Global assessment of marine boundary layer cloud droplet number concentration from satellite

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Global satellite data are used to infer the droplet number concentration of marine boundary layer clouds. In a first step, two and a half years (July 2002 to December 2004) of Moderate Resolution Imaging Spectroradiometer (MODIS, on board NASA’s Aqua satellite) level 3 data estimates of cloud effective radius and optical thickness are used to derive cloud droplet number concentration \( N \) and cloud geometrical thickness \( H \) under the assumption of adiabatically stratified clouds. Theoretical error estimates show that for a liquid water path higher than 30 g/m\(^2\) and a cloud fraction higher than 0.8, \( H(N) \) can be derived with a relative uncertainty of better than 20% (80%). To further validate the estimates of \( N \) and \( H \), cloud liquid water path is calculated and compared to independent observations of cloud liquid water path from the passive microwave Advanced Microwave Scanning Radiometer (AMSR-E), also on board Aqua. Good agreement between the two different data sets is found. In a second step, the global distribution of cloud droplet number concentration in stratiform boundary layer clouds is evaluated. The data are separated into observations that are likely to be drizzling and drizzle-free using published relations between drizzle rate and \( N \) and \( H \). It is found that the mean droplet number concentration over remote Northern Hemisphere oceans is higher than over the southern oceans (64–89 cm\(^{-3}\) in the Northern Hemisphere and 40–67 cm\(^{-3}\) in the Southern Hemisphere). Leeward of the major continents cloud droplet number concentration is generally high with maximum values close to the coasts. On the Southern Hemisphere, especially over the east Pacific Ocean, microphysical conditions were almost constant through the entire observation period. Over the southeast Atlantic Ocean, the cloud microphysical variability appears to be strongly influenced by the dry biomass burning season in Africa.


1. Introduction

Stratiform boundary clouds persistently cover large parts of the world’s oceans. They are especially frequent in the subtropical subsidence areas characterized by a strong inversion at the top of the boundary layer. Stratocumulus clouds are maintained by turbulent mixing due to longwave cooling at the cloud top and are sustained via a delicate balance between moisture supply from the ocean surface and entrainment of dry air from the free atmosphere. Other processes, such as drizzle formation or the absorption of solar radiation, also significantly affect the state of these clouds.

Stratiform boundary layer clouds also play an important role in modulating the earth’s climate. They typically occur persistently in the subtropical subsidence areas and reflect around 30% of the incoming solar radiation back to space. This reflection rejects energy from the earth-atmosphere system, especially over dark ocean surfaces. At the same time, longwave cooling rates are not affected very strongly because of the comparably low temperature difference between the ocean surface and the cloud top. The net energetic effect of these clouds is therefore a cooling of the atmosphere. Variations in cloud microphysics slightly alter their reflection behavior since clouds with a given amount of cloud liquid water but smaller cloud droplets will have a higher albedo than a similar cloud with less and larger droplets. An increase in cloud droplet number concentration via human induced air pollution and the resulting change in cloud albedo could possibly regionally counteract greenhouse warming. The overall magnitude of this first indirect aerosol effect is believed to be globally highly variable and on average in the range between \(-0.5\) W/m\(^2\) to \(-1.9\) W/m\(^2\) [Ramaswamy et al., 2001]. However, these estimates are highly uncertain and global climate model simulations show a wide range of uncertainty both in the magnitude of the effect as well as in its global distribution (for a detailed discussion, see Ramaswamy et al. [2001, chap. 6, and references therein]).
Satellite observations can help diagnose cloud microphysical properties and their link to cloud radiative properties. There is a vast body of literature dealing with satellite estimates of the indirect aerosol effect on a global and, perhaps more often, regional scale [e.g., Platnick and Twomey, 1994; Chen and Penner, 2005; Krüger et al., 2004; Chylek et al., 2006; Lohmann and Feichter, 2005; Ramaswamy et al., 2001, and references therein]. While almost all of these publications use retrieved cloud optical thickness and cloud effective radius from satellite data [see, e.g., Nakajima and King, 1990], in our investigation we derive cloud droplet number concentration $N$ and cloud geometrical thickness $H$ instead. The use of this slightly different coordinate system put forward by Brenguier et al. [2000] has the advantage of completely decoupling cloud microphysical parameters (described via $N$) from cloud geometrical parameters (described via $H$), as shown by, for example, Schüller et al. [2003, 2005]. Subsequently this important advantage of the new retrieval coordinate system is further expanded upon. It will also be shown that within the framework of an adiabatic cloud model, the two coordinate systems are equivalent and the effective radius at cloud top can be inferred given $N$ and $H$.

