieval module performs detection of precipitation areas, TBc correction using TBo over rain-

free areas, estimation of inhomogeneity of precipitation and CPF, retrievals using scattering signals, and retrievals using emission signals over ocean.

Detection of precipitation areas

In this study, we developed a new precipitation area detection method that regresses the DPR rain flag. This method incorporates surface conditions, environmental fields, and orographic precipitation indices as inputs, in addition to GMI EsEPC and TB/Ts. The specific inputs to the regression model consist of EsEPC (es18v, es18h, es23v, es36v, es36h, es89v, es89h), TB/Ts (For the precipitation area detection methods for GMI and AMSR3, tb166v/Ts and pct89/Ts are used; for the method for AMSR2, pct89/Ts is used), surface conditions (FOW, surface type), environmental fields (Ts, low-level RH), and orographic precipitation indices (orographic updraft, DFC, low-level moisture convergence, low-level lapse rate).

To account for regional variations in the relationships of EsEPC and TB/Ts versus the DPR rain flag, as well as variations in Miss events and orographic precipitation indices, the global domain was divided into distinct regions. Separate models were then constructed for land/coastal areas and oceanic areas within each region. Furthermore, because distinguishing between precipitating and non-precipitating areas is challenging over snow cover and sea ice, the target areas were restricted to regions outside of snow and sea ice cover using AutoSNOW.

We constructed the model to regress the DPR rain flag using a linear regression algorithm. The training data utilized for each region's land/coastal and oceanic models were GMI–DPR matchup data collected from June 2014 to May 2016. Notably, the training data were categorized into five classes based on the following Ts ranges: (-10~8C), (4~14 C), (10~20 C), (16~26 C), (22~50 C).

The output of this new precipitation area detection method shows an increased (decreased) precipitation area fraction over land and coasts (oceans) compared to the conventional method, bringing the estimates closer to DPR observations. Additionally, the correlation with the DPR rain flag improved relative to the conventional method, particularly along coastal zones. Furthermore, missed precipitation events in regions such as the western coast of Burma and the Western Ghats were reduced (see Fig. A1.1).

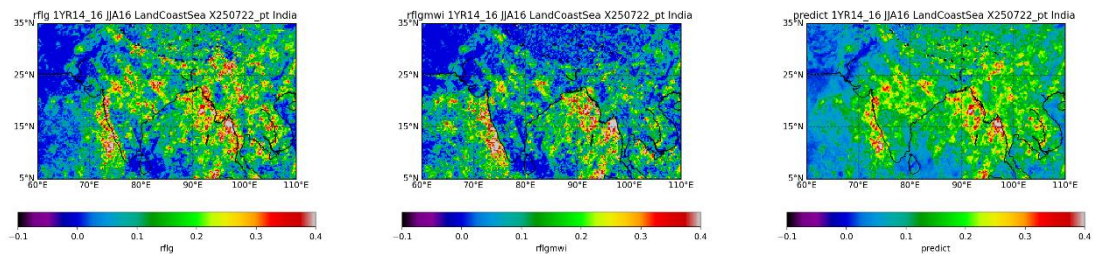


Fig.A1.1 Precipitation fraction average for June-August 2016 around India for (left) DPR rainflag, (center) retrievals from GMI TB with the conventional method, and (right) retrievals from GMI TB with the new precipitation detection method.

TBc correction using TBo over rain-free areas

The algorithm first classifies each pixel into land, coastal, and ocean classes. For each class, a correction value for the forward-calculated PCT36 and PCT89 of 0 mm/h is obtained from the area average of the PCTs for observed rain-free areas. In the ocean class, the correction values for the forward-calculated TB10v and TB18v of 0 mm/h were obtained in the same way.

Estimation of inhomogeneity of precipitation and CPF

We used high-resolution PCT89 for the estimation of Standard Deviation of Natural Logarithm of Precipitation (SDNLPR). First, we converted the PCT89 scattering signals into precipitation (Rain89) using LUTs for a prescribed value of SDNLPR (=1.0), and calculated the first guess of inhomogeneity (Sigma89) from Rain89 within TB10v FOVs. The LUTs for this inhomogeneity were used in the following retrieval procedures.

The algorithm estimated the FPD of each pixel (FPDpix) using GANAL atmospheric information and Rain89. A index of CPF for each pixel (CPFpix) was then estimated from the FPDpix, sigma89, and the 89 GHz polarization difference.

