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Accuracy of cloud liquid water path from ground-based microwave radiometry
2. Sensor accuracy and synergy

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[1] The influence of microwave radiometer accuracy on retrieved cloud liquid water path (LWP) was investigated. Sensor accuracy was assumed to be the sum of the relative (i.e., Gaussian noise) and the absolute accuracies of brightness temperatures. When statistical algorithms are developed the assumed noise should be as close as possible to the real measurements in order to avoid artifacts in the retrieved LWP distribution. Typical offset errors of 1 K in brightness temperatures can produce mean LWP errors of more than 30 g m^{-2} for a two-channel radiometer retrieval, although positively correlated brightness temperature offsets in both channels reduce this error to 16 g m^{-2}. Large improvements in LWP retrieval accuracy of about 50% can be achieved by adding a 90-GHz channel to the two-channel retrieval. The inclusion of additional measurements, like cloud base height from a lidar ceilometer and cloud base temperature from an infrared radiometer, is invaluable in detecting cloud free scenes allowing an indirect evaluation of LWP accuracy in clear sky cases. This method was used to evaluate LWP retrieval algorithms based on different gas absorption models. Using two months of measurements, the Liebe 93 model provided the best results when the 90-GHz channel was incorporated into the standard two-channel retrievals. *INDEX TERMS:* 3360 Meteorology and Atmospheric Dynamics: Remote sensing; 3394 Meteorology and Atmospheric Dynamics: Instruments and techniques; 6969 Radio Science: Remote sensing; 1640 Global Change: Remote sensing; 1655 Global Change: Water cycles (1836); *KEYWORDS:* microwave radiometer, cloud liquid water, sensor synergy, ground-based remote sensing

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1. Introduction

[2] Ground-based microwave radiometry is by far the most accurate method for determining the cloud liquid water path (LWP) [*Westwater*, 1978] as well as simultaneously retrieving the integrated water vapor (IWV). Because microwave radiometers are robust technology and need little maintenance, long-term time series of LWP and IWV can be derived from them at single stations [*Güldner and Spänkuch*, 1999; *Elgered and Jarlemark*, 1998; *Snider*, 2000]. While IWV can be validated with colocated measurements from other sensors such as radiosondes, GPS, and Raman lidar, assessment of LWP retrievals is harder to perform. In situ measurements of LWP from aircraft are not representative of radiometer sample volumes due to the long horizontal paths covered during ascent/descent within a cloud and the extremely small sampling volume of aircraft probes. Cloud radar measurements are affected strongly by the dependency of the reflectivity on the drop size distribution. Thus a lack of sufficient, and independent, measurements exists. A thorough evaluation of the LWP accuracy must be performed theoretically, taking all sources of error into account.

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[3] One can distinguish between errors in the brightness temperature (TB) measurements and errors in the algorithm, which retrieves the LWP from the measured TB's. Retrieval algorithms are mostly based on statistical relations between TB and LWP. To develop the statistical relationship radiative transfer calculations have to be performed which give a set of concurrent TBs and LWP for the expected range of atmospheric states. The statistics for atmospheric temperature and humidity are

relatively well known, but the profiles of the liquid water content (LWC) are much more difficult to assess. In part 1 of this paper, *Löhnert and Crewell* [2003] have already investigated the influence of the cloud model that is used to derive the necessary cloud water profiles. Significant differences can be observed when more than the two standard frequencies are combined in the retrieval. Note that uncertainties in the gas absorption model, which are largest for higher frequencies like 90 GHz, still exist, although some attempts have been made to reduce them [*Cruz Pol et al.*, 1998]. The influence of the gas absorption model on LWP retrieval was recently shown by *Westwater et al.* [2001]. Westwater el al. compared aircraft LWP observations of the Surface Heat Budget of the Arctic Ocean (SHEBA) project with ground-based microwave retrievals. For LWP values below 100 g m^{-2} a general overestimation of $\sim$20 g m^{-2} was found. This value was reduced to $\sim$10 g m^{-2} when the gas absorption model by *Rosenkranz* [1998] was used instead of the one by *Liebe ad Layton* [1987] used before. Especially for the SHEBA site, the uncertainty in cloud liquid water absorption at temperatures below zero is problematic [*Westwater et al.*, 2001].

[4] Although LWP can reach values of more than 500 g m^{-2} before precipitation occurs, the accurate retrieval of low LWP values is of particular interest due to two reasons. First, low LWP clouds are very frequent. Within the data set used in this paper more than half of the clouds had LWPs below 150 g m^{-2}. Second, solar transmission, a very important process especially for climate models, depends strongly on LWP. For low LWP values the transmission decreases strongly with LWP while for LWP values above $\sim$150 g m^{-2} the change in transmission with LWP is almost zero. Therefore accurate low LWP values are needed if a reasonable solar transmission sensitivity for all clouds is required.

