Table of Contents

1 Overview......................................................................................................................................2
2 AMSR-L1B......................................................................................................................................3
  2.1 Brightness temperatures – calibration and resampling.........................................................3
    2.1.1 Calibration.......................................................................................................................3
    2.1.2 Resampling......................................................................................................................3
  2.2 Sea Ice detection.....................................................................................................................4
  2.3 The Rain Indicator................................................................................................................4
  2.4 The retrieval algorithm..........................................................................................................5
    2.4.1 Overview........................................................................................................................5
    2.4.2 Basic approach................................................................................................................5
    2.4.3 Retrieval in rain – specifics..............................................................................................7
      2.4.3.1 Creation of the retrieval databases with modeled inhomogeneity............................8
      2.4.3.2 Assessing the inhomogeneity in the observed scene during the retrieval.............9
  2.5 Performance..........................................................................................................................9
    2.5.1 Representativeness of the sounding database.................................................................9
    2.5.2 General Performance of the algorithms..........................................................................9
    2.5.3 Comparison to estimates from other algorithms............................................................10
      2.5.3.1 Clear Air....................................................................................................................10
      2.5.3.2 Rain..........................................................................................................................11
3 L2A – The physical approach....................................................................................................13
  3.1 Retrievals of attenuation........................................................................................................14
  3.2 Retrievals of rain rate and precipitation backscatter.............................................................14
4 L2B – Corrected winds..............................................................................................................15
REFERENCES.....................................................................................................................................16
1 Overview

After Level 1A AMSR data (antenna counts) arrive at PO.DAAC from NASDA the process of retrieval of geophysical parameters and grouping with sigma_0 observations begins. This takes place in two steps and two level processors are involved - AMSR-L1B and a modified SeaWinds L2A. AMSR-L1B processor starts by converting the antenna counts into brightness temperatures. It then proceeds to retrieve geophysical parameters at each observation location.

The new L2A contains two sets of AMSR-based atmospheric correction to the scatterometer winds: the empirical correction and the physical correction. The physical correction groups the AMSR information as well as SWS sigma_0s into Wind Vector Cells Quadrants (WVCQ) and determines representative attenuation, precipitation backscatter and Rain Indicator value for each of them by using the AMSR-retrieved geophysical parameters that fall within the WVCQ. Finally, the L2B processor determines wind speed and direction for each WVC using the WVC-grouped sigma_0s and applying the AMSR-determined WVCQ atmospheric correction to the sigma_0s according to the quadrant in which they fall.

A flow diagram of the order of processing that takes place in AMSR L1B and L2A is given in Figure 1. Once the antenna counts have been converted into brightness temperatures (not shown in diagram) the processes of retrieval of geophysical parameters can begin.

Figure 1. Flow diagram of the order of processing in AMSR-L1B and L2A
2 AMSR-L1B

2.1 Brightness temperatures – calibration and resampling

2.1.1 Calibration

AMSR L1A data produced by JAXA was obtained for SeaWinds use via PO.DAAC. The AMSR L1A data contains Earth-located antenna measurements (counts) and other calibration data required to convert the counts into antenna temperatures and finally into observed brightness temperatures (Tb). As an aside, we found from comparisons of the mean AMSR Tb with WindSat Tb as a function of orbit position that a further calibration correction to the AMSR measurements was required to reduce ascending/descending biases that were found to be present if we used the JAXA calibration alone. Furthermore, using the JAXA calibration resulted in geophysical retrievals with large biases when compared to estimates from other instruments. After applying the determined by us calibration correction to the JAXA measurements we obtained geophysical retrievals that are in much closer agreement with retrievals from other instruments and algorithms.

2.1.2 Resampling

The next step is to construct new sets of observations that have multiple frequencies at the same spatial resolution. We refer to this process as resampling. It is needed since radiometers of different frequencies using a common antenna produce different gain patterns on the Earth surface (footprints with different spatial resolution). This complicates direct comparison of the measurements since the different frequency channels do not see identical scenes. Multifrequency observations cannot be used in the retrieval of geophysical parameters without a priori knowledge of their spatial variability (the well known non-uniform beamfilling problem).