Retrievals using scattering signals

The algorithm utilizes PCT89 as the scattering signal for precipitation intensity retrieval. In this retrieval, a weighted average of the land/coastal/ocean ratios from the Look-Up Tables (LUTs) for each precipitation type is applied (the same approach is used for emission retrieval).

Over land and coastal regions, the algorithm corrects the retrieved precipitation intensity values via a Support Vector Machine (SVM) using physical variables related to CPF and FPD (namely, precipitation non-uniformity, the 85-GHz polarization difference, Ts, RH, and atmospheric stability). A comparison of the two-dimensional histograms of the retrieved precipitation values against the DPR precipitation intensity before and after the SVM correction reveals that the correction reduces the overall scatter (see Fig. A1.2).

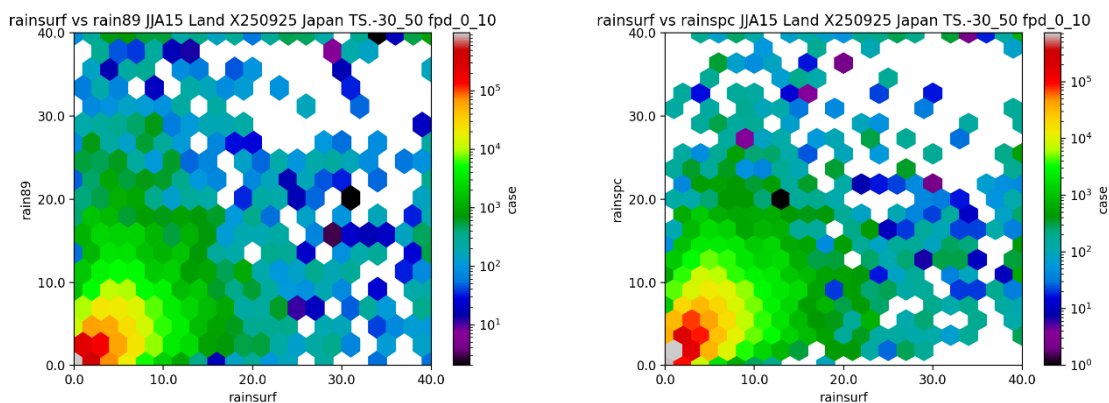


Fig. A1.2 2D histograms (DPR rainsurf vs GMI rain retrievals) for June-August 2015 over land around Japan for (left) retrievals before SVM correction and (right) retrievals after SVM correction.

Retrievals using emission signals over ocean

For the retrieval over ocean, emission signals at lower frequencies were available, in addition to the scattering signals. Following Aonashi et al (2009), the algorithm found the optimal precipitation over ocean by minimizing a cost function (J) that was a weighted sum of squares of differences between the observation and the forward calculation for TB10v and TB18v:

$$J = \sum_f \sum_{k=1}^{km} \frac{1}{2\sigma_f^2} \left\{ TB_f^o(\hat{y}_k) - TB_f^i[\hat{y}_k : r(\hat{x}_j)] \right\}^2, \quad (3)$$

where $r(\hat{x}_j)$ is the precipitation at point $\hat{x}_j$, $\hat{y}_k$ is the location of a TMI pixel, TB_f^o and TB_f^i represents the AMSR2 TBs and the FOV-averaged TBs calculated from $r(\hat{x}_j)$ at frequency f. σ_f is the standard deviation of the differences between TB_f^o and TB_f^i . Here $\sum_f$ represents summation for f=10 and 18 GHz, and $\sum_{k=1}^{km}$ is summation for AMSR2 pixels over ocean.

We adopted the scattering retrievals as the first guess for this minimization. For shallow precipitation with zero scattering retrievals, we employed precipitation retrieved from TB36v as the first guess.

However, this technique is not applied in low temperature regions (FLH<500m) because the emission signal is weaker.

In the forward calculation part, we calculate LUTs for homogeneous precipitation by incorporating physical variables of atmosphere and surface conditions except for sea surface temperatures from the Japan Meteorological Agency (JMA) Global Analysis (GANAL) and Japanese Reanalysis for Three Quarters of a Century (JRA-3Q) and precipitating cloud models based on TRMM observation etc. (Takayabu, 2008; Takahashi and Awaka, 2005) into the RTM program of Liu (2004). Sea surface temperatures are derived from JMA's Merged satellite and in situ data Global Daily Sea Surface Temperatures in the global ocean (MGDSST) data. AUTOSNOW, a daily global snow and ice flag from the National Snow and Ice Data Center (NSIDC) in the United States, as an indicator for snow cover and sea ice is also utilized. This program computed the TBc for the plane-parallel atmosphere by four-stream approximation. All the precipitation particles were assumed to be spherical, and the absorption and scattering coefficients as well as phase functions were computed from the Mie theory. We also calculate LUTs for orographic precipitation (see below for further details). We then derive LUTs for inhomogeneous precipitation from the above LUTs using the approximation of Aonashi and Liu (2000).

