# AMSR UNIFIED RAINFALL

Algorithm Theoretical Basis Document

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# 1.0 INTRODUCTION

## 1.1 Objectives

The Unified AMSR algorithm uses intercalibrated L1R data provided by JAXA for AMSR-E (flown on the EOS-Aqua) and AMSR2 (flown on GCOM-W) to create a consistent precipitation data record from the two satellites. The passive microwave algorithm is designed to take advantage of previously constructed *a-priori* databases of observed precipitation structures and their associated brightness temperature signals from the GPM mission. These databases are then used in conjunction with Bayesian inversion techniques to retrieve surface rainfall and integrated liquid and ice water contents. The specific implementation is described below. While the AMSR Unified algorithm is grounded in the same physics as the GPM constellation algorithm for precipitation, the AMSR algorithm differs in its reference calibration standard and use of ancillary data.

## 1.2 Purpose

This ATBD describes the AMSR unified (AMSR-E & AMSR2) passive microwave rainfall algorithm. It corresponds to largely to GPROF 2014 as described in the literature (Kummerow et al., 2010, 2015). The main output parameters of the algorithm are enumerated in Table 1. This document identifies the physical theory upon which the algorithm is based and the specific sources of input data and output from the retrieval algorithm. The document includes implementation details, as well as the assumptions and limitations of the adopted approach.

**Table 1**. Key output parameters from the Level 2A Rainfall Product.

| **Pixel Information** | | |
|---|---|---|
| **Parameter** | **Units** | **Comments** |
| Latitude, longitude | Deg. | Pixel earth coordinate position |
| Pixel Status | None | Identifies pixels eliminated by QC procedures |
| Surface Type | None | land surface emissivity class/ocean/coast/sea ice |
| Quality Flag | None | Pixels w/o good $T_b$ matches in database |
| Surface Precipitation | mm/hr | Total Precipitation |
| Surface Rain | mm/hr | Liquid portion of the Total Precipitation |
| Convective Precipitation | mm/hr | Convective portion of the Total Precipitation |
| Cloud Water Path, Rain Water Path, Ice Water Path | Kg/m$^2$ | Integrated from retrieved profile |

### 1.3 Scope

This document covers the theoretical basis for the retrieval of liquid and solid precipitation from the AMSR unified algorithm. Section 2 contains the algorithm description while section 3 describes the output geophysical parameters in detail.

## 2.0 ALGORITHM DESCRIPTION

The AMSR2 instrument is a twelve channel, six/seven frequency total power passive microwave radiometer system. It measures brightness temperatures at 6.925/7.3, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz. Vertically and horizontally polarized measurements are taken at all channels. Brightness temperatures at L1R (calibrated, geolocated and remapped to a consistent resolution) are provided by JAXA. Neither the 6.925 GHz channel, nor the offset 7.3 GHz channel used to detect active interference sources are used for precipitation.

The AMSR2 radiometer algorithm is based upon a Bayesian approach in which the GPM satellite was used to create an *a-priori* databases of observed cloud and precipitation profiles as described for GPROF 2014 in Kummerow *et al*., (2010, 2015). The cloud profiles in the database are created by the GPM Radar/Radiometer "Combined" algorithm over oceans, and by the Dual Frequency Radar (DPR) Ku radar product over land. The only exception is for snow covered areas, where ground based radar derived snowfall rates are matched directly to AMSR2 brightness temperatures to constitute the *a-priori* database, and very light oceanic precipitation where the GMI itself is used to determine precipitation. The cloud water to rainfall threshold used by GMI is based on a CloudSat climatology that provides the probability of precipitation for every Sea Surface Temperature (SST) and Total Precipitable Water (TPW) bin in 1K and 1mm intervals respectively.