We alleviate the problem by constructing several spatially-consistent sets. The Backus-Gilbert method (see Algorithm Theoretical Basis Document AMSR Level 2A Algorithm, Ashcroft and Wentz, 2000) can be used to bring the observations to a common resolution by either: i) spatial resolution enhancement (deconvolution) or ii) spatial averaging. The current algorithm employs spatial averaging since it permits noise reduction. The algorithm produces spatially consistent data sets, corresponding to the footprint sizes of the 6.9, 10.7, 18.7, 36.5 and 89 GHz channels.

The "constructed" or "effective" observations are linear combinations of actual observations that fall within the "constructed" gain pattern. The resampling (production of "constructed" observations) consists of combining neighboring actual observations \( \overline{Tb}_i \) with different relative weights \( a_i \).

\[
\hat{T}B = \sum_{i=1}^{21 \times 21} a_i \overline{Tb}_i \quad (1.1)
\]

where

\[
\overline{Tb}_i = \int Tb(\rho) G_i(\rho) dA
\]

or

\[
\hat{T}B = \int Tb(\rho) \sum_{i=1}^{21 \times 21} a_i G_i(\rho) dA
\]

In the above equations \( \rho \) indicates a particular location; \( G_i(\rho) \) is the antenna gain pattern at that location that corresponds to the \( i \)th observation; \( Tb(\rho) \) is the brightness temperature at the
location \( \rho \), and \( \hat{T}B \) is the reconstructed brightness temperature.

These sets of relative weights (coefficients) \( a_i \) can be obtained via the Backus-Gilbert method. This method approximates a given function as a linear superposition of other functions. A significant obstacle in applying the method is that calculation of weighting coefficients requires the computation and inversion of large matrices. Because of that, its real-time application is computationally prohibitive. However, \textit{a priori} information about the relative geometry of the actual observations allows the weighting coefficients to be calculated off-line. These weighting coefficients are unique for every position along the scan (depend on the relative geometry of the footprints) but do not vary from scan to scan. The real time resampling is then reduced to simply applying the weighting coefficients to the actual observations when the data is collected.

\textbf{2.2 Sea Ice detection}

The next step in the retrieval of geophysical parameters is to assure that only open water observations are considered. This requires excluding observations for which the radiometer's FOV (Field of View) has been contaminated by the presence of land (applying a land mask) or sea ice. Sea ice emissivity is very different from that of the open water. Because of that, failure to identify the presence of sea ice in the FOV of the AMSR instrument will lead to corruption of the AMSR-based retrievals of atmospheric parameters like the column-integrated water vapor and liquid water path.

The different radiometric characteristics of sea ice, as compared to that of open water, provide the means by which it's presence can be detected and it's type and concentration can be determined. We use the NASA Team sea ice algorithm (Cavalieri et al., 1984 and Gloersen and Cavalieri, 1986). The algorithm uses AMSR measurements of brightness temperatures at both vertical and horizontal polarization and at three different frequencies (18.7, 23.8 and 36.5 GHz). It should be noted that the algorithm uses "constructed" AMSR measurements, that are actual observations resampled to the spatial resolution of the 18.7 GHz channel.

\textbf{2.3 The Rain Indicator}

Cloud-model simulations of tropical storms (Hristova-Veleva, 2000) were used to develop a Rain Indicator that not only flags the observations for the presence of rain but also indicates the intensity of the rain. The Rain Indicator incorporates emission and scattering signals and borrows ideas from Liu et al., 1995. Microwave signals at the top of the atmosphere can be classified into two categories depending on how the microwave field interacts with the hydrometeors: i) emission signal that is dominant at lower frequencies and shows a warming signature in the presence of rain; ii) scattering signal that is dominant at higher frequencies and exhibits a cooling signature in case of heavy precipitation. Emission and scattering signals work favorably in different rainfall regimes with the emission signal working better in light rain conditions and the scattering signal working better in heavy rain cases. Hence, both emission and scattering signals have to be incorporated in the algorithms in order to cover the entire rainfall spectrum. The emission signal used here is a multichannel combination of Polarization Difference (PD) signatures defined as

\[
PD = \frac{TB_V - TB_H}{TB_{V\text{BackGround}} - TB_{H\text{BackGround}}}
\]