The retrieval part performs a detection of precipitation, a retrieval using scattering signals, and an over-ocean retrieval using emission signals. For the detection of precipitation, we adopt the methods of Seto *et al.* (2005), Kubota *et al.* (2007), and Kida *et al.* (2009) over land, coastal areas, and ocean,

respectively. In the retrieval using scattering signals, we employ dual frequency PCTs (at 37 and 85 GHz for TMI). We introduce an adjustment method using indices of frozen precipitation depth and surface temperature. In addition, we detect orographic precipitation areas where we use LUTs for orographic precipitation (Yamamoto and Shige, 2015). In the over-ocean retrieval using emission signals, we derive precipitation rate by minimizing a cost function for lower frequency, vertically-polarized TBs (10, 19, and 37 GHz for TMI) with the scattering retrievals as the first guess.

Orographic/nonorographic rainfall classification scheme

The orographic/nonorographic rainfall classification scheme is a revised scheme developed by Shige *et al.* (2013), Taniguchi *et al.* (2013), and Shige *et al.* (2014), Yamamoto and Shige (2014), and Yamamoto *et al.* (2017). The scheme consists of orographically forced upward motion w (m s^{-1}) and dTv/dz (K km^{-1});

$$w = \frac{Dh}{Dt} = u \frac{\partial h}{\partial x} + v \frac{\partial h}{\partial y} \quad (1)$$

$$Tv = T(1 + 0.61 \times q) \quad (2)$$

where $h(x, y)$ is the elevation (m) derived from 50-km averaged digital elevation map, u and v are upstream low-level tropospheric wind speed which was defined as averaging the wind field up to 2.5 km every 500 m from the surface within a distance of 0.5, Tv is virtual temperature, and T and q are upstream low-level tropospheric temperature and the water vapor mixing ratio, respectively. The orographic rainfall condition applied when thresholds w determined as follows and 15 g kg⁻¹ of q are exceeded:

$$w > 0.01 + 0.19 \times \text{weight}$$

$$\text{weight} = \begin{cases} 0 & \text{for } U < 10 \text{ m s}^{-1} \\ (U - 10) / 10 & \text{for } 10 \leq U \leq 20 \text{ m s}^{-1} \\ 1 & \text{for } U > 20 \text{ m s}^{-1} \end{cases} \quad (3)$$

In addition, the orographic rain condition is classified to the following 3 types (stable, neutral, and unstable).

$$\text{Stable: } -5.5 < dTv/dz$$

$$\text{Neutral: } -6.5 < dTv/dz \leq -5.5$$

$$\text{Unstable: } dTv/dz \leq -6.5$$

When both conditions are satisfied, the LUT switches from the original rain type to an orographic one.

The rainfall profile model for orographic rainfall was created with TRMM PR profile data under the orographic rain conditions, accumulated from 2003–2013 using the same method used to create rainfall profile models shown in this section. Convective and stratiform ratios (SPR) for orographic rainfall were also created under the same conditions. The minimum solid precipitation particle density for topographic rainfall was used.

Precipitation-size ice particle density for orographic rainfall is the smallest value of original ones.

Snowfall retrieval algorithm

The GSMaP_MWI snowfall algorithm is developed based on the approach of Liu and Seo (2013). That is, first, CloudSat/EarthCARE/GPM-DPR snowfall estimates and GPM GMI observed brightness temperatures are collocated to build an *a-priori* training database. This database is then used to train a machine-learning model for identification of snowfall occurrence (classification) and estimation of snowfall rate (regression). Detailed description of the snowfall algorithm is as follows.

We divide all conditions into 10 regimes as shown in Table A2.1 based on surface type (open water, land without snow cover, snow-covered land, sea ice, Greenland region and coast) and total precipitable water (TPW). Each regime has its own training database and brightness temperature to snowfall conversion model. At the retrieval step of the algorithm, a pixel's regime is first determined by its surface type and TPW, then the solution is determined by the conversion model that corresponds to the pixel's regime. A separate "Greenland" regime is designated because it is found that its frozen surface has very different microwave brightness temperature characteristics from those of other snow-covered surfaces. Observations over Antarctic are also grouped into this regime because of their similar surface characteristics.