Drizzle is frequently observed in maritime stratocumulus clouds and recent studies based on in situ observations by van Zanten and Stevens [2005], Pawlowska and Brenguier [2003], and Wood [2005] among others suggest a relation between drizzle intensity and cloud geometrical thickness and cloud droplet number concentration. Other work by Shao and Liu [2004] suggests a different empirical relation between drizzle detection which relies on effective radius and optical thickness. While the exact functional relation between the drizzle intensity and cloud microphysical parameters has not been determined, a conservative threshold for the onset of drizzle based on $N$ and $H$ is used in this study to estimate the relative occurrence of drizzle in stratocumulus clouds.

This study is organized as follows. In section 2 we briefly discuss the data sets and the investigation area. Section 3 gives an overview on the adiabatic cloud model and how it links to quantities that can be retrieved from satellite. Possible sources of errors and uncertainties are also discussed in section 3. In section 4 we present a global and regional assessment of cloud droplet number concentration from satellite.

2. Data Sets and Investigation Area

2.1. Data Sets

2.1.1. Moderate Resolution Imaging Spectroradiometer (MODIS)

MODIS is an imaging instrument flown both on the Aqua and Terra platforms. MODIS covers the entire solar and terrestial infrared spectral range with 36 bands and a spatial resolution of about 1 km dependent on the band. In this investigation we use global MODIS level 3 (collection 4) data derived from Aqua MODIS and mapped on a $1 \times 1^\circ$ grid. Note that the MODIS collection 4 data erroneously had the liquid water path calculated wrong by a constant factor (see http://modis-atmos.gsfc.nasa.gov/MOD06_L2/qa.html) which we correct for in this investigation. Of particular interest are the MODIS cloud mask [Ackerman et al., 1998, 2002], cloud fraction, warm cloud fraction, MODIS cloud optical thickness, cloud effective radius, and cloud liquid water path [King et al., 1998, 2003]. Level 3 products are further described by Platnick et al. [2003].

2.1.2. Advanced Scanning Microwave Radiometer (AMSR)

AMSR is a six frequency conically scanning microwave radiometer on board Aqua. In this investigation we use gridded daily Aqua level 3 data as provided by Remote Sensing Systems (RSS). Level 3 products provide sea surface temperature, sea surface wind speed, water vapor column amount, cloud liquid water, and rain rate globally averaged onto a $0.25 \times 0.25^\circ$ grid (version 5). The native resolution of the AMSR products (except for sea surface temperature) is that of the 36 GHz channel. The algorithms used to derive those data are described by Wentz and Meissner [2000], Wentz and Spencer [1998], and Wentz [1997]. Particularly, we use the cloud liquid water path [see Wentz and Spencer, 1998] for the current investigation. We remap the AMSR data to match the MODIS resolution of $1 \times 1^\circ$.

2.2. Data Coverage

Figure 1 (left) shows the average global cloud cover derived from MODIS level 3 data for the year 2004. Figure 1 (middle) shows the relative fraction of liquid clouds (as seen from satellite) and Figure 1 (right) shows the average cloud liquid water path derived from AMSR. The total global cloud fraction between 60$^\circ$ north and south derived from MODIS level 3 data is 57% with a relative frequency of liquid clouds of 55%. In this investigation we focus on the five areas highlighted in Figure 1. Those areas are mostly located in the subtropical subsidence areas and the relative frequency of liquid clouds is in the order of 70–95%. The annually averaged AMSR derived cloud liquid water path in those areas is low, in the order of 40 g/m$^2$. In total, 2.5 years of data are evaluated, starting in July 2002 and ending in December 2004.