[5] In this study we focus on instrumental effects and address two points. First, the influence of errors in the measured TB is investigated. Usually measurement errors are taken into account in retrieval development as randomly distributed noise with a standard deviation between 0.5 K and 1.0 K. However, in most microwave radiometers the noise ($\sim$0.2 K) is much smaller than the absolute accuracy ($\sim$1.0 K). The effect on LWP accuracy of potential bias errors can be significant for long-term time series (section 2). The second aim of the paper is to investigate how the LWP retrieval accuracy can be improved. This is of interest both for developing new systems and upgrading old ones. Two possibilities exist. The first possibility is the addition of one or more frequency channels to a standard dual-channel instrument. The second one involves combining microwave radiometer measurements with data from other ground-based sensors. Quite often measurement facilities equipped with a microwave radiometer also host other sensors that are sensitive to clouds. Infrared (IR)-radiometers and lidar ceilometers are two prominent examples, so their data can be included together with standard measurements of ground-level temperature, humidity and pressure (section 3).

[6] The synergy of the sensors mentioned above can also be exploited in another way. Cloud-free scenes can easily be identified by IR and ceilometer measurements and hence used to evaluate absolute (BIAS) and root-mean square (RMS) errors in the microwave retrievals during clear sky conditions. We apply this method to two months of continuous LWP retrievals (section 4), and we also use it to assess the accuracy of the gas absorption model (section 5). In the conclusions (section 6) we propose future activities for improvement in LWP retrievals.

2. Accuracy of Microwave Radiometer Brightness Temperatures

[7] The noise generated inside a microwave radiometer is characterized by the receiver noise temperature (T_r), which is typically much higher than the atmospheric brightness temperature (T_a). The total system noise together with the frequency bandwidth ($\Delta\nu$) and integration time (τ) define the radiometric noise level ΔT_B via the radiometer formula $\Delta T_B = (T_r + T_a)/\sqrt{(\tau \cdot \Delta\nu)}$. For typical values of state-of-the-art radiometers the noise level, which also defines the minimum detectable signal, is about 0.2 K. Microwave components are sensitive to variations of the environmental temperature. Even a change of less than a tenth of a degree in amplifier temperature can cause changes of a few Kelvin in TB. Drifts in receiver properties can lead to significant changes in TB with time (see cartoon in Figure 1). Therefore in most instruments periodic calibrations are performed to reduce this problem. However, each calibration itself involves different sources of uncertainties, thus resulting in BIAS errors in the measured TB. Additionally, non-linearity in the detector response function can cause errors up to 1 K in the TB, but these errors can be overcome by thorough calibration [*Kazama et al.*, 1999]. Studies of radiometer accuracy [*Crewell et al.*, 2001; *Han and Westwater*, 2000] have shown that absolute errors are generally much higher than relative ones. Typically, the relative accuracy is determined from TB time series taken with the antenna pointing to a target of known, constant temperature. Thus the TB RMS includes the effects of radiometric noise and short-term stability with typical values of 0.5 K.

2.1. Radiometric Noise

[8] First, we wanted to investigate the effect which radiometric noise has on estimated LWP accuracy. We

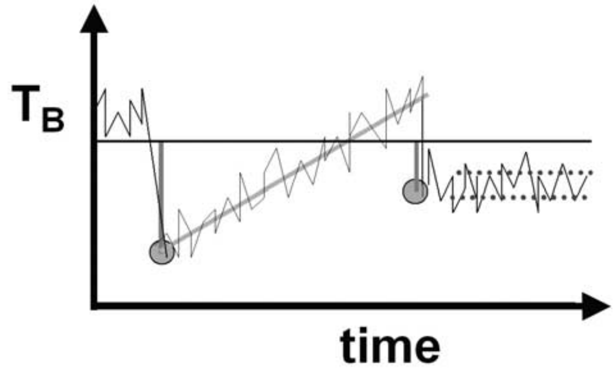

Figure 1. Illustration of the different error sources involved in TB measurements. The thin solid line gives a hypothetical TB measurement when the true TB is constant with time. The RMS noise level is indicated by the two dotted curves. The circles mark absolute calibrations with their errors given by the vertical lines. Between absolute calibrations drifts, which are not necessarily linear, lead to a change in TB accuracy with time. See color version of this figure at back of this issue.

demonstrate this for a dual-channel radiometer with frequencies at 22.925 and 28.235 GHz. These two frequencies were already used in part 1 of this paper [*Löhnert and Crewell*, 2003] because measurements at these two frequencies are routinely performed by the Microwave Radiometer for Cloud Cartography (MICCY) [*Crewell et al.*, 2001]. We only use zenith observations because they are the most favored operational mode and avoid problems due to the horizontal inhomogeneity. The LWP retrieval algorithm was developed from a data set of concurrent TB and LWP values using a linear, multiple regression scheme that included the quadratic terms of TB. This is the Q2 algorithm following the notation of *Löhnert and Crewell* [2003, Table 3], where a description of the algorithm frequencies is given. The only difference in the development here from *Löhnert and Crewell* [2003] is the inclusion of cloud-free scenes in the retrieval development. About half of the database was used for algorithm development. The second half was used for evaluation.