Table A2.1 Surface and Atmosphere Regimes

Regime No.	Description
1	open water, dry (TPW <5.0 kg m ⁻²)
2	open water, moderate wet (TPW 5.0-7.0 kg m ⁻²)
3	open water, wet (TPW >7.0 kg m ⁻²)
4	land (no snow cover)
5	snow cover land, dry (TPW <2.5 kg m ⁻²)
6	snow cover land, moderate wet (TPW 2.5-5.0 kg m ⁻²)
7	snow cover land, wet (TPW >5.0 kg m ⁻²)
8	sea ice
9	over Greenland
10	coast

The *a-priori* database is used to train the inversion part of the algorithm; we built it based on satellite observations for global coverage, i.e., collocated satellite observations from CloudSat and EarthCARE CPRs, GPM DPR and GPM GMI.

CloudSat satellite was launched in 2006 and its CPR observations cover the latitudes between 82°S and 82°N at W-band. Analysis of in-orbit data has shown that the CPR's minimum detectable radar reflectivity factor is about -27 dBZ, sensitive enough to detect snowfall. However, the CPR has difficulties of measuring heavy snowfall due to hydrometeor's attenuation and non-Rayleigh scattering effects, which limits the upper bound of the CPR reflectivity to about 20 dBZ. Since the GPM core satellite was launched in 2014 and observations cover latitudes between 65°S and 65°N, the collocated CloudSat CPR and GPM GMI data cover the period of 2014 to 2020 and latitudes equatorward of 65°. The collocated dataset is described in Turk et al. (2021). Our matchups require the time difference within 15 minutes and the maximum pixel-center distance less than 3 km between GMI and CPR observations. Snowfall rate is derived from snowfall rate retrievals of the lowest

uncontaminated level in 2C-SNOW_PROFILE product (Wood et al. 2014).

EarthCARE satellite was launched in 2024 and is currently in operation. Similar to CloudSat, its CPR operates at W-band with a sensitivity of about -36 dBZ, and covers the latitudes between 82°S and 82°N. A collocated EarthCARE – GPM dataset was put together by Aoki et al. (2026). Because EarthCARE CPR does not have a standard product of snowfall rate, we use a radar reflectivity (Z) - snowfall rate (S) relation derived by Heymsfield et al. (2018):

$$S = 0.083e^{0.211dBZ}.$$

In deriving the above relation, data of CloudSat CPR radar reflectivity and 2C-SNOW-PROFILE snowfall rate from December 2007 through December 2008 are used. Currently, EarthCARE CPR – GPM GMI matchups from 2024 and 2025 are used in the *a-priori* database, although its volume will be increased as more observations accumulate.

The GPM DPR operates at Ku- and Ka-band with a minimum detectability of about 13 dBZ. The DPR derived snowfall can be used to compensate the weakness of CloudSat/EarthCARE CPR snowfall retrieval for heavy snowfall events. Using GPM DPR alone to estimate snowfall has its own weakness. Due to its low detectability, many light snowfall cases cannot be detected by the DPR radar. For this reason, we only use the DPR-GMI matchup data as “a supplement” to compensate the deficiency of CPR’s inability for measuring heavy snowfall events. For DPR snowfall rate, we use official surface precipitation rate product when our algorithm determines a pixel is under snow-favorable condition. Since DPR and GMI are onboard the same GPM Core satellite, number of collocated pixels are overwhelmingly larger than that of CPR-GMI matchups. Only one year (2018) of nadir DPR data are used for the *a-priori* database creation.

In the left panel of Fig.A2.1, we show the number distribution of matched data points as a function snowfall rates for the 3 sets of matchups. Note that points with 0 snowfall rate are not included in the plot which are about 75%, 60% and 93% of their corresponding total points, respectively, for CloudSat-GMI, EarthCARE-GMI and DPR-GMI matchups. Also noted that the data points from DPR-GMI matchups are several orders bigger than the other two sources, which is undesirable because it would result in the trained algorithm being disproportionally skewed to DPR-GMI matchup dataset if the three datasets are treated equally when training algorithms. This problem is handled by using a “sample weight” parameter in the XGBoost retrieval to adjust the weight of each sample point. After adjusting, the “effective” number of samples (i.e., number times weight) are the solid curves as indicated in the right panel of Fig.A2.1. As expected, CPR detects more light snow cases while DPR detects more heavier ones.