Strong emission in the atmosphere reduces the polarization difference of the radiation emitted from the highly polarized ocean surface. The polarization difference is, thus, representative of the atmospheric emission itself. Using PD instead of TBs to characterize the atmospheric emission has advantages because of lower sensitivity to background effects such as
atmospheric temperature and surface emissivity. The emission signal used here incorporates PD signatures not only at 19 and 23 GHz but also at 37 and 89 GHz to benefit from the higher sensitivity and better spatial resolution of the higher frequency channels. The emission signal is complemented with a scattering signal

\[ RI_{scattering} = 1 - \frac{(1+0.818) \times TB_{V85} - 0.818 \times TB_{H85}}{(1+0.818) \times TB_{V85\text{BackGround}} - 0.818 \times TB_{H85\text{BackGround}}} \]

to form the Rain Indicator (RI)

\[ Rain \ Indicator = a \times RI_{emission} + b \times RI_{scattering} + c \times RI_{scattering}^2 \]

used in this algorithm. This is done in order to increase the dynamic range of the Rain Indicator as already discussed. The Rain Indicator was found to vary between roughly -6 and +6. A value of \( RI < 0.5 \) indicates non-raining conditions.

### 2.4 The retrieval algorithm

#### 2.4.1 Overview

For retrieval of geophysical parameters in non-rainy conditions, we have adopted the method proposed by Wentz and Meissner, 2000. The algorithm uses linear regression to retrieve Sea Surface Temperature SST, near-surface Wind speed W, columnar Vapor V and columnar Liquid L.

We have developed a precipitation retrieval algorithm (with the corresponding retrieval databases) that addresses in a new way the issues of non-uniform beam filling and hydrometeor structure uncertainty. This involves the design and use of multiple retrieval databases, each representing a particular rain intensity and inhomogeneity regime. For each observational scene, the algorithm uses the specially developed Rain Indicator (RI) to determine the intensity and degree of homogeneity of the rain within the satellite's Field of View (FOV). With this information in hand, it then selects the appropriate retrieval database to estimate a number of geophysical parameters. All of the retrieval databases were built based on a large number of observed atmospheric structures.

Both the non-rainy and the rain retrieval algorithms use the same inversion technique – multiple linear regression. Below is a description of how some of the main ingredients of the algorithm were developed.

#### 2.4.2 Basic approach

Approximately 20,000 soundings from a number of island locations covering ~ 3 year period between 1978 and 1982 were used to develop the retrieval coefficients for both the rainy and non-rainy conditions. Columnar vapor and columnar cloud liquid water were diagnosed from the soundings following the same approach used by Keihm et al., 1995 (see below for details). Histograms of the distributions of columnar vapor and liquid for each of the two groups (not shown) reveal that the sounding database has quite an uniform distribution of water vapor across the range of expected values. At the same time, the columnar liquid has a rather different distribution. The number of cases is almost exponentially decreasing with the increasing value of columnar liquid. Indeed, this is the type of distribution noted in the literature. All this indicates two things: the soundings database is very comprehensive; the method developed by Keihm et al., 1995 and used here to diagnose the columnar liquid in the atmosphere is indeed appropriate.

Next, each sounding was used to create 50 different scenes by placing it over an ocean
surface with SST and W that were randomly varied in the ranges of -1 to 36 deg C and 0 to 30 m/s respectively. The so-created ensemble of scenes spans the expected range in all geophysical variables of interest (SST, W, V and L). However, the expected correlations between the surface and atmospheric parameters are left out. In nature such correlations exists. We chose not to incorporate them in the ensemble of scenes in order to allow for the retrieval of the usual and the unusual with equal probability.

Once the ensemble of scenes was created, a full radiative transfer model and a surface emissivity model were used to compute the TOA brightness temperatures at the AMSR frequencies and polarizations for each of the environmental scenes that are included in the ensemble. Noise was added to the simulated AMSR Tbs. This noise represents the measurement error. A database that contains the simulated brightness temperatures and the geophysical parameters of interest (SST, W, V and L) was created in that manner. Next, multiple linear regression was used to derive the coefficients that relate each of the geophysical parameters to the TOA brightness temperatures associated with them. The resulting coefficients provide the algorithm with a globally applicable estimates of SST, W, V and L.

Using linear regression as an inversion technique poses some problems due to the non-linearity of the Tb-geophysical parameter relationships. Indeed, the relationship between the geophysical parameters and the TOA brightness temperatures could be easily linearized only in a piece-wise manner. What that means is that the retrieval coefficients would vary from one sub-regime to another. Different sets of retrieval coefficients were computed for different sub-regimes of the geophysical parameters. During the real-time retrieval, the algorithm uses the different sets of coefficients in an iterative and step-wise manner described below.