[9] The RMS errors in the retrieved LWP depend on the noise in TB (Figure 2a), which is assumed to be normally distributed and to have the same standard deviation (σ) for both frequency channels. Three different scenarios are compared. The first is for retrieval RMS errors for which the algorithm was applied to data with exactly the same noise levels as the brightness temperatures used for developing the algorithm. For the other two scenarios an algorithm developed from data with noise levels of 0 and 2 K was applied to different data sets with varying noise levels. As Figure 2a illustrates, if too much noise was present in the algorithm development, the LWP RMS errors increased by about 75% in low noise conditions. In a range of about ±0.5 K around the fixed noise level of 2 K there was no significant difference from the algorithm developed for the exact noise level of 2 K. When no noise at all was assumed in algorithm development the resulting algorithm could be applied to data with noise of up to 1 K without increasing the LWP RMS errors. However, this result assumes that there are no offset errors, an effect which will be investigated in the next section.

[10] Another interesting parameter that defines the quality of the retrieval is the explained relative variance given by the square of the linear correlation coefficient (COR^2) between the retrieved and the true LWP. If LWP was retrieved from noise-free brightness temperatures, 97% of the real LWP variance in the data set could be explained (Figure 2b). The 3% of the variance that could not be explained was due to the ill-conditioned problem deriving LWP from two-channel brightness temperatures. Noise in the brightness temperatures reduced the explained variance strongly. For example, when the noise level exceeded 2 K, less than 80% of the LWP variance could be explained.

[11] When atmospheric model predictions are compared to LWP observations [e.g., *Crewell et al.*, 2002],

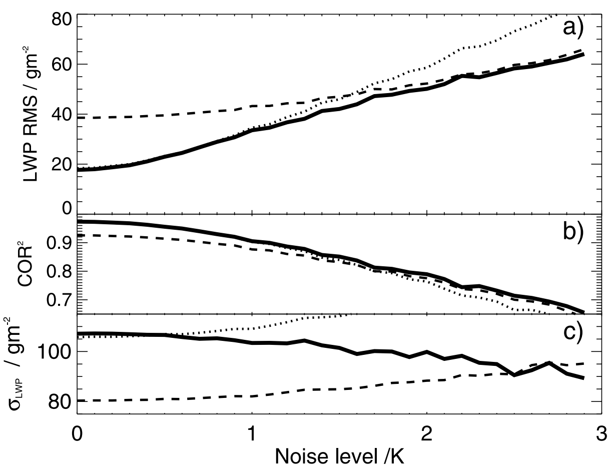

Figure 2. Sensitivity of retrieved LWP to noise in terms of (a) RMS error, (b) explained variance (COR^2) and (c) standard deviation of retrieved LWP σ_{LWP}. The true σ_{LWP} is 109 gm^{-2}. The thick line shows the results for the Q2 algorithm (22.985, 28.235 GHz) when the standard deviation (σ_{noise}) of the Gaussian noise added to the training data set is the same as the one in the evaluation data. For the dotted line the algorithm was developed using noise free data and applied to data with varying noise level. The dashed line was developed assuming σ_{noise} = 2 K.

Table 1. Difference of Retrieved Mean LWP and IWV Compared to the True Mean Values for Different Combinations of Offset Errors in the Two Brightness Temperatures[a]

Offset 22.985 GHz, K	Offset 28.235 GHz, K	Difference in Mean LWP, g m^{-2}	Difference in Mean IWV, kg m^{-2}
0	0	0.3	0.0
−1	0	+7.2	−0.73
1	0	−8.0	0.68
0	−1	−23.6	0.31
0	1	+23.6	−0.38
1	1	+15.9	0.33
1	−1	−31.3	1.02
−1	1	+31.1	−1.08
−1	−1	−16.1	−0.39

[a]Where mean LWP = 82.6 g m^{-2}; mean IWV = 14.9 kg m^{-2}.

single clouds will never occur at exactly the same time and position in the model prediction as in reality. Therefore probability density distributions (PDF) of LWP need to be compared instead of the LWP of an individual cloud. To investigate the effect of the retrieval algorithm on the LWP PDF we looked at the first two moments of the PDF, namely on the mean and the standard deviation of LWP. Even for high noise levels the mean LWP (82.5 g m^{-2}) was reproduced by the retrieval to a degree better than 2%. As Figure 2c reveals, noise in the brightness temperatures influenced the standard deviation of retrieved LWP strongly, and led to a decrease in LWP standard deviation with increasing noise level. Compared to the true value (109 g m^{-2}), a noise level of 2 K reduced the standard deviation by 12%. Even stronger deviations from the true LWP were found when too much or too little noise was added in simulations. The assumption of high noise levels in algorithm development led to a large artificial reduction in the retrieved LWP standard deviation. The assumption of too little noise had the opposite effect. Therefore it is important to choose the correct noise level in algorithm development in order to avoid artifacts in LWP PDFs. This is extremely important when statistical properties of observed LWP time series are compared with those derived from numerical weather or climate prediction models.