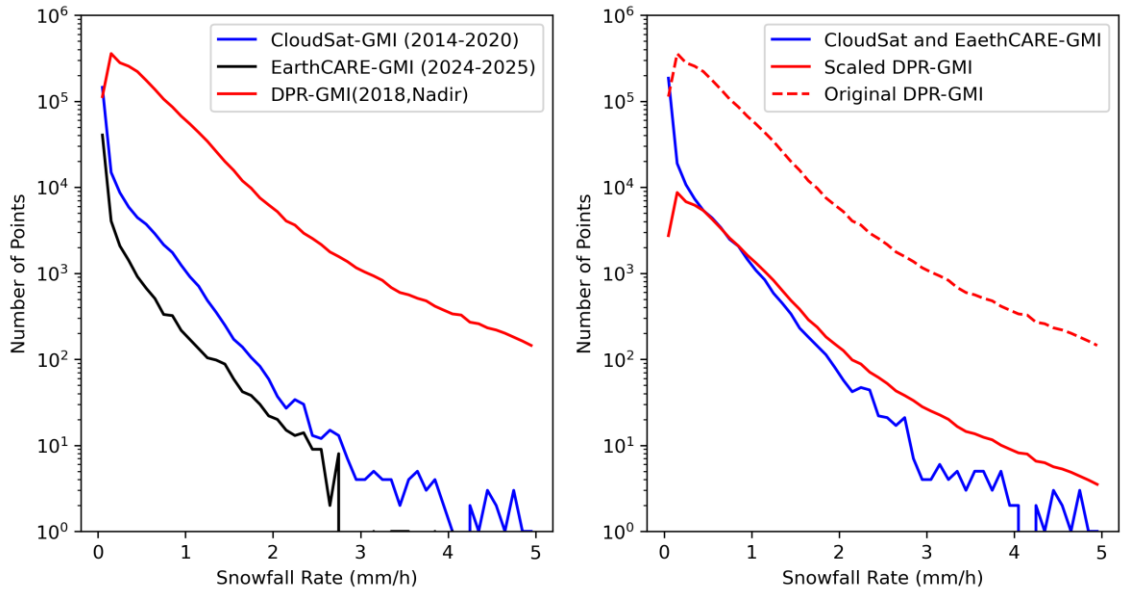


Fig.A2.1 (left) The number distribution of data points with snowfall rate in the training database from 3 matchup sources. (right) Same as left, but CloudSat and EarthCARE CPR with GMI matchups are combined, and DPR-GMI matchups are scaled. Note that values for 0 snowfall rate are not plotted.

In recent years, machine learning techniques have been increasingly used in many research areas including satellite remote sensing. To take the advantage of the rapid development of machine learning techniques, we apply the XGBoost (Extreme Gradient Boosting) method (Chen and Guestrin, 2016) to perform brightness temperature to snowfall rate conversion.

XGBoost is an ensemble machine learning method that builds many decision trees sequentially, where each tree learns to correct the errors made by the previous ones. During prediction (retrieval), the input variables (brightness temperatures) are passed through all the trees in the trained model. Each tree contributes a small score, and the scores are combined to produce the final prediction (snowfall rate). There are several hyperparameters in the XGBoost model that are tunable in the training phase for the best performance of retrieval. Because the training (building the retrieval model) phase and the prediction (performing retrieval) phase are separated, the computation time for retrievals is very short regardless the size of training dataset. There is an assignable “sample weight” parameter in the method which allows us to give a “weight” to each data point in the training dataset, effectively to control which data points are more important than the others when training the retrieval model.

For each regime listed in Table A2.1, we have developed two XGBoost models trained by the *a-priori* database: one for classification which separates precipitation and non-precipitation pixels, and the other for regression which calculates snowfall rate. The classification model requires observed brightness temperatures at and above 18 GHz, 2-m temperature, 2-m relative humidity and total precipitable water as input, and determines whether a pixel is precipitating or not. The regression model only requires brightness temperatures at and above 18 GHz as input, and outputs snowfall rate. Observational data at frequencies lower than 18 GHz are not used in the snowfall retrieval.

Finally, there are several hyperparameters can be adjusted in training the XGBoost models,

which are tunable for the best performance of the algorithms. Our test indicated that a large value of “number of estimators” with a small value of “learning rate” gives the best algorithm performance. Currently, we chose learning rate of 0.1 and 0.05 with “numbers of estimators” of 400 and 800 for classification and regression, respectively. All other hyperparameters are tuned accordingly for the best *AUC* (area under the curve) for classification and *RMSE* (root mean squared error) for regression. In future, these hyperparameters will be further tested for better algorithm performance and then implemented in later algorithm upgrades.