Over-Ocean Rainfall Retrieval from Multisensor Data of the Tropical Rainfall Measuring Mission. Part II: Algorithm Implementation

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ABSTRACT

The objective of this paper is to establish a computationally efficient algorithm making use of the combination of Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) and precipitation radar (PR) observations. To set up the TMI algorithm, the retrieval databases developed in Part I served as input for different inversion techniques: multistage regressions and neural networks as well as Bayesian estimators. It was found that both Bayesian and neural network techniques performed equally well against PR estimates if all TMI channels were used. However, not using the 85.5-GHz channels produced consistently better results. This confirms the conclusions from Part I. Generally, regressions performed worse; thus they seem less suited for general application due to the insufficient representation of the nonlinearities of the TB–rain rate relation. It is concluded that the databases represent the most sensitive part of rainfall algorithm development.

Sensor combination was carried out by gridding PR estimates of rain liquid water content to 27 km × 44 km horizontal resolution at the center of gravity of the TMI 10.65-GHz channel weighting function. A liquid water dependent database collects common samples over the narrow swath covered by both TMI and PR. Average calibration functions are calculated, dynamically updated along the satellite track, and applied to the full TMI swath. The behavior of the calibration function was relatively stable. The TMI estimates showed a slight underestimation of rainfall at low rain liquid water contents (<0.1 g m⁻³) as well as at very high rainfall intensities (>0.8 g m⁻³) and excellent agreement in between. The biases were found to not depend on beam filling with a strong correlation to rain liquid water for stratiform clouds that may point to melting layer effects.

The remaining standard deviations between instantaneous TMI and PR estimates after calibration may be treated as a total retrieval error, assuming the PR estimates are unbiased. The error characteristics showed a rather constant absolute error of <0.05 g m⁻³ for rain liquid water contents <0.1 g m⁻³. Above, the error increases to 0.6 g m⁻³ for amounts up to 1 g m⁻³. In terms of relative errors, this corresponds to a sharp decrease from >100% to 35% between 0.05 and 0.5 g m⁻³. The database ambiguity, that is, the standard deviation of near-surface rain liquid water contents with the same radiometric signature, provides a means to estimate the contribution from the simulations to this error. In the range where brightness temperatures respond most sensitively to rainwater contents, almost the entire error originates from the ambiguity of signatures. At very low and very high rain rates (<0.05 and >0.7 g m⁻³) at least half of the total error is explained by the inversion process.

1. Introduction

Building on the analysis of retrieval databases presented in the first part of this paper, an intercomparison of different retrieval techniques is carried out to investigate whether the database or the inversion represent the most vulnerable parts of passive microwave rainfall retrieval. From the experience of various Special Sensor
Microwave/Imager (SSM/I) rainfall retrieval algorithm intercomparisons (e.g., Ebert and Manton 1998; Smith et al. 1998), there was no clear evidence that a particular algorithm type outperformed others. Compared to ground-based radar observations, there were physical, physical–statistical as well as purely empirical algorithms that performed consistently better than other techniques of similar types. Since all algorithms differed in both training dataset and inversion method, no clear indication of a superior approach was provided.

This paper covers the intercomparison of different retrieval techniques trained on the same data. Among these are regressions, neural networks, and Bayesian estimators. The latter were developed using empirical orthogonal functions (EOFs) with and without 85.5-GHz channels. That these channels may deteriorate database representativeness and thus retrieval performance was concluded from the results of Part I of this study (Bauer 2001).

The paper also presents a new approach for the combination of measurements from the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) and the precipitation radar (PR) (Kummerow et al. 1998). The TMI standard product 1B11 version 5 (V.5) contains brightness temperatures at 10.65, 19.35, 21.3, 37.0, and 85.5 GHz on a conical scan. All channels are available with both vertical and horizontal polarization while the 21.3-GHz channel is only vertically polarized. In this study, navigated profiles of attenuation corrected reflectivities at 13.8 GHz and the rain-type classification from PR level-2 product 2A25 (V.4 and V.5) were used. Between versions 4 and 5, a change of retrieval algorithm was implemented (Kozu et al. 1999). Algorithm performance is also evaluated against product 2A12 (V.5), which contains profiles of hydrometeor water/ice contents retrieved from TMI with the technique of Kummerow et al. (1996).

In contrast to TRMM standard TMI–PR product 2B31 (Haddad et al. 1997) our technique relies primarily on a stand-alone TMI retrieval. This has the advantage of being transferrable to other sensors such as the SSM/I, the Advanced Microwave Scanning Radiometer, or other radiometers being represented in the future Global Precipitation Mission. The PR observations are used for comparison with the TMI estimates on identical grids and reference altitudes over their common swath (≈220 km). This feeds a dynamically updated database that is used to calibrate the TMI estimates over the full swath (≈760 km).

The idea of using the PR rainfall estimates as a calibration tool rather than as an input for the retrieval procedure itself has two major advantages. First, the problem of different viewing geometries of TMI and PR is avoided. This would require either the accumulation of a three-dimensional data space with PR profiles within the TMI effective field of view (EFOV) or a strong simplification of the match-up geometry. The latter would average out the spatially well-defined information available from the PR in the first place. Second, usage of PR data as a retrieval variable restricts the application of the combined algorithm to the narrow swath where both data sources are available. Missing this information on the wide swath would produce algorithm instability compared to a simple rain rate dependent calibration. Again, a calibration of this kind may be easier transferred to other sensors if it is globally stable.