2.2. Offset Errors

[12] We next investigated the effect of offset errors in TB. This was done by applying the retrieval algorithm developed with $\sigma = 1.0$ K to data sets with an offset error of 1 K, a typical value for the absolute accuracy of radiometer brightness temperatures. As Table 1 illustrates, an absolute error in the higher frequency channel has more than twice the effect of one in the lower frequency channel for the LWP accuracy, while the opposite situation prevails in determination of IWV. These tendencies are due to cloud liquid water absorption increasing with frequency. For LWP retrieval the lower channel provides a minor correction term for water vapor emission and vice versa for IWV retrieval. The highest error occurred when both channels had an offset error of 1 K but with opposite sign, yielding a 31 g m^{-2} (1.0 kg m^{-2}) error in the mean LWP (IWV). If offset errors occurred in both channels, it was favorable to have the same sign in both channels giving an overall error of 16 g m^{-2} (0.4 kg m^{-2}). Because calibration errors in the two channels are often positively correlated (e.g., temperature of calibration loads) the more favorable bias error will be more frequent in reality.

3. Improvement of LWP Retrieval Accuracy

[13] Now that we have shown the influence of instrumental errors on the LWP accuracy the question arises as to how the retrievals themselves can be improved. One possibility is to shift the 28.235 GHz channel to a slightly higher frequency, like 31.4 GHz, which is often used in two-channel radiometers. This shift, however, only reduces the LWP RMS errors by ~3 g m^{-2}. Since additional channels are already available in modern microwave radiometers [*Solheim et al.*, 1998; *Crewell et al.*, 2001, *Del Frate and Schiavon*, 1998] that are intended for profiling atmospheric temperature and humidity, we will investigate the impact of additional microwave frequencies on LWP retrieval. While studies attempting to derive cloud liquid water profiles from such measurements [*Solheim et al.*, 1998; *Crewell et al.*, 1999] have been performed with unsatisfying results, no systematic study of LWP improvement has been undertaken.

[14] Another option for improving LWP retrieval accuracy is the inclusion of auxiliary measurements from colocated instruments. Here we have used standard instruments that are relatively inexpensive and do not require costly maintenance. Besides the standard surface meteorological measurements of temperature, humidity, and pressure, we included measurements from an IR-radiometer and a lidar ceilometer. Previous studies have used more complex sensor packages, for example a radio acoustic sounding system (RASS) [*Han and Westwater*, 1995], to estimate the complete atmospheric state (e.g., profiles of temperature, humidity and cloud liquid water). These studies predict a significant improvement of nearly a factor of two in LWP accuracy.

3.1. Additional Microwave Frequencies

[15] In order to investigate the possibilities of additional channels we used the 19 frequencies of MICCY. The radiometer measures atmospheric emission at nine

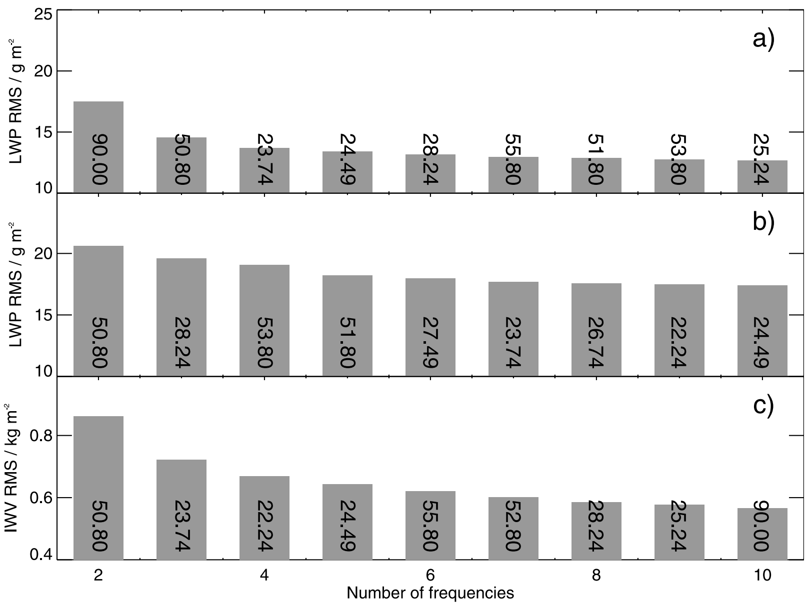

Figure 3. LWP (a and b) IWV (c) accuracy as a function of the number of frequency channels used within the algorithm. The noise level in TB is 1 K for training and testing the algorithm. The channels added to the algorithm were chosen with respect to their effect on RMS improvement. The first channel is always 22.985 GHz. The decrease of LWP RMS is shown once including the 90 GHz channel (Figure 3a) and once without it (Figure 3b).