The geophysical parameters of the *a-priori* database derived from the GPM Combined products over oceans or Dual Frequency Radar products over snow-free land surfaces, are then used to compute the brightness temperatures corresponding to the AMSR2 channels, view angels and footprint resolutions. Any residual biases discovered in the match to GMI during the database creation are applied to the AMSR instruments also as the channels, view angles and footprints are relatively similar to GMI and biases tend to be small (generally 1-3K). The overall bias between GMI and the AMSR2 L1R Tb is obtained from the GPM projects that tracks differences as part of the sensor intercalibration project (Berg ref).

Other than the bias adjustment to account for the difference in overall calibrations of the AMSR2 L1R and the GPM GMI sensor, the database used in the unified AMSR algorithm is the same one used for GPM using global coverage from Sept. 1, 2014 to August 30, 2015 (Sept 1, 2014 to August 30, 2016 for the snow covered surfaces matched to ground based radars). Once this database of profiles and associated brightness temperatures is established for AMSR2, the retrieval employs a straightforward Bayesian inversion methodology. In this approach, the probability of a particular profile **R**, given $\mathbf{T_b}$ can be written as:

$$\Pr(\mathbf{R} \mid \mathbf{T_b}) = \Pr(\mathbf{R}) \text{ x } \Pr(\mathbf{T_b} \mid \mathbf{R}) \qquad (1)$$

where Pr(**R**) is the probability that a certain profile **R** will be observed and $\Pr(\mathbf{T_b} \mid \mathbf{R})$ is the probability of observing the brightness temperature vector, $\mathbf{T_b}$, given a particular rain profile **R**. The first term on the right hand side of Eqn. (1) is derived from the *a-priori* database of rain profiles established by the radar/radiometer observing systems described in Kummerow et al, 2014. The second term on the right hand side of Eqn. (1), is obtained from radiative transfer computations through the cloud model profiles. The formal solution to the above problem is presented in detail in Kummerow *et al*., (1996). In summary, the retrieval procedure can be said to compose a new hydrometeor profile by taking the weighted sum of structures in the cloud structure database that are radiometrically consistent with the observations. The weighting of each model profile in the compositing procedure is an exponential factor containing the mean square difference of the sensor observed brightness temperatures and a corresponding set of brightness temperatures obtained from radiative transfer calculations through the cloudy atmosphere represented by the model profile. In the Bayesian formulation, the retrieval solution is given by:

$$\hat{E}(R) = \sum_j R_j \frac{\exp\left\{-0.5\left(Tb_o - Tb_s(R_j)\right)^T (O+S)^{-1} \left(Tb_o - Tb_{s(R_j)}\right)\right\}}{\hat{A}} \qquad (2)$$

Here, $R_j$ is once again the vector of model profile values from the *a-priori* database model, $Tb_o$ is the set of observed brightness temperatures, $Tb_s(x_j)$ is the corresponding set of brightness temperatures computed from the model profile $R_j$. The variables $O$ and $S$ are the observational and model error covariance matrices, respectively, and $\hat{A}$ is a normalization factor. The profile retrieval method is an integral version of the well-known minimum variance solution for obtaining an optimal estimate of geophysical parameters from available information (Lorenc, 1986, for a general discussion).

While the mechanics of Bayesian inversions are fairly well understood, the AMSR code does not search the entire a-priori database but instead searches only a subset of profiles with coincident near surface temperature ($T_{2m}$) and Total Column Water Vapor (TCWV) within 16 distinct surface classes as described by Prigent and Aires ref. The surface database is static and given in Figure 1, except for the snow/no-snow classification which, like $T_{2m}$ and TCWV, is provided by the Global Modeling and Assimilation Office Forward Processing for Instrument Teams (GEOS-5 PF-IT) product produced at Goddard Space flight Center. Explicitly, the GEOS-5 PF-IT provides $T_{2m}$, TCWV, snow cover, and sea ice coverage. Because of the ancillary data requirements, GPROF runs in two steps. The pre-processor which ingests the AMSR L1R and the ancillary data and produces an intermediate file for use by the GPROF algorithm, and the GPROF algorithm code that reads the database profiles and computes the most likely precipitation rate.