Calibrating TMI retrievals with PR estimates is based on the assumption that the PR estimates are unbiased. A by-product of the calibration is the estimation of the common uncertainty, that is, the remaining random “error.” This is very important information, for example, when these products are assimilated in forecast models (e.g., Marécal and Mahfouf 2000).

Following Part I (Bauer 2001), several inversion techniques were implemented to compare the dependence of retrieval performance versus retrieval database. These techniques are introduced in section 2. Section 3 presents the layout of the adjustment of TMI retrievals by PR standard product output. In section 4, all algorithms are evaluated in a number of case studies leading to conclusions and a summarizing discussion in section 5. Figure 1 gives an overview of algorithm setup and evaluation.

2. TMI retrievals

An important issue to be covered in this study is the choice of variables to be retrieved and those used as predictors. The strong correlation among passive microwave channels can be used to reduce the dimension
of the predictors. Seven to nine brightness temperatures (TBs) may be replaced by two to three EOFs. These represent about 98% of the total variance (Bauer 2001). Even though liquid water and ice contents in adjacent layers are also correlated, the retrieval of tropospheric profiles of hydrometeor contents of different species from the available channels is an ill-posed problem. For unconstrained retrievals, rather strong assumptions have to be made on the statistical distributions of those parameters that mainly drive the signal. In case of rainfall retrievals, only little information is available for constraining radiometer algorithms. Even collocated radar estimates require assumptions on particle size distributions and attenuation correction. They also have to be made comparable to radiometer estimates, as already mentioned.

An approach focused on the plain information content in simulations/observations would have to reduce the number of retrievable variables significantly. These had to be bulk cloud properties rather than profiles and TBs (EOFs) rather than statistical (e.g., spatial TB variability) or climatological information. Of course, this method would have less information available for solving the ambiguity of the parameter–TB relationship, but it would also suffer less from possible errors in this information. The issue of database representativeness was extensively discussed in Part I (Bauer 2001). Given the few available high-resolution mesoscale cloud model experiments, TMI observations were covered by simulations to 80%–99% depending on lower rain intensity thresholds.

The variables selected for the retrieval in this study are quantities that are as closely as possible related to the primary signal to reduce the previously mentioned underdetermination. For this reason, the rain liquid water content \( w \), and not the rain rate, was chosen as a retrieval parameter because it is volume emission (and scattering) that determines the signal at the TMI frequencies. The uncertainty of size spectra under local conditions affects the rain rate more than the liquid water content due to the dependence on drop terminal fall velocity. Since we aim at the comparison and combination of quantities obtained from both passive and active microwave measurements, the radar data were also analyzed in terms of water contents. Backscattering is also much better correlated to rainwater content than to rain rate. For the allocation of rainwater content to a certain level, an evaluation of the TMI weighting functions was carried out. Even though the weighting functions at window frequencies are rather broad and strongly variable, the maximum of the weighting function provides a decent measure for the location of the bulk emission at lower frequencies. Instead of the maximum, the center of gravity of the weighting function at 10.65 GHz, \( z_C \), was chosen. This avoids ambiguities produced from multiple maxima if the absolute maximum of the weighting function is chosen. Here \( z_C \) is defined as (Bauer et al. 1998)

\[
z_C = \left[ \int_{z_T}^{x_T} C^*[T(z), \mu] \, dz \right]^{-1} \int_{z_T}^{x_T} zC^*[T(z), \mu] \, dz,
\]

with the normalized weighting function, for example, for the upward directed beam (Mugnai et al. 1993)

\[
C^*[T(z), \mu] = \frac{k(z)}{\mu TB} J[T(z), \mu] \exp \left[ - \int_{z}^{x_T} k(z) \, dz \right].
\]

The altitude of the top of the atmosphere of the upward and downward directed slant paths in our plane-parallel radiative transfer model (Bauer 2001) are denoted by \( z_T \) and \( -z_T \), respectively; \( J[T(z)] \) is the radiation source function at level \( z \) with temperature \( T \) and the cosine of the observation zenith angle \( \mu = \cos \theta \); and \( k(z) \) denotes the extinction coefficient. The conversion of \( w(z_C) \) to rain rates at the surface has to be carried out, if desired, accounting for size distribution shape as well as evaporation depending on \( z_C \). Figure 2 shows the frequency
distribution of $z_{CG}$ at 10.65 GHz from the simulations introduced in Part I. All cases show $z_{CG} < 1$ km so that a close relationship to near-surface rainfall rate with negligible evaporation may be assumed. Negative $z_{CG}$ stems from partial EFOV coverages with rain where the reflected beam dominates the total signal. The distribution shows two maxima near $\sim 0.3$ and 0.7 km, which correspond to shallow convective/stratiform and deep convective systems. All retrieval techniques introduced below will provide $z_{CG}$ and rain liquid water content $w$ at $z_{CG}$. For the gamma-type raindrop size distribution with shape parameter $\gamma = 1$ as used in the simulations (Bauer 2001), a conversion to rain rate is possible with $RR = 20.95 w^{1.12}$ where $[RR] = \text{mm h}^{-1}$ and $[w] = \text{g m}^{-3}$. The error of this fit is well below 1% for $w \in [0, 2 \text{ g m}^{-3}]$.

In summary, the choice of $z_{CG}$ and $w(z_{CG})$ as retrieval variables best represents the local weighting function variability with respect to the hydrometer profiles. It also allows a much closer comparison to $w$ estimated from radar observations accounting for the vertical reflectivity variations. The physical relation between rainwater contents and microwave radiation emission and scattering is more direct than for rain rates. The range of $z_{CG}$ at 10.65 GHz is close enough to the surface that $w(z_{CG})$ can be considered a near-surface variable directly transferable to a rain rate.