frequencies along the high frequency wing of the water vapor line (22.235–28.235 GHz), nine frequencies along the lower frequency wing of the oxygen complex (50.8–58.8 GHz) and at 90 GHz. The latter frequency has attracted the most interest for LWP retrieval due to its strong response to cloud liquid water, which is about 6 times higher than that at 30 GHz. At 90 GHz the ratio of droplet size to wavelength is sufficiently large that scattering must be accounted for [*Bobak and Ruf*, 2000]. Therefore all radiative transfer calculations included Mie scattering. As long as no larger cloud droplets (>50 μm) occur, the effects of varying drop size distribution can be neglected. The influence of larger cloud droplets (drizzle and rain) is investigated in part 1 of this paper [*Löhnert and Crewell*, 2003]. Another uncertainty at 90 GHz is the gas absorption model used in the radiative transfer. In our data set the mean difference between the two most frequently used Liebe models [*Liebe*, 1989; *Liebe et al.*, 1993] was about 8 K for clear sky conditions (see section 5).

[16] As a first step, we assumed that the 22.985-GHz channel always has to be included in the retrieval because at the wing of the water vapor line the absorption coefficient is nearly independent of height and this channel will provide the necessary information about the integrated water vapor. In fact, the 22.985 GHz channel retrievals were always among the two-channel results that showed the largest correlation with the target variable. Generally, the optimum frequency for IWV retrieval along the water vapor wing depends slightly on the site statistics and the beam elevation angle [*Elgered*, 1993]. We then searched for the second MICCY frequency that combined with 22.985 GHz yielding the best estimate of LWP in terms of RMS errors. We repeated this process until all MICCY frequencies were used (Figure 3). Using more than four channels did not significantly improve the LWP RMS errors. For example, using frequencies in the 51–59 GHz range did not improve retrieval performance because they receive radiation mostly from the lowest atmospheric levels that are mostly below cloud level. Without incorporating the 90-GHz channel into the retrieval (Figure 3b), the LWP RMS error was barely reduced by using additional channels ($\sim$3 g m^{-2}). Using all MICCY channels except for the one at 90-GHz had the same effect as using only two channels when one channel was 90-GHz. While the improvement in LWP RMS due to additional channels compared to a dual-channel retrieval was about 25% (18%) with (without) the 90 GHz channel, IWV RMS error was reduced by about 36%. The reason for the larger improvement in IWV are the additional channels along the water vapor line since these channels contain more

Table 2. LWP and IWV RMS for Regression Q3(50) and Neural Network (NN) Algorithms[a]

Input Variables	Q3(50) LWP RMS, g m^{-2}	NN LWP RMS, g m^{-2}	Q3(50) IWV RMS, kg m^{-2}	NN IWV RMS, kg m^{-2}
3 TB	20.4	18.0	0.90	0.74
3 TB + T_{gr}	20.1 (1.5%)	18.0 (0.0%)	0.84 (6.6%)	0.71 (4.0%)
3 TB + p_{gr}	17.4 (14.3%)	16.8 (6.6%)	0.86 (4.5%)	0.72 (2.7%)
3 TB + q_{gr}	19.9 (2.5%)	17.9 (0.6%)	0.79 (12.3%)	0.68 (9.2%)
3 TB + z_{clb}	18.8 (7.8%)	15.1 (16.1%)	0.88 (2.3%)	0.70 (5.4%)
3 TB + T_{clb}	19.1 (6.4%)	15.0 (16.6%)	0.84 (6.6%)	0.66 (10.8%)
3 TB + z_{clb},T_{clb}	18.8 (7.8%)	14.9 (17.2%)	0.83 (7.8%)	0.66 (10.8%)
3 TB + T_{gr}, p_{gr}, q_{gr}	17.0 (16.6%)	16.7 (7.2%)	0.75 (16.6%)	0.66 (10.8%)
3 TB+ T_{gr}, p_{gr}, q_{gr}, z_{clb}, T_{clb}	15.6 (23.5%)	13.7 (23.8%)	0.73 (18.8%)	0.62 (16.2%)

[a]Data were gathered using brightness temperatures at three frequencies (22.985, 28.235, 50.8 GHz) and auxiliary information about ground level temperature (T_{gr}), pressure (p_{gr}), specific humidity (q_{gr}), cloud base height (z_{clb}) and cloud base temperature (T_{clb}) as input. In brackets the improvement (percent) compared to the retrieval with brightness temperatures only is given.

information on the vertical humidity structure of the atmosphere.

3.2. Sensor Synergy

[17] Standard meteorological measurements of temperature (T_{gr}), specific humidity (q_{gr}) and pressure (p_{gr}) at the ground can easily be performed together with the microwave radiometer measurements, if they are not already available from nearby synoptic stations. These data have already been shown to improve temperature and humidity retrievals in the lower atmosphere from microwave profiler data [*Crewell et al.*, 2001; *Del Frate and Schiavon*, 1998]. The connection between these data and LWP, however, is much more indirect.