**Step-wise approach.**

The step-wise approach retrieves different geophysical parameters in consecutive steps using different sets of channels. If various frequencies are to be used together to arrive at a certain geophysical parameter, all of the frequencies must be reduced to a common basis so that the measurements apply to the same area. This limits the resolution of the retrieved parameters to the spatial resolution of the lowest frequency used. Since the two lowest frequency AMSR channels (the 6.9 and the 10.7 GHz channels) are the ones that are most sensitive to the surface parameters (SST and W), the spatial resolution of the retrieved SST and W is limited to the resolution of these two channels. During the retrieval of SST and W one could simultaneously retrieve also V and L. However, such an approach is not desirable since achieving the highest possible spatial resolution is always of interest. Indeed, this is why we use the step-wise approach in which first SST and W are retrieved by making use of all channels. Next, V and L are retrieved by using only 18.7, 23.8 and 36.5 GHz channels all resampled to the 18.7 GHz footprint resolution. The already retrieved SST and W values are used in an iterative manner to specify the surface conditions regime (the sub-regimes in SST and W) in which the V and L are to be retrieved.

**Iterative approach - regime-specific**

The iterative nature of the algorithm stems from the fact that the relationship between the observed TOA brightness temperatures and the geophysical parameters of interest could be easily linearized only in a piece-wise manner. What that means is that the matrix that expresses the relationship between the brightness temperatures and the geophysical parameters of interest has elements that change with the regime of the geophysical parameters. To alleviate this problem, the following approach is adopted: when a geophysical parameter is retrieved for the first time, coefficients that were derived from the global unrestricted database are used. The initial estimate is used as guidance in selecting two sets of retrieval coefficients, derived from the restricted
databases, which included only values encompassing our first guess value. Then two new retrievals are obtained using the two restricted-set coefficients. A final estimate is then obtained by averaging the two restricted-set retrieved values, each one weighted by the relative distance between the initial estimate and the central value for each of the restricted sets. This procedure helps avoid discontinuities in the retrieved geophysical parameters. Using regimes helps reduce the uncertainty in the retrievals.

The flow diagram below illustrates the main features of the retrieval. The BASE approach is what we have adopted.

2.4.3 Retrieval in rain – specifics

The retrievals in rain follow the same basic approach as the retrievals in non-rainy conditions. The difference is that rain retrievals use three different retrieval databases, as compared to only one for non-rainy conditions. Please, note that each retrieval database contains the whole observed variety of surface conditions and columnar vapor distributions and, hence, is used to develop retrieval coefficients for each of the parameter sub-regimes. The three databases differ
in the intensity and spatial inhomogeneity of the rain that were assumed in their development. The value and the spatial variability of the Rain Indicator are used to determine the retrieval database that is most appropriate for a particular observed scene.

Another difference between the rain and non-rain retrievals is that in cases of more significant rain the sea surface conditions (temperature and wind speed) are not retrieved. Instead they are estimated from the surrounding non-rainy areas and these estimates are then used to specify the surface conditions in which the columnar liquid should be retrieved. This approach has been used by Wentz and Spenser, 1998. Using neighborhood observations instead of climatology should be superior since storms modify the surface conditions and they deviate from climatological values. Sensitivity tests that we have conducted showed that accounting for the specific surface conditions reduces the uncertainty in the retrieved total liquid.

2.4.3.1 Creation of the retrieval databases with modeled inhomogeneity

OFF-LINE - several databases (used for development of the retrieval coefficients) are constructed such that they have different degrees of inhomogeneity. There are several steps involved in that:

i) Creating the "scenes" - a large set of soundings (10 000) is used together with randomly varying surface conditions (SST and W) to construct a large number of scenes. The columnar liquid is diagnosed from the soundings in the following manner (Keihm et al., 1995): the radiosondes provided atmospheric profiles of temperature, pressure and dew point depression; vertical profiles of vapor density and relative humidity can be constructed from that; cloud liquid was deemed present in atmospheric layers for which the radiosondes indicated relative humidity > 94%; the cloud liquid density profile was then calculated by assuming that half the amount of water corresponding to the difference in absolute humidity between the cloud base and the cloud altitude in question was in the form of liquid. The factor 0.5 for computing liquid density is based on aircraft measurements of liquid density within stratus and cumulus clouds (see Keihm et al., 1995). After applying this cloud model to the radiosonde database it was found that about 20% of the soundings contained light to moderate rain (columnar value of < 8 mm) and about 2-3% of all soundings contained heavy rain. A threshold value was set to help partition the liquid between cloud and rain. At each level, liquid mixing ratio amounts that exceeded the cloud liquid mixing ratio threshold were considered to be rain. Mie scattering and Marshall-Palmer DSDs were considered for the rain. TOA brightness temperatures at the AMSR frequencies were computed for each scene. In addition the Rain Indicator was computed for each scene and included as part of the database.