### a. Regressions

The advantage of regression-type retrievals is clearly their simple development as well as their computational efficiency. For rainfall retrievals, however, the frequency dependent nonlinearity of $w$–TB relations causes problems. With increasing noise contributions at lower rain rates (through background emission), the regression trends to return the average value of the sample, thus it generally overestimates rain rates in weak situations. Regressions also capture less well the frequency dependence of the nonlinear and nonunique $w$–TB relation since all frequencies are used at the same time. For completeness, a regression approach is presented here that includes a linearization of the $w$–TB relation and employs a multistage regression depending on cloud opacity.

The basic estimator for cloud opacity is the normalized polarization difference (NPD; e.g., Petty 1994), which relates the observed polarization difference at a given frequency $i$ to its value in cloud-free situations:

$$\text{NPD}_i = \frac{\TB_i - \TB_{i,\text{clr}}}{\TB_{v,\text{clr}} - \TB_{h,\text{clr}}}. \quad (3)$$

Indices “v” and “h” refer to vertically or horizontally polarized measurements of TB. For the simulations, a clear-sky calculation is carried out while from the measurements the most recent cloud-free observation is taken. To account for nonlinearities, the vector of input variable was chosen to contain $\TB_i = [\text{NPD}, \text{NPD}^2, \TB_{i,\text{v}}, \TB_{i,\text{h}}]$ for 10.65, 19.35, 37.0, and 85.5 GHz. The advantage of using NPDs is the lower sensitivity to background effects such as atmospheric temperature and surface emission. The reduction in sensitivity to rainwater at a specific frequency is roughly represented by NPD approaching zero. This fact is used to carry out a weighted summation over four regressions only including those frequencies for which $\text{NPD}(i) > 0$ at 10.65, 19.35, 37.0, and 85.5 GHz, respectively:

$$P = \frac{\sum_i \text{NPD}_i a_{i,0} + \sum_{j=1}^{n_i} a_{i,j}\TB_{i,j}^j}{\sum_i \text{NPD}_i}, \quad (4)$$

thus $n_i = 4, 8, 12, 16$. This ensures that once NPD$_i$ becomes zero, the regression that includes NPD$_i$ is not used.

From the simulations, the merged database described in Part I (including 85.5-GHz channels) serves as input. Regression coefficients for $w$ and $z_{CG}$ were derived from a subset of the database where the desired quantities are equally distributed over their dynamic range ($z_{CG} \in [0, 2 \text{ km}], w \in [0, 2 \text{ g m}^{-3}]$). The liquid water content is retrieved as $\log_{10}(w)$ to increase the resolution over the dynamic range according to the logarithmic probability distribution of rain rates.

### b. Neural networks

For rainfall retrievals there were only a very few attempts (e.g., Tsintikidis et al. 1997) to use neural networks (NNs). This is partly because it is much more difficult to generate a training dataset that covers all possible observations since NNs have problems extrapolating from the training data. Neural networks have the advantage over regression-type techniques that nonlinearities in the TB–parameter relations are more efficiently captured.

The NN design employed here is fairly simple and was carried out using the free-ware Stuttgart Neural Network Simulator. A feed-forward architecture with backward propagation during the training phase was chosen due to its common application range. The same input parameters that serve the regressions were used (without the quadratic terms) with two hidden layers and a single output node for either $w$ or $z_{CG}$. As in (4), a classification into four different training datasets was carried out, thus the number of input nodes are $n_i = 2, 4, 6, 8$ for NPD, and horizontally polarized TB, at 10.65, 19.35, 37.0, and 85.5 GHz, respectively. The $w$ or $z_{CG}$ were also equally distributed and normalized to numbers between 0 and 1. Finally, a weighted sum as in (4) was
calculated because the \(i\)th training dataset only contains data where \(NPD_{\text{i}} > 0\).

c. Bayesian estimators

Both 2A12 and 2B31 TRMM standard algorithms rely on the Bayesian estimator, which provides the most probable solution for a given TB vector (including PR reflectivity profiles in the case of 2B31). The actual procedure requires an a priori probability distribution of possible solutions as close as possible to real observations. Theoretically, this probability distribution is multivariate, representing the correlation of all quantities (surface, atmosphere, observation conditions) as they occur in the atmosphere. The maximization of probability involves a minimization of a cost function giving a measure for the deviation of the actual guess from a previous estimate in parameter and observation space. This requires 1) a stable minimization technique that accounts for the possibility of multiple minima during the optimization and 2) the necessity of a forward operator providing simulations of observations using the actual state vector. Evans et al. (1995) chose the clean, but computationally more expensive, way by creating a subset of a global a priori database with TBs near the observations and a subsequent optimization of the cost function. Olson et al. (1996) and Kummerow et al. (1996) introduce the assumption that the global database itself represents the correct probability distribution of cloud profiles and surface conditions. Then, the optimization procedure reduces to an integration over the whole database, giving weights to each simulation according to their distance from the \(i\)th observations in TB space:

\[
E(P_i) = \sum_{i=1}^{n} P_i \exp[-0.5J(P_i)]
\]

\[
J(P_i) = [TB_o - TB_s(P_i)]^T [O + S]^{-1} [TB_o - TB_s(P_i)].
\]

Here \(E(P)\) denotes the expected state vector, \(TB_o\) the observed TBs, the forward operator is \(TB_s\), and observation and simulation error covariance matrices are given by \(O\) and \(S\), respectively. Due to the lack of better knowledge, the latter are usually assumed to comprise only uncorrelated radiometric noise and no simulation errors (e.g., Olson et al. 1996).