3. Physical Properties of Stratiform Boundary Layer Clouds

The following section gives a brief overview of the physical properties of stratiform boundary layer clouds as far as they are relevant to this paper. Wherever possible we refer to the existing body of literature in order to keep this description concise. We adapt the notation of Brenguier et al. [2000], who outline the below model in more detail.

3.1. Vertical Structure

The cloud liquid water content of stratiform boundary layer clouds is determined primarily by the temperature at cloud base and the cloud vertical extent. Air parcels rising within the cloud will stay at saturation with respect to water and the excess water vapor will be converted into liquid water. There is ample observational evidence that the profiles of liquid water content in actual stratiform boundary layer clouds follows this so-called adiabatic cloud model [e.g., Duynkerke et al., 1995; Pawlowska and Brenguier, 2000]. However, according to those studies, the average liquid water content of stratiform boundary layer clouds is around 80% of its maximum value determined by strict
adiabaticity. Only in the entrainment zone near cloud top \((h \geq 0.8 * H)\) is a significantly smaller liquid water content found. A simple adiabatic model for the liquid water content of maritime boundary layer clouds is thus:

\[
wh(h) = c_w h
\]  

where \(w(h)\) is the cloud liquid water content in kg/m\(^3\) and \(h\) is the height above cloud base. The constant \(c_w\) is the condensation rate in kg/m\(^4\) that only depends on the excess water vapor and thus, to first order, only on temperature.

Figure 2 shows the condensation rate as a function of temperature. Shown is the condensation rate at 80% of its adiabatic value \((c_w = 0.8 * H)\). It further follows from equation (1) that the total liquid water path is purely a function of \(c_w\) and the cloud geometrical thickness \(H\):

\[
W = \frac{1}{2} c_w H^2
\]  

[12] Entrainment of dry air, especially at the cloud top, is not accounted for in this simple model. At cloud top warm, dry air from above the inversion is mixed into the cloud which reduces cloud liquid water content near cloud top, leading to the aforementioned reduction in \(W\).

3.2. Cloud Microphysics

[13] Measurements of cloud microphysical properties of stratocumulus clouds indicate that the droplet number concentration \(N\) within the cloud is constant to a good approximation. The value of \(N\) depends on the availability of cloud condensation nuclei (CCN), their size distribution and chemical composition, as well as on the maximum supersaturation in the cloud which depends on the updraft velocity. \(N\) can vary for different air masses between about 25 cm\(^{-3}\) for pristine air to more than 1000 cm\(^{-3}\) for polluted air.

[14] As a consequence of a constant \(N\), marine boundary layer clouds exhibit a strong vertical structure in their microphysical properties. This structure is predominantly defined by the number of CCN that get activated at cloud base. Activated cloud droplets will move up in the cloud and grow by water vapor deposition while the cloud droplet number concentration \(N\) remains fixed. Thus, at any given height \(h\) the available liquid water is distributed over the same amount of \(N\) cloud droplets per unit volume. Therefore the average volume radius \(r_v\) does not depend on the particular shape of the cloud droplet size distribution and is only a function of \(N\) and the liquid water content \(w(h)\):

\[
r_v(h) = \left[ \frac{1}{N} \int_0^\infty r^2 N(r) dr \right]^{1/3} = \left[ \frac{1}{N} \int_0^\infty \frac{w(h)}{\pi \rho_l} \frac{dr}{dr} \right]^{1/3} = \left[ \frac{c_w}{\frac{4}{3} \pi \rho_l} \right]^{1/3} h^{1/3} N^{-1/3}
\]  

[15] The generation of drizzle within the stratiform clouds might significantly alter both the liquid water content as well as the shape of the cloud droplet size distribution.

Figure 2. Condensation rate \(c_w\) at 80% of its adiabatic value as a function of temperature.
Observational studies by Comstock et al. [2005] and van Zanten et al. [2005] show that drizzle is localized in pockets of intense precipitation rather than in a horizontally homogeneous fashion. In those pockets a reduction in cloud droplet number concentration (due to autoconversion and accretion) and a resulting increase of supersaturation with subsequent activation of smaller CCNs is possible [Rogers and Yau, 1996]. Results of Pawlowska and Brenguier [2003] indicate further that on the large scale the production of drizzle in the cloud equals the consumption of drizzle (precipitation), thus indicating that the boundary layer is at steady state. These considerations suggest, in turn, that for high values of \( W \) the cloud droplet number concentration \( N \) is reduced (because of a higher likelihood of drizzle and accretion).