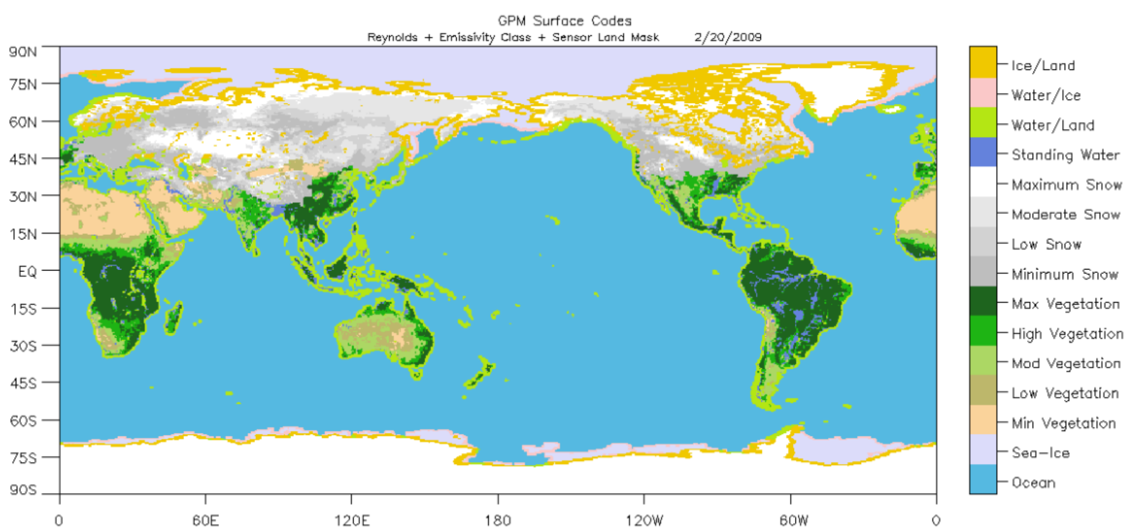
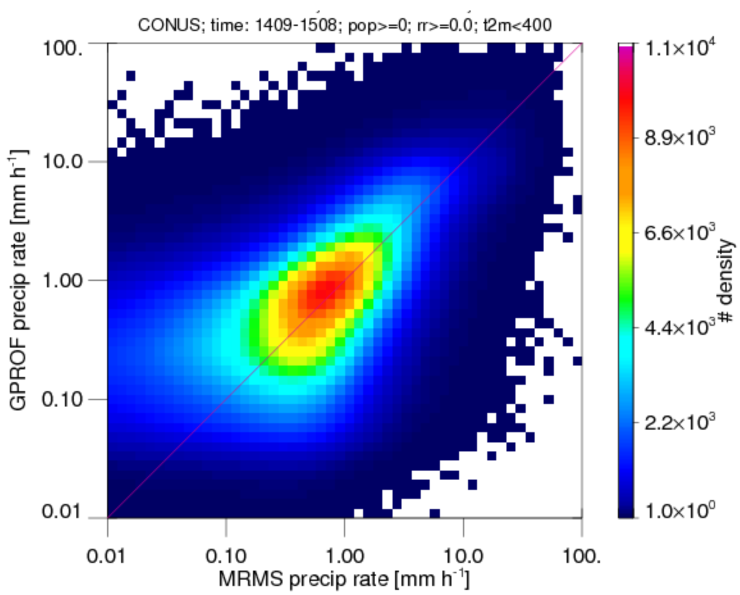



Figure 1 – GPROF static surface classes. If GEOS5 FP-IT suggests that no snow is present in a snow-covered class, the most recent vegetated class for that pixel is used. If, conversely, snow is indicated by GEOS5 FP-IT in a vegetated class, then minimum snow is assigned to that pixel. Sea ice is assigned dynamically based upon GEOS5 FP-IT.