[18] Infrared radiometers operate in the atmospheric window region (9.6–11.5 μm) where clouds strongly absorb radiation and the influence of the atmospheric gases is relatively small. Therefore the temperature measured by an IR radiometer (T_{ir}) is usually close to the cloud base temperature (T_{clb}), except in warm and humid conditions when differences of up to 10 K can occur. Furthermore, when optically thin clouds are present, the contribution of the clear sky cold background to T_{ir} can be quite important. When we calculated the IR temperature from atmospheric profiles using the specific wavelength response function we found that more than 82% of the time the IR temperature agreed with the cloud base temperature to better than 2 K. Therefore we assumed that the IR radiometers give a cloud base temperature to within an accuracy of 1 K, a reasonable estimate for their calibration accuracy.

[19] Another cloud sensitive instrument is the lidar ceilometer that measures the backscattering by hydrometeors at about 900 nm wavelength. Due to the strong backscatter of cloud droplets the cloud base height (z_{clb}) can be detected with an accuracy of about 30 m with this instrument. Standard instruments can cover altitudes up to 7.5 km. As a result of their easy and reliable operation IR radiometers and ceilometers have been used together in the Cloud Detection System (CDS) network [*Feijt and Van Lammeren*, 1996].

[20] We developed algorithms for LWP (and IWV) retrieval that use T_{gr}, rh_{gr}, p_{gr}, T_{clb} and z_{clb} in addition to the microwave TBs. For these parameters we assumed uncertainties of ΔT_{gr} = 1 K, Δq_{gr} = 1 g kg^{-1}, Δp_{gr} = 2 hPa, ΔT_{clb} = 1 K, and Δz_{clb} = 50 m. To investigate the effects of including these parameters we chose the three brightness temperatures of 22.895, 28.2335 and 50.8 GHz as a base input and incorporated the other variables into the algorithm using both the regression method (Q3(50)) and a neural network (NN) approach. As seen in Table 2, the NN algorithms in general perform slightly better than a regression algorithm, as can be expected for a well-trained network. The inclusion of all parameters led to an overall improvement of ~24% (~18%) in LWP (IWV) RMS error compared to the retrieval with brightness temperatures only, both for the regression and the NN. The NN made much better use of the intermittent parameters (T_{clb}, z_{clb}) leading to a strong improvement in LWP accuracy. There was no significant improvement when higher order terms for these parameters were used within the regression.

[21] While temperature and humidity at ground level had almost no effect on the retrievals, a noticeable LWP RMS error reduction was evident for the pressure. The reason was the sensitivity of the 50.8 GHz channel to pressure (oxygen) variations. For IWV the humidity information at the ground provided valuable information. The temperature and height of the cloud base provided essentially the same information on the existence of a cloud and led to similar results. As expected, including all parameters yielded the best RMS value of 13.7 g m^{-2}.

The improvement in LWP RMS error due to the inclusion of cloud base (T_{clb}, z_{clb}) information (17.2%, see Table 2) was even more pronounced when only dual-channel retrievals were considered (27%, not shown). The improvements are in qualitative agreement with the ones of *Liljegren et al.* [2001] and *Westwater et al.* [2001] who both developed physical algorithms for dual-channel measurements incorporating radiosonde, surface observations and cloud base information. While they incorporated all information at once, our statistical approach allowed us to identify the most valuable parameters. Note that for both statistical approaches, regression and neural network, the use of complete atmospheric statistics in the development data set is important in order to avoid poor performance when the algorithm is applied to novel data.

[22] Accurate colocation in time and space is absolutely necessary for application of these algorithms. While microwave radiometers and IR radiometers mostly have comparable spatial ($\Delta\theta$ = 1 to 5 deg) and temporal (Δt = 1s) resolutions, the temporal resolution of the ceilometer is about 15 s. However, temporal and spatial resolutions are not independent. For example, a radiometer with a 5 deg full-width at half maximum observes a cloud with a resolution of about ~100 m at 1 km height. With an advection speed of 10 m s^{-1}, it will take about 10 s for this cloud to move out of the radiometer field of view, which is roughly the ceilometer integration time.