Here, the approach of Kummerow et al. was used with some important modifications.

- As shown in Part I of this paper, the cloud simulations do not represent the probability distribution required for the reduction of the minimization procedure per se. The intercomparison of EOFs from various models and simulations had shown that, particularly when including the 85.5-GHz channels, discrepancies occurred between all tested situations. As a consequence, a merged database was constructed from all cloud model simulations and 130 orbits of TMI data. This will represent real situations without the bias in TB distributions as introduced by single simulations.
- The cost function, \(J(P_i)\), is calculated in EOF space and not in TB space. This reduces the dimension of the matrix operations from 9 or 7 to 2. As a consequence, the error covariance matrices are also transferred into EOF space, thus \((O + S)^{-1}\) becomes \([E_s(O + S + E_sE_s)^{-1}]\) where \(E_s\) contains the eigenvectors of the simulations.
- The modeling errors are not assumed to be zero even though the forward operator itself may be technically very accurate. There is no common estimate of microwave radiative transfer errors in the presence of clouds; however, the uncertainty introduced by the additional surface variability model (see section 4 of Part I) as well as numerous problems associated with, for example, particle shape and size spectra, multidimensional radiative transfer, etc., will amount to errors other than zero. Thus we assumed errors of \([2, 4, 4, 6, 10\, \text{K}]\) for \([10.65, 19.35, 21.3, 37.0, 85.5\, \text{GHz}]\). There was no correlation between errors of different channels assumed so that \((O + S)\) is diagonal.
- Database integration is only carried out once for all possible EOF combinations. This reduces the computational effort to a simple two-dimensional lookup table during application.

3. TMI–PR combination

TMI data are ingested as in the 1B11 standard product (calibrated and navigated TBs) on a grid according to the conical TMI scan. The TBs are recalibrated accounting for a bias not corrected for in products prior to V.5 (Schluessel and Albert 2001). For enhancement of spatial resolution and TB dynamic range, a deconvolution technique is applied to the TBs at 10.65 GHz (Bauer and Bennartz 1998) making use of the strong overlap of adjacent EFOVs. This provides a resolution of 27 km \(\times\) 44 km, which represents the reference resolution for 104 EFOVs along the scan for all further analyses (=EFOV\text{\textsubscript{ref}}). The TMI-only retrievals described in the previous section provide the effective sensing altitude, \(z_{\text{CG}}\), and the rain liquid water content, \(w_{\text{TMI}}\), at that altitude and at EFOV\text{\textsubscript{ref}}.

a. \(w\text{–}Z\) relationships

For the radar data analysis, the attenuation corrected effective reflectivity profiles from the 2A25 standard product are taken along with its cloud classification. Two versions of 2A25 have been used (V.4 and V.5) so that two different approaches for retrieving \(w\); that is, two different \(w\text{–}Z\) relations, were employed. The retrieval technique is based upon the concept of gamma...
drop size distributions (DSDs) with normalized offset, \( N_w^* \) (Dou et al. 1999a,b). The general form of the \( w-Z \) relationship (with \( w \) in g m\(^{-3}\) and \( Z \) in mm\(^6\) m\(^{-3}\)), is given by
\[
\text{w}_{\text{PR}} = a(N_w^*)^{1-b}Z^c.
\]
(6)

Principally, there are three possible estimates of \( w \) in analogy to rain retrievals (Ferreira et al. 2001): the standard \( w-Z \) algorithm, the above approach using \( N_w^* \) (6), and through the attenuation \( k \), that is, a \( k-Z \) relationship. With the 2A25 V.4 reflectivity output, (6) translates to
\[
\text{w}_{\text{PR}} = 3.069438 \times 10^{-6}(N_w^*)^{0.4554}Z^{0.545},
\]
(7)

which was determined from Mie calculations at 13.8 GHz over a temperature range of 273–293 K and a reflectivity range of 20–50 dBZ assuming a gamma DSD with shape parameter \( \gamma = 1 \). Please note that the same assumptions on rain DSD were made for the simulation of TMI TBs (see Part I). To adjust to the 2A25 conditions, the above relations were tuned with \( N_w^* \) values implied by the initial \( Z-k \) and \( Z-R \) relations used for the 2A25 product. The initial relations in 2A25 are based on ground-based DSD data collected near Darwin, Australia, also assuming \( \gamma = 1 \). According to Ferreira et al. (2001), the initial values are \( N_w^* = 5.1 \times 10^5 \) m\(^{-4}\) for stratiform rain types and \( N_w^* = 16.6 \times 10^5 \) m\(^{-4}\) for convective rain types.

Thus, the standard \( w-Z \) relations used for the retrieval of stratiform and convective rain, \( \text{w}_{\text{PR},s} \) and \( \text{w}_{\text{PR},c} \), from 2A25 V.4 data are
\[
\text{w}_{\text{PR},s} = 3.46 \times 10^{-3}Z^{0.545},
\]
\[
\text{w}_{\text{PR},c} = 5.92 \times 10^{-3}Z^{0.545},
\]
(8)

while the alternative estimates are given by
\[
\text{w}_{\text{PR},s}(k-w) = \text{w}_{\text{PR},s}(N_w^*)^{e_{\text{PR}}^{\text{a}}}	ext{ and}
\]
\[
\text{w}_{\text{PR},c}(N_w^*) = \text{w}_{\text{PR},c}(N_w^*)^{e_{\text{PR}}^{\text{b}}}.
\]
(9)

This follows from \( k = \alpha Z^\beta \) and an adjustment of \( \alpha \) by the range-free hybrid scaling factor \( e_i \) in the 2A25 algorithm (Iguchi et al. 2000). Profiles of all \( w \) can be computed directly from the output parameter file of the 2A25 using the profile of attenuation corrected \( Z \), \( \beta = 0.761 \) (constant in 2A25 V.4), and \( b = 0.545 \) as provided by the previously mentioned computations. Uncertainties in the results according to temperature variations were neglected because a comparison of (7) with temperature-dependent calculations produced errors below 5%. Throughout the present study, \( \text{w}_{\text{PR},s}(k-w) \) was used based on the results of Ferreira et al. (2001).