[16] The experimental studies by both Pawlowska and Brenguier [2003] and van Zanten et al. [2005] find that the drizzle rate at cloud base scales with the average \( H^3/N \). While both investigations show an almost linear relation between drizzle intensity and \( H^3/N \), the slope of this relation differs by a factor of about five. Independent data compiled and published by Wood [2005] do not show as clear a relation between the two variables, but lie more on the side of the relation reported by van Zanten et al. [2005].

In the adiabatic cloud model the quantity \( H^3/N \) can be expressed in terms of \( W \) and the volume mean radius at cloud top \( \langle r_{v,\text{max}} \rangle \) as \( H^3/N \sim W \cdot \langle r_{v,\text{max}} \rangle \), using equations (3) and (2). The exact relation between \( H^3/N \) and the drizzle rate is not yet well established, mainly because of uncertainties in the in situ instrument calibration [J.-L. Brenguier, personal communication, 2006], but ultimately it might allow to estimate drizzle rates from \( N \) and \( H \). Subsequently, a value of \( H^3/N > 0.4 \) \( \text{m}^3 \) is used in this study to identify areas where drizzle is likely to occur. This threshold corresponds to drizzle rates of 0.5 mm/day if the relationship by van Zanten et al. [2005] is applied and to about 2.5 mm/day if the relationship derived from Pawlowska and Brenguier [2003] is applied. Note that the publication by Pawlowska and Brenguier [2003] had erroneously reported wrong drizzle rates. Here the corrected drizzle rates are applied (F. Burnet et al., personal communication, 2006). Note further that Pawlowska and Brenguier [2003] fit drizzle rate against \( H^3/N \) but for this study we refit this against \( H^3/N \).

### 3.3. Horizontal Variability

[17] Stratiform marine boundary layer clouds exhibit a large variability of the horizontal structure on the mesoscale. This structure is mostly driven by the turbulent mixing state of the boundary layer as well by microphysical processes such as the aforementioned drizzle generation. Wood and Hartmann [2006] perform a thorough analysis of the mesoscale variability of liquid water path and optical depth in maritime boundary layer clouds. They conclude that the variability of optical depth is well described using the adiabatic cloud model and a Gaussian distribution of mean cloud liquid water path, cloud fraction and variability in liquid water path which is driven by either the subscale distribution of supersaturation or by the distribution of cloud height. The horizontal structure is of particular importance for remote sensing observation, since three-dimensional radiative transfer effects as well beam-filling effects due to nonlinear inversion functions significantly reduce the accuracy of remote sensing estimates of cloud properties. The findings of Wood and Hartmann [2006] are used in the subsequent error analysis to assess the error in \( N \) and \( H \) retrievals.

### 3.4. Optical Properties of Boundary Layer Clouds

#### 3.4.1. Visible and Near Infrared Spectral Range

[18] In the near infrared \( (0.6 \mu \text{m} \leq \lambda \leq 2.5 \mu \text{m}) \), cloud droplets are much larger than the observed wavelength and can be considered to be close to the geometrical optics limit (size parameter \( \chi = \frac{2 \pi r}{\lambda} \geq 30 \)). Thus the dependency of the extinction efficiency \( Q_E \) on size parameter is weak and \( Q_E \approx 2 \). While at short wavelengths \( (\lambda \leq 1.2 \mu \text{m}) \) scattering is basically conservative, at somewhat higher wavelengths cloud droplets partly absorb radiation and their single scatter albedo decreases with increasing droplet radius. Remote sensing observations at one nonabsorbing and one absorbing wavelength will therefore allow to retrieve both the optical thickness of the cloud \( (\tau) \) as well as one piece of information on the average size of the cloud droplets. The latter is typically expressed as the cloud droplet effective radius \( (r_{\text{eff}}) \), which for a vertically homogeneous cloud is the third moment of the droplet size distribution over its second moment. For a vertically homogeneous cloud, the cloud liquid water path can be calculated from those two quantities as:

\[
W = \frac{2}{5} \rho_l \tau r_{\text{eff}},
\]

where \( \rho_l \) is the density of liquid water. However, since typical boundary layer clouds are not vertically homogeneous, the interpretation of the effective radius is not straightforward. The retrieved effective radius represents a weighted vertical average over the cloud depth, where the weighting is primarily determined by the average penetration depth of solar radiation into the cloud, which in turn depends on observation geometry and wavelength [Nakajima and King, 1990]. This effect can be corrected for by using, for example, the technique outlined by Nakajima and King [1990].