ii) Creating the "observations" that contain inhomogeneity of rain inside the satellite Field of View (FOV) - three different databases were constructed that have different degree of inhomogeneity and/or rain intensity. These are the Lighter Intensity Homogeneous database (LIH), the Heavier Intensity Homogeneous database (HIH) and the Inhomogeneous database (INH). The "observations" that went into each of the three databases were constructed in the following manner: for each "observation" 9 different scenes are considered. The "observation" is constructed by linearly averaging the geophysical parameters over the 9 points. The brightness temperature of the "observation" is, instead, a weighted average of the 9 brightness temperatures with an approximate 19 GHz antenna pattern that gives the central observation a weight of 0.2 and gives a weight of 0.1 to all of the other 8 surrounding scenes. The three databases (LIH, HIH and INH) differ in the way the scenes that go into the averaging are selected. Each "observation" in the LIH database consists of scenes that have 0.5<RI<2.5; the HIH database consists of "observations" created only from scenes with 2.5<RI<6. Finally, the INH databases consists of "observations" that could have scenes
with any value of RI - the only requirement is that the central scene has a RI value that is greater than 0.5 and less than 6. (i.e. we only know that the central scene falls into the Rain category but we pose no restrictions on the surrounding 8 points. They could, and do, have no precipitation, light-to-moderate precipitation or heavy precipitation).

2.4.3.2 Assessing the inhomogeneity in the observed scene during the retrieval

ON-LINE - at each AMSR observation, the RI at that point is considered together with the RI of the 8 surrounding observations in determining which retrieval database (LIH, HIH or INH) is appropriate for performing the particular retrieval. With that information in hand, a multistage retrieval is performed in the same manner as already discussed.

2.5 Performance

Validation, so far, of the AMSR-based geophysical retrievals has shown very good results. Even more importantly, applying the AMSR-based atmospheric correction to the scatterometer observations has resulted in significant improvement of the scatterometer winds in rainy conditions (as shown in section 4). Up until now, rain contamination has been one of the most vexing problems for Ku-band scatterometer ocean wind data. All this shows the high potential of our current AMSR-based geophysical retrieval algorithm.

2.5.1 Representativeness of the sounding database

As discussed, the algorithm’s retrieval databases were constructed using a large number of atmospheric soundings collected in 20 different oceanic stations between 1978 and 1982. To test the representativeness of the sounding database, the algorithm was used to perform retrievals on a totally independent database constructed from 35,000 soundings collected from 20 completely different oceanic sites and over a three year period (1998 and 2001) 20 years later. The rms error for the independent database was essentially the same as that when the retrieval was performed on the original (retrieval database). This assures that the atmospheric structures that were used to build that retrieval database are, indeed, very representative.

2.5.2 General Performance of the algorithms

The overall performance of the algorithms is illustrated here by the retrievals of vertically integrated liquid that were produced using AMSR observations from 11 September, 2003. Presented are the retrievals over Super Typhoon MAEMI that was observed just south-west of Japan (Figure 2). The ability of the algorithm to resolve fine structures is clearly illustrated. Multiple precipitation bands and the storm's eye are quite clearly distinguishable. These structures are very different from the isolated convection to the south of the typhoon. Figure 2b illustrates the capability of the Rain Indicator to distinguish between rainy and non-rainy areas. Furthermore, a comparison to the retrieved columnar liquid (Figure 2a) shows that RI is quite successful in depicting the intensity and revealing the finer structures in the spatial variability of the precipitation. The statistics show that the Rain Indicator marks about 14% of all open ocean observations as containing light-to-moderate rain and only less than 1% as containing heavy rain. Furthermore, the spatial variability of the RI results in the following classification of the rainy areas: ~40.5% are classified as LIH (Low Intensity Homogeneous); ~ 58.2% are INH; only about 1.3% of all precipitating areas are classified as HIH.
The performance of the Rain Indicator as a rain-no rain flag was evaluated by comparing it to TRMM classifications. To do that, the Rain Indicator algorithm was applied to a limited number of TRMM (TMI) observations. The flagging rate of the Rain Indicator was in a very good agreement with that of the TRMM algorithms - 93.72 % agreement in identifying rainy conditions and 96.66 % agreement in identifying non-rainy conditions, thus bring the overall rate of having the two independent rain flags in agreement to 96.51.