For V.5 data, the initial \( N_w^* \) for stratiform and convective precipitation change to \( 7.4 \times 10^5 \) m\(^{-4}\) and \( 15.7 \times 10^5 \) m\(^{-4}\), respectively. This leads to a modified form of (8) that is
\[
\text{w}_{\text{PR},s} = 4.9911 \times 10^{-3}Z^{0.537},
\]
\[
\text{w}_{\text{PR},c} = 7.0701 \times 10^{-3}Z^{0.537}.
\]
(11)

In this estimate, \( b = 0.537 \) and \( \beta = 0.7923 \) for stratiform and \( \beta = 0.7713 \) for convective rain. It is important to note that in V.5, \( \epsilon_i \) is much closer to 1 than in V.4 so that the differences between the alternative \( w-Z \) estimates diminish. However, between V.4 and V.5 retrievals there are significant differences that depend on the stratiform–convective fraction in the sample. All coefficients of the above procedure are summarized in Table 1.

### Table 1. Coefficients for \( w-Z \) relations depending on rain type and 2A25 version.

<table>
<thead>
<tr>
<th>Rain type</th>
<th>a, V.4</th>
<th>b, V.4</th>
<th>a, V.5</th>
<th>b, V.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stratiform</td>
<td>0.003460</td>
<td>0.545</td>
<td>0.004991</td>
<td>0.537</td>
</tr>
<tr>
<td>Convective</td>
<td>0.005920</td>
<td>0.545</td>
<td>0.007070</td>
<td>0.537</td>
</tr>
</tbody>
</table>

b. TMI–PR collocation

Since the coordinates of the \( \text{w}_{\text{PR}} \) profiles are determined by the PR scan geometry at \( x_{\text{PR}} = (x, y, z)_{\text{PR}} \), a gridding on the TMI reference system at coordinates \( x_{\text{TMI}} = (x, y, z_{\text{CG}})_{\text{TMI}} \) has to be carried out:
\[
\text{w}_{\text{PR}}(x_{\text{TMI}}) = \int_{EFOV_{\text{ref}}} \int_{(z_{\text{CG}} - \sigma(z_{\text{CG}}))}^{(z_{\text{CG}} + \sigma(z_{\text{CG}}))} \text{w}_{\text{PR}}(x_{\text{PR}})G_{\text{TMI}}(x, y)_{\text{PR}} dx_{\text{PR}} dy_{\text{PR}}.
\]
(12)

This includes the following.

1. The convolution with the antenna gain function \( G_{\text{TMI}} \) of dimensions \( EFOV_{\text{ref}} \), which was approximated by a Gaussian-shaped function with 3-dB half-widths of 27 km in cross-track direction and 44 km in along-track direction.

2. The averaging over altitude due to the uncertainty in the estimation of \( z_{\text{CG}} \) expressed by the retrieval standard error \( \sigma(z_{\text{CG}}) \).

3. A threshold of 80% of the TMI \( EFOV_{\text{ref}} \) covered with valid PR estimates (having the classification “rain certain” or “no rain” from the 2A25 rain flag terminology) to avoid errors introduced by insufficient PR samples for calculating (12).

This procedure minimizes the effects of collocation problems due to the different observation geometries of both sensors. First, the retrieval of single-level values instead of profiles avoids the effort of matching beams, which can only be achieved by increasing the volume considerably thus losing profile information again. For example, assuming a pixel size of 45 km and a zenith angle of 52° would require radar profiles over a distance of 85 km if the reflected atmospheric contribution is to be accounted for. Second, the variation of \( \text{w}_{\text{PR}} \) over \( EFOV_{\text{ref}} \) provides an estimate of the expected accuracy once \( \text{w}_{\text{PR}} \) and \( \text{w}_{\text{TMI}} \) are compared. The estimation of sur-
face rain liquid water content (or rain rate) may seem to be independent of reference altitude variations; however, passive microwave measurements provide volume rather than level information so that rain profile variations contribute to the evaluation of a spatial average. The 2A12 product was treated in a similar fashion to the PR data. The original estimates comprise surface rainfall rates and hydrometeor concentration profiles at predefined levels that were gridded to the spatial sampling on the 85.5-GHz pixel locations. As in (12), the actually retrieved \( z_{CG} \) was used to select the profile level followed by a spatial integration of \( w_{2A12} \) at this altitude over EFOV ref. With this procedure, all products to be compared refer to the same altitude and resolution.

c. Calibration

During the following procedure, the estimates of \( w \) from both TMI and PR algorithms are compared as a function of \( w \). Due to the lognormal probability distribution of \( w \), the maximum range of \( \log_{10}(w) \) was divided into intervals with indices

\[
i_w = \begin{cases} 
10 \log_{10}(w): & w \leq 0.5 \text{ g m}^{-3} \\
26w - 16: & w > 0.5 \text{ g m}^{-3},
\end{cases}
\]