[19] Similar to the retrieval of cloud optical thickness \( \tau \) and cloud effective radius \( r_{\text{eff}} \), cloud geometrical thickness \( H \) and cloud droplet number concentration \( N \) can be retrieved for clouds under the more realistic assumption of an adiabatic stratification. The former retrieval \( (\tau - r_{\text{eff}}) \) is described in general by Nakajima and King [1990] and applied to MODIS by King et al. [2003]. For a general discussion of the \( (N-H) \) retrieval see Brenguier et al. [2000]. Schiller et al. [2005] apply this methodology to MODIS data. For stratiform boundary layer clouds, the N-H coordinate system is advantageous over \( (\tau - r_{\text{eff}}) \) in particular because it decouples cloud microphysical effects \( (N) \) from cloud dynamics effects \( (H) \). In contrast, \( r_{\text{eff}} \) will also depend strongly on \( W \) in a marine boundary layer cloud and thus it will be positively correlated also with \( \tau \). This finding can be easily proven by correlating \( r_{\text{eff}} \) with \( W \) [e.g., Han et al., 1998].

[20] In the adiabatic cloud model the optical thickness of a cloud can be related to \( N \) and \( H \) as follows:

\[
\tau = \frac{3}{5} \pi Q \left[ \frac{3c_w}{4\pi n_l} \right] ^{2/3} [kN]^{1/3} H^{5/3}
\]
where $Q$ is the scattering efficiency ($\approx 2$) and $k = (\frac{c}{\omega})^3$ is the ratio between the volume mean radius and the effective radius which has been found to vary between 0.5 and 0.9 [Lu and Seinfeld, 2006]. From the above equation (5) and the relation $r_{\text{eff}} = r_k^{-1/3}$, the following relation between the liquid water path $W$ and $r_{\text{eff}}$ and the effective radius at cloud top ($r_{\text{eff,max}} = r_c(H)$) can be derived [see, e.g., Wood and Hartmann, 2006]:

$$W = \frac{5}{5} \rho \tau r_{\text{eff}}. \quad (6)$$

[21] Note that equations (4) and (6) differ by a constant factor of 0.83. This factor will be verified in this investigation by comparing passive microwave estimates of cloud liquid water path with those derived from the MODIS level 3 data (which are derived using equation (4)).

3.4.2. Microwave Spectral Range

[22] Passive microwave remote sensing observations of boundary layer clouds enable the determination of cloud liquid water path using an entirely different physical mechanism than near infrared observations. For typical passive microwave observations with a wavelength of about 1 cm, cloud droplets (with $r_{\text{max}} < 30 \mu m$) are in the Rayleigh scattering regime (size parameter $\chi = \frac{2\pi r}{\lambda} \approx 0.02$). From Mie-theory it follows that the scattering efficiency of a small droplet decreases with $\chi$ whereas the absorption efficiency only decreases linearly with $\chi$. Thus, as long as there is nonnegligible absorption, small enough particles will interact with radiation as pure absorbers/emitters with negligible scattering. As a result, the total optical depth of a water cloud at microwave frequencies is merely its vertically integrated liquid water path $W$ times the mass absorption coefficient $\sigma_{\text{MW}}$:

$$\tau_{\text{MW}} = W \cdot \sigma_{\text{MW}} \quad (7)$$

[23] Passive microwave remote sensing techniques make use of this very direct relation to retrieve liquid water path from observed brightness temperatures. Another clear advantage of passive microwave observations is that they are independent of solar insolation, and that true three-dimensional radiative transfer effects are negligible, since the radiative transfer occurs in a pure emission/absorption regime. Several other atmospheric parameters affect passive microwave observations and need to be accounted for (and can be jointly retrieved) in actual passive microwave retrieval algorithms. These parameters are water vapor column amount, sea surface temperature, sea surface wind speed, and possible rain contamination. Additionally, partial filling of the microwave observation with clouds may lead to an underestimation of cloud liquid water path because of the exponential relation between observed brightness temperatures and cloud liquid water path. For a detailed discussion of passive microwave retrievals of cloud parameters see for example Petty [1994] or Wenzl [1997].