2.5.3 Comparison to estimates from other algorithms

All geophysical retrievals have been compared to estimates from other algorithms and the comparisons are quite satisfactory.

2.5.3.1 Clear Air

The performance of the algorithms in non-rainy conditions is illustrated by the error matrix in Figure 3. The AMSR geophysical retrievals compare very well to retrievals from other instruments (F15 and SeaWinds winds). This implies that: i) the brightness temperatures are well calibrated; ii) The Forward model we use is now correctly tuned. iii) The retrieval algorithms are working properly. Hence, we can have confidence in the general approach.
Rain estimates are associated with significant sources of uncertainty. The major ones are: i) the uncertainty in the spatial variability of rain inside the sensor’s FOV – the Beam Filling (BF); ii) the uncertainty in the cloud versus rain partitioning; iii) the unknown Drop Size Distributions (DSDs). In addition, rain rate estimates carry the additional uncertainty in the assumed by the algorithm rain column height H.

All of these factors are geographically and/or seasonally dependent and some are dependent upon the type of precipitation (convective versus stratiform). For example: convective and stratiform precipitation types have different beam-filling, different DSDs and different cloud versus rain partitioning. Geographically dependent are H, DSD and BF. Seasonally dependent are: H, DSD, BF.

We have performed comparison versus estimates from F15. The specifics of the comparisons are: i) time difference within 30 min; ii) AMSR total liquid (LWP) and water vapor (V) averaged to a 0.25 degree grid; iii) F15 rain rate and cloud liquid water converted to total liquid (LWP).

For this particular comparison there are some additional sources of additional uncertainty: i) Allowing for more than 10 min time difference. Please, note: the life cycle of individual convective cells is on the order of 20-30 minutes. Hence, allowing for more than 10 min time
difference should result in higher standard deviation; ii) Converting rain rate (RR) to rain mass (RM) - we used a relationship published in the literature – not sure how it compares to what went into the F15 RR determination; iii) Using grid averages for the conversion. However, RR to RM relationship is non-linear. Hence, using averaged RR to obtain the average RM will not produce the same result as if individual RR were converted to RM and then averaged; iv) F15's RR_{max} = 25 mm/h – imposes an upper limit on the computed by us LWP from F15.

Comparison of Water Vapor in rainy conditions

Figure 4. Comparison of water vapor estimates in rainy conditions. Top two graphs show the mean F15 values for each 1mm bin of the JPL values. Bottom two graphs are the same style as the graphs in Figure 3.
Considering all the uncertainties that are associated with rain retrievals in general and with rain estimate comparisons we can conclude that the AMSR and the F15 estimates of LWP are in a very reasonable agreement.

The comparison shows that overall the two independent estimates of LWP show a monotonic relationship. This is necessary to allow for a successful empirical correction of the atmospheric effects.

3 L2A – The physical approach

The scatterometer signal that propagates through rain is impacted in three ways: the signal is attenuated by the rain, clouds and vapor in the atmosphere; the signal is augmented by the backscatter from rain droplets; finally, the signal is augmented by the rain-induced roughening of the ocean surface (“splash”). It is, thus, very important to properly account for the three rain effects and to correct the sigma0 measurements before they are used to estimate wind vectors.

The first and second components of the atmospheric impact, the attenuation and precipitation backscatter are estimated inside the L2A processor based on the AMSR retrievals of columnar liquid water, water vapor and sea surface temperature. WVCQ representative values are computed as linear averages of the estimates from all AMSR observations that fall within the quadrant.

The third rain effect, the rain-induced surface roughening, is accounted for during the L2B processing. The “splash” is computed as a function of the rain rate (the precipitation backscatter in L2A).
3.1 Retrievals of attenuation

Two-way nadir attenuation by vapor, ozone and liquid is estimated as a function of the AMSR-derived geophysical parameters. The approach is similar to the one described by Wentz and Meissner, 2000. The coefficients that relate the different attenuation components to the geophysical parameters were derived using the retrieval databases. In this process, a radiative transfer model was used to compute the attenuation at 13.4 GHz which was then related to the corresponding amounts of vapor, liquid and SST.