## 2.1 Product Strength, weakness, and uncertainties

The performance of AMSR2 against surface radar observations derived from NOAA's Multi Radar/Multi Sensor System (MRMS) is shown in Figure 2. Biases are less than 10% and correlations are 0.6. The agreement is relatively good above 1 mm/hr. Large outliers are possible because of slight colocations errors due to the 53° view angle of the AMSR instruments.




Some weaknesses are known:

1. Shallow orographic precipitation remains a challenge for passive microwave sensors. Without an ice scattering signature, it is very difficult to distinguish shallow warm rain often associated with orographic precipitation from noise..
2. High latitude oceanic precipitation remains a problem. GPM radars do not have enough sensitivity to detect light drizzle while the AMSR instrument, by itself, has difficulties separating cloud water from drizzle. The results are thus uncertain in areas where much of the precipitation falls as drizzle.
3. Light snow fall is difficult to detect by AMSR as snow on the ground can look similar to light precipitating snow. This can be remedied with higher frequency channels (e.g. 166 and 183 GHz) but these are not available on AMSR.

# 4.0 Output Variables and Flags

## 4.1 Orbit Header Record Variable Specifications

```
type :: Date6
   integer(kind=knd2):: year       ! for file creation dates
   integer(kind=knd2):: month
   integer(kind=knd2):: day
   integer(kind=knd2):: hour
   integer(kind=knd2):: minute
   integer(kind=knd2):: second
end type Date6

type :: Date7
   integer(kind=knd2):: year       ! for scan date w/millisecs
   integer(kind=knd2):: month
   integer(kind=knd2):: day
   integer(kind=knd2):: hour
   integer(kind=knd2):: minute
   integer(kind=knd2):: second
   integer(kind=knd2):: millisec
end type Date7

type :: OrbitHdr                        ! 400 bytes /  file
   character(len=12) :: Satellite
   character(len=12) :: Sensor
   character(len=12) :: PreProcessorVersion
   character(len=12) :: AlgorithmVersion
   character(len=128):: ProfileDatabaseFile
   character(len=128):: RadiometerFile
   type(Date6)          :: FileCreationDate
   type(Date6)          :: GranuleStartDate
   type(Date6)          :: GranuleEndDate
   integer              :: GranuleNumber
   integer(kind=knd2):: NumScansGranule
   integer(kind=knd2):: NumPixelsScan
   integer(kind=knd1):: ProfStructFlag
   character(len=51) :: Spares
end type OrbitHdr


type :: ScanHdr                         ! 28 bytes per scan
   real            :: Sclat
   real            :: Sclon
```

```
    real              :: Scalt
    type(Date7)       :: ScanDate
    integer(kind=knd2) :: Spare
 end type ScanHdr

  type :: DataRec                          ! 88 bytes in the Datarec/pixel
    integer(kind=knd1) :: PixelStatus
    integer(kind=knd1) :: QualityFlag
    integer(kind=knd1) :: L1CQualflag
    integer(kind=knd1) :: SurfaceTypeIndex
    integer(kind=knd1) :: TotalColWaterVaporIndex  !model nint(tcwv)
    integer(kind=knd1) :: ProbabilityofPrecip      !0 or 100
    integer(kind=knd2) :: Temp2MeterIndex          !model nint(T2m)

    integer(kind=knd2) :: CAPE                     !model derived CAPE
    integer(kind=knd1) :: SunglintAngle
    integer(kind=knd1) :: Spare1

    real              :: Latitude
    real              :: Longitude
    real              :: SurfacePrcp
    real              :: FrozenPrcp
    real              :: ConvectivePrcp
    real              :: RainWaterPath
    real              :: CloudWaterPath
    real              :: IceWaterPath
    real              :: MostLikelyPrcp
    real              :: Prcp1stTertial
    real              :: Prcp2ndTertial


end type DataRec
```

## 5. 0 REFERENCES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