3.3. Additional Frequencies Versus Sensor Synergy

[23] In the context of the current retrieval algorithms, the question of what is the most effective way to improve a standard two-channel radiometer retrieval can be answered easily. When using the regression approach the inclusion of cloud base information reduced the LWP RMS error of the dual-channel algorithm (Q2) from 33.1 to 28.9 g m^{-2} while the inclusion of the 90-GHz channel (Q3(90)) without any cloud base information reduced the LWP RMS error to 16 g m^{-2}. For a dual-channel neural network retrieval, the decrease due to cloud base information was higher (~8 g m^{-2}) compared to the regression, but it was still not as effective as the inclusion of the 90 GHz information (~12 g m^{-2}). These results clearly show that the inclusion of a 90-GHz frequency channel is the preferred option in terms of gain in LWP retrieval accuracy. When even more microwave frequencies were considered, the improvement due to additional instrumentation was only marginal. However, if the cost of the system is taken into consideration, this is not the preferred solution. Due to the large difference in wavelength between the channels, completely separate receivers must be built in order to detect the 90-GHz radiances. With this thought in mind there might be another reason why IR radiometer and ceilometer data are valuable additions to LWP retrievals. This consideration is investigated in the next section.

4. Experimental Evaluation of LWP Accuracy

[24] As discussed in the previous section, ceilometer and IR radiometer measurements facilitated the detection of cloud-free scenes and therefore offered the possibility of detecting bias errors in LWP. The scatter of LWP values during clear sky conditions, preferably around zero LWP, also provided an estimate for the RMS error at low liquid water contents. In order to further pursue this idea, we developed algorithms based again on a data set that included clear sky cases. The results of two months of LWP retrieval using MICCY microwave profiler brightness temperatures and the four-channel (Q4) algorithm are shown in Figure 4. The retrieval results in Figure 4 are for cloud-free scenes only, where cloud-free scenes are defined as samples when the ceilometer does not detect any cloud base and the infrared temperature is below −40 deg C. Note that the daily mean values of LWP varied more than their standard deviation within a day. This is evidence for our earlier statement that offset errors are more important than the noise in the measurement. Part of these deviations might also be due to the ill-posed problem in retrieving LWP from TBs. The retrieval fell well within the theoretical accuracy of the Q4 algorithm of about 16 g m^{-2}, which was derived with a noise level of 1 K (2 K for the 90 GHz channel) [*Löhnert and Crewell*, 2003]. This confirms both the quality of the measurements and the method that we used to theoretically predict the accuracy of the LWP estimates. The variation in mean LWP showed no clear correlation with the times when absolute skydip/hot-cold calibrations were performed. This implies that slight changes in the environmental conditions and more frequent gain adjustments can change the offset error with time in a way that is difficult to diagnose or even to predict.

5. Evaluation of the Gas Absorption Model

[25] All previous algorithms in this study were based on the gas absorption model by *Liebe et al.* [1993] (hereinafter referred to as Liebe 93). Another frequently used gas absorption model is the one by *Liebe* [1989] (hereinafter referred to as Liebe 89), which gives similar results as the one of *Rosenkranz* [1998] used by *Westwater et al.* [2001]. While for the two lower frequencies (i.e., 22.985 and 28.235 GHz) the mean differences between Liebe 93 and Liebe 89 are in the range of the absolute accuracy of the brightness temperature measurement (1–2 K), systematic differences of −4.9 K and 8.4 K

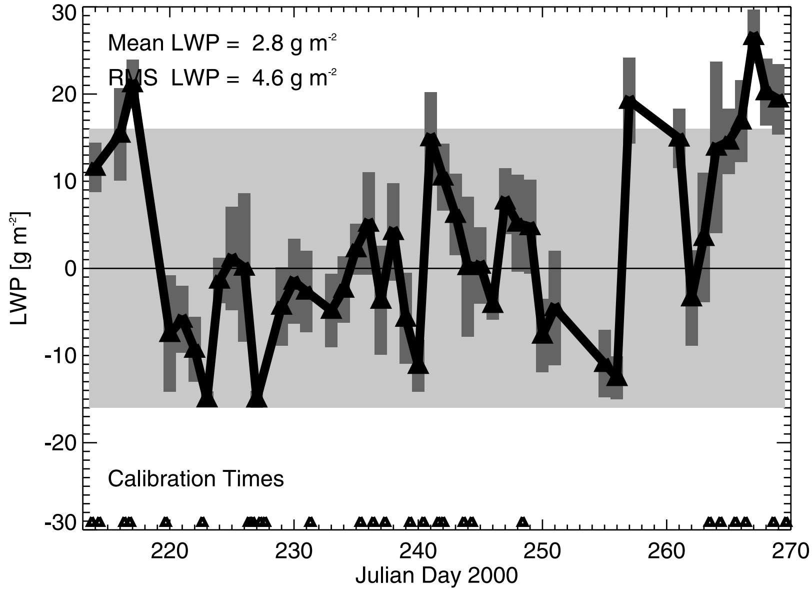

Figure 4. Time series of daily mean LWP in case of clear sky cases as determined from lidar ceilometer and infrared radiometer measurements. LWP is determined from four brightness temperatures measurements of MICCY in Geesthacht, Germany. The standard deviation is shown by the dark error bars. The light gray range illustrates the theoretical accuracy of the measurements as derived in the algorithm evaluation.