The two-way nadir attenuation is converted to 2-way path integrated attenuation by a standard accounting for the incidence angle of the scatterometer observations.

3.2 Retrievals of rain rate and precipitation backscatter

As already mentioned, in rainy conditions, the AMSR algorithms for retrieval of geophysical parameters provide estimate of the vertically integrated liquid. This liquid includes both cloud liquid water and rain. The next step in the current algorithm is to provide the partitioning between the two components and to compute the rain rate. Estimating rain rate from the columnar liquid, to which the satellite is sensitive, is an interesting problem in itself since this is the parameter that the atmospheric community is most familiar with. However, rain rate estimates are beneficial in another way. While, the cloud liquid water contributes only to the atmospheric attenuation and plays no role in generating atmospheric backscatter at the frequency of the scatterometer instruments, the rain contributes to all three components of atmospheric impact on the scatterometer observations: attenuation, backscatter from the rain, surface roughening that is proportional to the rain rate. Hence, any attempt to correct the scatterometer signal for atmospheric impact should include estimation of the rain rate as well.

We do the partitioning between cloud and rain in a manner that is different from some of the published studies (e.g. Wentz and Spencer, 1998) in which the relationship between the cloud and the rain takes on a parameterized form. Instead, we do the partitioning on a case-by-case basis in the following manner. We start with the fact that the columnar liquid $L$ is equal to the sum of the columnar cloud liquid $C$ and the columnar rain $R$. We then make the assumption that the columnar liquid attenuation $A_{\text{tot}}$ is equal to the sum of the columnar cloud attenuation $A_{\text{tot}C}$ and the columnar rain attenuation $A_{\text{tot}R}$.

$$A_{\text{tot}} = A_{\text{tot}C} + A_{\text{tot}R} \quad (1)$$

In developing the AMSR algorithms we have established relations that allow us to compute the columnar attenuation by cloud and that by total liquid as functions of the estimated cloud and total liquid. To estimate the columnar attenuation by rain we use a DSD-dependent relationship between the rain rate and the associated attenuation as determined by Haddad et al., 1997. After making the DSD assumptions and substituting all the known parameters in (1), we come up with an equation where the only unknown is the rain columnar mass. From there, the rain rate can be estimated using the assumed DSD and the height of the rainy column which we infer from the retrieved SST in a way similar to the one described in Wentz and Spenser (1998).

The advantage of our approach is that it allows for making scene-specific DSD assumptions, thus accounting for the existing differences in DSD parameters between convective and stratiform precipitation. Sensitivity tests have shown that this new approach produces better results than when a single parametric relationship is used to perform the cloud-versus-rain partitioning.

The radar reflectivity at 13.4 GHz can be easily computed once the rain rate has been
determined and the DSD assumptions have been made. The radar reflectivity is then used to compute the volumetric precipitation backscatter. In this process, the attenuation of the intervening layers is also accounted for.

4 L2B – Corrected winds

Applying the AMSR-based atmospheric correction to the scatterometer observations has resulted in significant improvement of the scatterometer winds in rainy conditions. Up until now, rain contamination has been one of the most vexing problems for Ku-band scatterometer ocean wind data. The presence of rain in the scatterometer FOV often results in the retrieval of winds that are erroneously oriented in a cross-track direction (at ~90 and ~270 degrees) and have higher speed than both buoy and global model winds suggest. Figure 6 shows the distributions of the uncorrected scatterometer winds (in black) and compares them to the distributions from two global models (two shades of green) and two versions of AMSR-corrected winds (red for physical correction and cyan for empirical). The effect of the rain contamination on the uncorrected scatterometer winds is illustrated by how the black curve deviates from the two green curves as the amount of the rain increases inside the satellite's FOV (from top to bottom). It is obvious that applying the AMSR-based corrections (red and cyan curve) results in wind distributions that are free from the rain-induced artifacts. All this shows the high potential of our current AMSR-based geophysical retrieval algorithm and validates the approach that we took.

Figure 6. Distribution of wind direction (left column) and speed (right column) for three different categories of retrieved total liquid: non-rainy areas (top row); medium intensity rain (middle) and high intensity rain (bottom). Shown are five different fields: ECMWF and NCEP model fields are shown in two shades of green; uncorrected scatterometer winds are shown in black; two different corrections based on the AMSR retrievals are shown in red (the physical correction) and cyan (the empirical correction).
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