[24] The most important advantage of passive microwave observations in the context of this study is that they are entirely independent of any cloud microphysical parameters; that is, there is no dependency on the cloud droplet average radius. Thus passive microwave observations provide a crucial piece of information to decouple cloud thickness effects on cloud droplet radius from indirect aerosol effects caused by the availability of condensation nuclei.

3.5. Deriving $N$ and $H$

[25] We use observations of liquid water path $W$ (either from MODIS or AMSR) together with MODIS observations of $\tau$ to derive $N$ and $H$ from the above equations (2) and (5). Noting that the microwave derived $W$ is the average liquid water path over the entire grid box (including cloud-free areas), the fraction of warm clouds $C_F$ is used to rescale $W$ to its averaged value for the cloudy part. The following equations are obtained from equations (2) and (5):

$$H = \left[ \frac{2 W}{C_F} \right]^{1/2} \quad (8)$$

$$N = 2^{\frac{5}{2}} \frac{1}{k} \tau^{1/2} \left[ \frac{W}{C_F} \right]^{-5/2} \left[ \frac{3}{5} Q \right]^{-3/2} \left[ \frac{3 \pi Q}{4 \pi \rho \tau} \right]^{-1/2} C_F^{1/2} \quad (9)$$

[26] These equations allow to derive $N$ and $H$ from three independent pieces of information, namely $W$, $C_F$, and $\tau$. Additionally the three parameters $k$, $c_{\text{in}}$, and $Q$ affect the retrieval accuracy. Their value is associated with some uncertainty and it is worthwhile to study the impact of errors not only in the input variables ($W$, $C_F$, $\tau$), but also the impact of uncertainties in $k$, $c_{\text{in}}$, and $Q$ on estimation errors in $N$ and $H$.

3.6. Error Estimates

3.6.1. Error Propagation

[27] Note that the relations between each input variable $\chi_{\text{in}}$ and the output variables $\chi_{\text{out}}$ in the above equation (8) strictly follow a power law, i.e., $\chi_{\text{out}} = \chi_{\text{in}}^\alpha$. Thus the sensitivity of any output variable $\chi_{\text{out}} \in \{H, N\}$ to any input variable $\chi_{\text{in}} \in \{W, C_F, k, c_{\text{in}}, Q\}$ can be written as:

$$\frac{\partial \chi_{\text{out}}}{\partial \chi_{\text{in}}} = \alpha \frac{\chi_{\text{out}}}{\chi_{\text{in}}} \quad (10)$$

where $\alpha$ is the exponent in the particular power law relation between $\chi_{\text{in}}$ and $\chi_{\text{out}}$. Using Gaussian error propagation we can write the relative error of the above equations (8) and (9) as:

$$\frac{\delta H}{H} = \frac{\delta W}{W} + \frac{\delta C_F}{C_F} \quad (11)$$

$$\frac{\delta N^2}{N^2} = \frac{\delta k^2}{k^2} + \frac{\delta \tau^2}{\tau^2} + \frac{5}{2} \frac{\delta W^2}{W^2} + \frac{5}{2} \frac{\delta C_F^2}{C_F^2} \quad (12)$$

[28] Assuming a 10% relative error in each $\chi_{\text{in}}$ would then simply yield $\delta H = 0.09H$ and $\delta N = 0.56N$. This simple calculation already shows that the estimate of $N$ is more uncertain than $H$ and that the factors that dominate the errors in $N$ are obviously those that appear to high powers in
A more realistic error estimate can be obtained by modeling the contributions of the different error sources and by accounting for possibly systematic errors versus random noise.