(13)

so that \( i_w \in [-20, 10] \) for \( w \in [0.01, 1] \) g m\(^{-3}\). The switch to a linear relationship in (13) ensures a better resolution at higher \( w \). Ratios of \( w_{PR} \) over \( w_{TMI} \) are collected in the intervals with a dynamic adjustment along the satellite track:

\[
c(i_w) = n(i_w)^{-1} \sum_{n(i_w)} \frac{w_{PR}(x_{TMI})}{w_{TMI}(x_{TMI})}
\]

(14)

Here, a number of 10 samples per interval is accumulated and an average ratio is calculated after each new entry. If more than 10 data pairs accumulate, the oldest is deleted and the most recent is included. A number of 10 has been chosen to find a compromise between stability and flexibility. Tests with larger numbers did not give substantially different results. Finally, all TMI samples over the swath are corrected by

\[
w_{TMI}^c(x_{TMI}) = c(i_w)w_{TMI}(x_{TMI}).
\]

(15)

Since only the inner part of the TMI swath is covered by PR samples, an application of the calibration to the total swath assumes a certain constancy over the swath and over time (see section 4b).

4. Results

a. Algorithm intercomparison

Figure 3 shows the 19.35-GHz horizontally polarized TBs of those cases for which the retrieval techniques were tested. Table 2 summarizes orbit numbers, locations of the cloud systems, and brief comments of the selection. It was attempted to cover a large variety of situations including tropical cyclones, deep and shallow convection, and squall lines as well as frontal systems. For orbit 15438, no valid 2A12 data were available. The following algorithms were applied to all cases: the regression (REG), the NN, the Bayesian technique using two EOFs from seven TBs (BAY-7) and that for two EOFs from nine TBs (BAY-9). Two EOFs only represent 92%–94% of total variability for nine-channel TB datasets. The third EOF, however, is less representative of near-surface precipitation (see Part I), so it was omitted in the retrieval.

Tables 3 and 4 summarize the statistics for all cases in terms of average water contents \( \overline{w} \), standard deviations \( w' \), biases, root-mean-square errors (rmse’s), and correlations \( R \) relative to \( w_{PR} \). Results are shown for the TMI-only product, that is, the above algorithms before (TMI) and after calibration (TMI–PR) versus 2A12. The results for 2A12 are not identical when compared to different algorithms because only data were used for which all \( w_{PR} \), \( w_{TMI} \), and \( w_{2A12} \) were above 0.01 g m\(^{-3}\).

Principally, all algorithms produce lower \( \overline{w} \) than \( w_{PR} \) for stronger convective cases (orbits 1171, 15795, 16059) while there is some overestimation for the weaker convective situations (orbits 1273, 4283). For the frontal situations all algorithms give similar results. When comparing BAY-7 and 2A12, similar performance is observed; \( \overline{w} \) and \( w' \) are very close to each other except for those cases where also large differences with the PR estimates occur. This points at a \( w \)-dependent performance. Biases and rmse’s are fairly small and consistent throughout the cases, except for orbits 1171, 15795, and 16059. There, the PR tends to give extremely high \( w \) in the convective cores. While 2A12 performs somewhat better in errors, BAY-7 shows similar correlations. It is noteworthy that in the case of rainfall evaluation, biases and rmse’s are dependent on \( w \) so that overall statistics may be misleading. Cases 295 and 16151 are rather difficult because even after calibration, the scatter between TMI and PR estimates is large, mainly due to a small number of points on the common swath.

All other algorithms perform less well against 2A12 and BAY-7. BAY-9 and NN are almost similar (with slight advantages for NN), while REG is clearly the weakest technique. After calibration all algorithms perform similarly. It may be concluded that the primary TMI algorithm is of little importance as long as an online calibration source is available. However, the application over the wide swath requires a stable primary TMI algorithm, so this argumentation is weak. REG shows the already mentioned tendency to overestimate \( w \). The intercomparison leads to the conclusion that radiometer algorithm performance depends on both training dataset and inversion technique. The inversion technique, however, seems less important since BAY-9 and NN perform very similarly. A regression technique cannot capture the nonlinearity of the \( w \)--TB relation accurately enough. The different performances of BAY-7 and BAY-9 confirm the results from Part I: Even though BAY-9 is more sensitive to low rainfall intensities, the
Fig. 3. TBs at 19.35 GHz (horizontal pol.) of 12 test cases used for retrieval evaluation (see Table 2).
large contribution of 85.5-GHz signatures to the retrieval at moderate to high intensities weakens the performance. This is because the simulated database shows its deficiencies to be most pronounced at 85.5 GHz where scattering is very efficient. BAY-7 performs very well despite the simplicity of the inversion. Please note that only two independent predictors are used. On the contrary, 2A12 is constructed from much fewer cloud simulations, without the slant path modification of the plane-parallel radiative transfer model and without the melting layer. On the inversion side, 2A12 uses several constraints supporting the Bayesian estimator. Predictors are TBs and emission/scattering indices. The estimator also includes a stratiform–convective classifier and information about the geometrical distance of the observation from the center of the convection. Thus a weaker database is combined with a more detailed inversion, leading to similar results as our technique.

Figures 4, 5, and 6 show examples of BAY-7 retrievals before and after calibration, the corresponding $w_{PR}$ distribution and 2A12 estimates. One obvious feature is the greater degree of detail in the BAY-7 distributions of $w$. The deconvolution technique increases the spatial resolution of the 10.65-GHz channel, and the large numbers of events require a more detailed characterization of the signal.