occurred between the two models at 50.8 GHz and 90 GHz, respectively. In order to evaluate which gas absorption model is closer to reality, we first used the ceilometer/IR method for diagnosing cloud-free cases. We then applied two versions of the Q2, Q3(50), Q3(90), and Q4 retrieval algorithms, one version based on Liebe 89 and another based on Liebe 93, to the same data set as shown in Figure 4, except for brief periods in the beginning and ending of the time series. Results in terms of the mean LWP and its standard deviation are shown in Table 3. As Table 3 illustrates, this time experimentally, inclusion of the 90-GHz channel strongly decreased the LWP standard deviation from $\sim$9 g m^{-2} to 1.5 g m^{-2}. For the two-channel algorithm the Liebe 93 model produced a larger mean LWP compared to Liebe 89, which was not significant considering the specified accuracy of about 30 g m^{-2}. However, for the other three algorithms the mean LWP was much closer to zero when Liebe 93 was used, suggesting this gas absorption model may better reflect reality.

6. Conclusions

[26] We have investigated the effect of bias and noise errors in microwave radiometer measured brightness temperatures on retrieved LWP accuracy. To avoid problems when long-term LWP retrievals intended for climate studies are performed, a careful specification of instrument errors is needed. An indirect evaluation of retrieved LWP during cloud-free conditions diagnosed by ceilometer and IR radiometer measurements is one way to assess retrieval errors. The analysis of a two-month time series showed that daily LWP offsets are about one magnitude higher than the noise level. This was consistent with the fact that the MICCY brightness temperatures had a higher absolute error than the noise level. Moreover, the offset varied from day to day, indicating that one can interpret these variations as a kind of noise and therefore use the absolute error of the measurement as the noise level within the retrieval algorithm.

Table 3. LWP Accuracy for the Case of Clear Sky Measurements Diagnosed From Lidar Ceilometer Measurements and Infrared Temperature Measurements[a]

	Liebe 89		Liebe 93	
Algorithm	LWP_{mean}	σ_{LWP}	LWP_{mean}	σ_{LWP}
Q2 (22.985, 28.235)	−1.84	9.35	−15.26	8.70
Q3 (22.985, 28.235, 50.8)	−36.25	3.18	−16.57	3.41
Q3 (22.985, 28.235, 90.0)	−32.45	1.6	1.01	1.55
Q4 (22.985, 28.235,50.8 90.0)	17.9	1.41	−0.75	1.40

[a]Where mean LWP_{mean} and standard deviation σ_{LWP} (g m^{-2}). Values are derived for four different frequency combinations (algorithms) and two different gas absorption models.

[27] We investigated how the LWP accuracy from a standard two-channel microwave radiometer can be improved and found the addition of a microwave channel at 90 GHz reduced the retrieval error the most (about 50% reduction). This option was even more favorable than using multifrequency information as measured by radiometers profiling the 22-GHz water vapor line and the 60-GHz oxygen complex. Because of the uncertainty of the gas absorption model at this frequency an indirect evaluation of LWP retrieval during cloud-free scenes was performed. We found that the Liebe 93 model led to the smallest residuals. The application to longer time series and also to other radiometers might give more insight for other frequencies.

[28] The inclusion of auxiliary ceilometer and IR radiometer information into the retrieval algorithm yielded the best results when a neural network approach was used to incorporate information about the existence of a cloud. This approach also avoided below-zero LWP values. Further improvement in LWP RMS errors was achieved when standard meteorological information was also included. However, neural networks require robust training sets if they are to be reliable and well behaved when applied to novel data. Therefore especially for a multichannel radiometer, using this multitude of new information within a physical algorithm may be a better approach. In the future, the algorithm by *Löhnert et al.* [2001], which combines LWP and cloud radar measurements to liquid water profiles, will be expanded to make full use of multispectral brightness temperatures by integrating the microwave radiative transfer into the algorithm.

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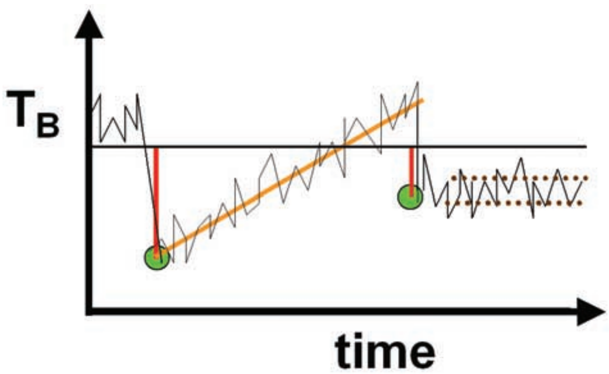

Figure 1. Illustration of the different error sources involved in TB measurements. The thin solid line gives a hypothetical TB measurement when the true TB is constant with time. The RMS noise level is indicated by the two dotted curves. The circles mark absolute calibrations with their errors given by the vertical lines. Between absolute calibrations drifts, which are not necessarily linear, lead to a change in TB accuracy with time.