### 3.6.2. Random Versus Systematic Errors

In this section, uncertainties in the six parameters \(\chi_{in}\) are discussed and roughly divided into random versus systematic errors. It has to be noted that for some variables the error estimates themselves are highly uncertain. For some of the input data no error estimates are available or error estimates are purely based on simulations. The exercise still proves to be worthwhile since it allows insight into the relative importance of different errors on the retrieved values of \(N\) and \(H\).

1. Errors in liquid water path (\(W\)): The random error in \(W\) for individual retrievals is assumed to be in the order of 25 g/m\(^2\) with only about 20% of this error caused by radiometric noise. For a detailed discussion of these errors see Wentz [1997]. Averaging over several 100 measurements in a \(1 \times 1^\circ\) box reduces the remaining error by about 5 g/m\(^2\) to a value of 20 g/m\(^2\). Our own subsequent findings show that at the low end the estimates of \(W\) are biased positive with a value of about 20 g/m\(^2\). This value has been obtained by studying microwave retrievals of \(W\) for cloud-free scenes (visually inspected from MODIS). The uncertainty at the low end has been found to be in the order of 15 g/m\(^2\) and thus somewhat smaller than the above estimate by Wentz [1997]. The low-end bias value is, however, higher than that reported by Wentz [1997] (5 g/m\(^2\)). Since this bias has been estimated for cloud-free scenes only, it is unclear as of now if it occurs under fully cloudy conditions, too. Since our subsequent investigations are mainly concerned with cloudy pixels, we do not account for this bias, which could possibly be another source of error. Subsequently, we will, however, show that a good agreement between the microwave and the near infrared estimate of cloud liquid water path exists for overcast clouds under nondrizzle conditions. On the basis of these findings we assign an error of 15 g/m\(^2\) to the \(1 \times 1^\circ\) estimates of \(W\).

2. Errors in optical thickness \(\tau\): The MODIS cloud optical thickness product used in this investigation is described by Platnick et al. [2003]. Quantitative error estimates for this retrieval technique are given by Nakajima and King [1990] and King et al. [1998]. Furthermore, Platnick et al. [2003] discuss possible systematic error sources in great detail and also lay out a decision tree logic that allows to retrieve optical thickness (and effective radius) only for MODIS observations that are deemed fully cloudy. In particular, mixed phase scenes (e.g., stratocumulus with underlying cirrus) and broken clouds are addressed. Some of the relevant details of their approach are discussed below when we address the cloud fraction error. According to the above references, we assume errors in \(\tau\) for individual retrievals to be in the order 10% with a relative random component of 20% so that after sufficient spatial averaging a remaining error of 8% is assumed.

3. Errors in the fraction of liquid clouds \(C_F\) within a \(1 \times 1^\circ\) box contribute the same weight to the total error budget of \(N\) and \(H\) as errors in \(W\). In order to keep consistency between the optical thickness estimate and cloud fraction we use the variable “cloud_fraction_water” in the MODIS level 3 data to estimate cloud fraction.

Following Platnick et al. [2003], this variable is defined as the number of pixels with successful retrieval of water cloud properties over the total number of cloudy and cloud-free pixels. Pixels on which no successful retrieval could be performed (i.e., cloud edges, thin, broken clouds) are not included. Thus \(C_F\) only provides an estimate of the true cloud fraction and the accuracy of this estimate depends on how many pixels had to be excluded. In particular, if a large number of observations is contaminated with cirrus, the estimate of \(C_F\) becomes more uncertain. Contrarily, the daytime detection of clouds over water surfaces is most reliable because of the high contrast between bright clouds and dark ocean surface in the solar spectral range. In light of the above uncertainties we assign \(C_F\) an error of 10% absolute. For more details on the cloud detection see Platnick et al. [2003] and Ackerman et al. [1998].

4. Errors in \(c_w\): From Figure 2 we find that \(c_w\) varies slightly with temperature. Additionally, as outlined above, the profile of liquid water content typically shows values of a factor of about 0.8 of the maximum adiabatic liquid water profile. Obviously, the uncertainty in this factor drives the uncertainty in \(c_w\). We assume \(c_w\) to vary with \(\pm 0.1\) which is justified by the range of variability shown in the liquid water profiles given by Duynkerke et al. [1995] and Pawlowska and Brenguier [2000]. Uncertainties in \(c_w\) are likely to be spatially correlated, which is to say that for a given cloud system the degree of subadiabaticity varies less strongly than between different cloud systems.