### Table 2. Twelve cases selected for algorithm evaluation.

<table>
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<tr>
<th>Date</th>
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<th>2A25 version</th>
<th>Center lat, long</th>
<th>Rain type</th>
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<td>00295</td>
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<tr>
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</tr>
<tr>
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<td>18°N, 70°E</td>
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<td>3°N, 70°E</td>
<td>Monsoon scattered convection, Indian Ocean</td>
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</table>

### Table 3. REG and NN performance vs 2A25 V.4 and V.5 at the same resolution and reference altitude ($z_{ref}$). Bold entries mark significantly better performance by one TMI-only algorithm (average $\bar{w}$, standard deviation $w'$, bias, rmse, and correlation $R$ vs $w_{PR}$). Missing entries are for missing data.

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**NN:**
Table 4. BAY-7 and BAY-9 performance vs 2A25 V.4 and V.5 at same resolution and reference altitude (z_C). Bold entries mark significantly better performance by one TMI-only algorithm (average \( \bar{w} \), standard deviation \( w' \), bias, rmse, and correlation \( R \) vs \( w_{PR} \)). Missing entries are for missing data.

<table>
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<th>( w' ) TMI-PR 2A12</th>
<th>( w' ) TMI-PR 2A12</th>
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<th>rmse</th>
<th>( R )</th>
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<th>( w' ) TMI-PR 2A12</th>
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b. Calibration

Figures 7 and 8 present examples of pointwise intercomparisons between \( w_{TM} \) and \( w_{PR} \) before and after calibration. The deep tropical convection (Fig. 7a) shows moderate scatter, a TMI overestimation at very low and high rain intensities. After calibration (Fig. 7d), the bias is corrected and standard deviations between PR and TMI estimates below 25% for \( w > 0.1 \) g m\(^{-3}\) remain. Hurricane Bonnie produces more scatter (Fig. 7e), in particular at lower rainwater contents, which cannot be corrected by the calibration. 2A12 performs very similarly (Fig. 7g). The Pacific Ocean convection (Fig. 8a) is almost unbiased for \( w > 0.1 \) g m\(^{-3}\); both TMI algorithms overestimate for less rainfall. The bias-corrected standard deviation (Fig. 8d) reproduces the previous results. The frontal rainband off the East Coast of the United States produces less total rain but more scatter between the products (Figs. 8e,f,g), thus the bias-corrected standard deviation remains higher (Fig. 8h).
Figure 4. Distributions of retrieved $w$ from (a) TMI-only (BAY-7) algorithm, (b) PR estimates averaged to TMI reference resolution, (c) calibrated $w$, and 2A12 V5.5 algorithm; case: 980210.01171.

Figure 9a presents the average calibration curve that is the average ratio of $w_{\text{PR}}$ and $w_{\text{TMI}}$ from all cases, that is, ~6600 samples. The same ratios are shown for the calibrated data (dotted line) and 2A12 (thick dashed line). The calibration compensates for underestimations for $w < 0.1$ g m$^{-3}$ and for $w > 0.8$ g m$^{-3}$. For the latter range, there is less data available to stabilize the calibration. The systematic differences are fairly small and well below the standard deviation of the calibration coefficients per interval (error bars). 2A12 tends to have less bias for $w < 0.1$ g m$^{-3}$ but more above.

The statistics in Tables 3 and 4 did not indicate a significant total algorithm bias. The distribution of the biases per $w$ interval together with the frequency distribution of $w$ obviously compensate each other. Thus, general statistics may lead to misleading results. Figure 10 gives further insight into the interpretation. Average calibration factors $C$ per rain type are shown as a func-
tion of \( w \) and fractional cloud coverage in EFOV \( \text{ref} \). The rain type classification is accumulated from the 2A25 standard product. Stratiform scenes reach higher coverages than convective or other types (including warm rain). The average distributions do not show an obvious influence of beam filling on calibration factor. For both cloud types, the gradient of the calibration factor has a similar shape; however, convective rain has less structure and therefore more natural variability, which is not captured by either \( w \) or coverage.

Beam filling seems well covered in the simulations on which the algorithm was trained. It is evident, that the TMI–PR bias does not only depend on \( w \). Beam filling and cloud-type dependent retrievals (as included in the PR \( w-Z \) relations) cannot explain the rather consistent shape of the calibration curve. The upper right feature in the stratiform case may indicate an insufficient coverage of strong bright bands in the database that were included but through a rather conservative approach (Bauer 2001).
Figure 9b presents the remaining standard deviations between calibrated TMI and PR estimates. They remain comparably constant at 0.05 g m$^{-3}$ between 0.01 and 0.1 g m$^{-3}$. In terms of relative errors, we obtained 100% at $w = 0.05$ g m$^{-3}$ = 0.5 mm h$^{-1}$, 50% at $w = 0.1$ g m$^{-3}$ = 1.3 mm h$^{-1}$, and 30%–35% at $w = 0.5$ g m$^{-3}$ = 9.6 mm h$^{-1}$. These standard deviations do not contain errors from the PR retrievals. Assuming a 1-dBZ calibration accuracy, PR retrieval uncertainties are of the order of 15%, which must be taken into account when total errors are calculated.

It is interesting to notice that the ambiguity of the database, that is, the standard deviation of $w$ for similar EOFs, is enveloped by the TMI–PR error curve. A possible interpretation is that it represents the relative contribution to the total retrieval error. This relative contribution would increase from low to moderate rain intensities and decrease again for high intensities. Be-
Fig. 7. TMI-only (Bayesian) vs PR estimates [(a),(c)] before and [(b),(f)] after calibration, [(c),(g)] 2A12 V.5 vs PR estimates and [(d),(h)] remaining standard deviation after calibration for cases 980216.01273 and 980826.04283.

Between 0.1 and 0.5 g m$^{-3}$, that is, 1.3 and 9.6 mm h$^{-1}$, the bulk retrieval error would be due to signal ambiguity. This would also suggest that the error of the inversion is small in this range. Generally speaking, the contribution from the surface decreases with increasing atmospheric opacity. On the other hand, sensitivity to liquid precipitation decreases once noise from microwave scattering at precipitating ice particles increases and brightness temperatures saturate while polarization ratios approach zero. This, in fact, would suggest that the
pure inversion error is lower in the middle range. However, the large ambiguity of different situations with the same gross emission and scattering features reaches a maximum so that the overall error remains constant. Thus Fig. 9b may be interpreted as a basic quantification of database versus inversion error as a function of rain intensity.

5. Summary and conclusions

An approach for a combined TMI–PR retrieval technique was presented to obtain rain liquid water contents at levels close to the surface. This technique is based on a primary estimation of water contents from passive microwave radiometer observations. Retrieval algo-
Algorithms were developed using radiative transfer simulations applied to a large set of cloud model simulations. Part I of this paper describes the generation of retrieval databases and their evaluation while Part II compares different inversion techniques. A regression approach, a neural network, and a simplified Bayesian technique were implemented. The first two techniques used brightness temperatures and/or normalized polarization differences as input parameters while the Bayesian methods only used two EOFs as predictors.

For the evaluation and later for the calibration, the PR effective reflectivities were converted to rain liquid water contents. Both radar reflectivities and brightness temperatures are more sensitive to rainwater content than rain rate because of their independence of particle fall speeds. In all cases, water contents were retrieved at the center of gravity of the TMI 10.65-GHz weighting function. This represents the altitude from which the channel that is most sensitive to rain receives a maximum contribution. All products were convolved with an idealized 10.65-GHz TMI antenna pattern to a resolution of 27 km × 44 km. This procedure avoids all problems of beam adjustment due to the different scanning geometry and spatial resolution of both sensors. For profile retrievals, these can only be overcome by increasing the investigated volume considerably averaging out large information contents.

It was demonstrated that regressions performed worse than other techniques. Neural networks showed a similar accuracy to the Bayesian method once all TMI channels were included. This leads to the conclusion that a major requirement for algorithm improvement is the development of better databases because the choice of the inversion technique adds little skill to the retrieval. The exclusion of the 85.5-GHz channels confirmed the results from Part I. Even though the database coverage statistics suggested less sensitivity at lower rainfall intensities, the overall statistics after application to test cases showed superior results. Thus the best algorithm turned out to be a two-EOF Bayesian technique that also performed very well against TMI standard product 2A12 without relying on similar constraints such as stratiform–convective separation or geometric distance to convection. Our technique also provides more spatial details since the reference resolution is better than that of the nominal 10.65-GHz EFOV. Thus more spatial details are obtained in situations of heavy precipitation.

The TMI–PR sensor combination developed in this study compares independent TMI and PR estimates of rainwater content over the common swath at the reference resolution and altitude. Dynamically adjusted calibration coefficients are determined that correct the TMI estimate. The calibration coefficients are a function of rainwater content itself to account for nonuniformities over the dynamic range. It is assumed that the calibration curve is a slowly varying parameter so that it can be applied over the full TMI swath after adjustment over the common part. This allows the full usage of the TMI swath with a constantly updated quality control by the PR. Analysis of the calibration curve shows that for 0.1 g m⁻³ < w < 0.8 g m⁻³, the calibration is rather neutral while for smaller/larger contents an underestimation by the TMI algorithm occurs. Different sensitivity to spatial rainfall variability and the different sensitivity of radiometer and radar signals to rainfall as a function of intensity may explain this behavior. In any case, the algorithm allows both calibration and stand-alone TMI usage. The systematic differences show little dependence on beam filling and some dependence on w in case of stratiform rain. The latter may point at a more flexible treatment of melting layer effects, which has only been conservatively included in the retrieval database.

A by-product of the algorithm is the calculation of the remaining standard deviation between TMI–PR estimates once the bias was removed. These may be considered as an instantaneous retrieval error estimate. It was found to be fairly constant at 0.05 g m⁻³ for low
FIG. 10. Average calibration factors as a function of cloud type, i.e., (a) other, (b) stratiform, (c) convective, (d) stratiform with bright band, and (e) warm rain, stratified by $w$ and fractional coverage inside EFOV$_{sw}$.

to moderate rain rates. Thus relative error decreases from above 100% to below 35% as a function of $w$. The database ambiguity—which was estimated in Part I of this study—seems to explain a large fraction of the total retrieval error at moderate to high rain rates. Between 1 and 10 mm h$^{-1}$ the error of the inversion would therefore be small due to the strongest gradient of the TB–$w$ response curve in that range.

It is obvious that the quality of the combined TMI–PR product is driven by the PR since it represents the calibration data source. Thus any change in PR standard products used as input data will change this reference. However, the TMI-only algorithm provides retrievals in any case and can be operated independently. Computational efficiency of the TMI-only technique is very high because only a two-dimensional lookup table is used. The most time-consuming factor during application is the convolution of the PR estimates to the TMI reference resolution, if a swath-by-swath calibration is desired. This could be simplified by a globally valid calibration. This is subject of further studies towards the development of intersatellite calibration for GPM.

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