5. Uncertainties in \(k\): The variable \(k\) relates the volume mean radius to the effective radius of a droplet size distribution and is determined by the skewness and dispersion of the droplet size distribution [Martin et al., 1994], Lu and Seinfeld [2006] compile values for \(k\) found experimentally by different authors. Values of \(k\) range between \(k = 0.5\) and \(k = 0.9\). Lu and Seinfeld [2006] further propose a relation between the dispersion of the droplet size distribution and the droplet number concentration of maritime clouds [Lu and Seinfeld, 2006, Figure 16]. Together with equation (11) in their publication, this relation can be used to derive a formulation for \(k = k(N)\) which can be accounted for in equation (9). On the basis of the findings by Lu and Seinfeld [2006], we find that if \((NK)\) is retrieved in equation (9) instead of \(N\) (as suggested by Pawlowska and Brenguier [2000]), the value of \(N\) can be derived from \(N = (2.3 NK)^{0.9}\) with a high accuracy in the range \(0 < N < 200\) cm\(^{-3}\) under the assumption \(k = k(N)\). The root mean square deviation between the true \(N\) and approximated \(N\) is 3.8 cm\(^{-3}\). However, as Lu and Seinfeld [2006] point out, the underlying relation between \(N\) and the dispersion of the droplet spectrum is highly variable and there is no conclusive evidence at this point that the above proposed relation is valid or superior to any other ad hoc assumption about \(k\). Therefore, in this work we hold \(k\) fixed at a value of 0.8 ± 0.1. Subsequently, in the results section, we will revisit the issue of the variability in \(k\) and also compare the results derived from a fixed \(k\) with those assuming the above relation between \(N\) and \(k\).

6. Uncertainties in the scattering efficiency \(Q\): In the geometrical optics limit it follows that \(Q = 2\). However, in our case the size parameter is only around 30, so that \(Q\) should vary slightly around a value of 2 depending on the effective radius. We chose \(Q = 2 ± 0.1\).
On the basis of the above error estimates we constructed a large set of simulated scenes with variable cloud fraction, liquid water path, and cloud optical thickness. Within the cloudy part of those scenes we accounted for subscale variability of cloud liquid water using subscale distributions of $W$ as proposed by Wood and Hartmann [2006] (Gaussian-$h$). We then derived $N$ and $H$ on the scene averaged values using equation (8) and compared the retrieval results to the true scene averaged values. Figure 3 summarizes the uncertainties in $N$ and $H$ that result from the above error model. Figure 3 (top) shows the relative uncertainties in $H$ (Figure 3, top left) and $N$ (Figure 3, top right) as function of variables that dominate the error budget. Errors in $H$ decrease with increasing cloud fraction or increasing liquid water path. For a cloud fraction $C_F > 0.8$, errors in $H$ are in general smaller than 20%, except for cases with very low liquid water. As already found above, $N$ has higher relative errors. Especially for low cloud fractions ($C_F < 0.1$), the errors in $N$ can be up to 260%, while for cloud fractions above 0.8 the relative retrieval error in $N$ will be smaller than 80%. Figure 3 (bottom) shows the relative contribution of the six different input variables to the total variance in the estimate of $N$.

While the magnitude of the error estimates presented above is subject to the particular choice of the individual errors used in the input data, the above considerations allow a few general conclusions. In order to minimize noise, particularly in the estimate of $N$, it seems highly desirable...
to restrict the data evaluation to scenes with comparably high cloud cover and high cloud liquid water path. We thus restrict our investigation here to only those cases where $C_F > 0.8$ and liquid water path $W > 25 \text{ g/m}^2$.

[38] In accordance with Pawlowska and Brenquier [2000] we note that the particular choice of $k$ does not have a big impact on the retrievals compared to other sources of error. The same statement holds true for $c_w$ and $Q$. Note that the three input parameters $Q$, $c_w$, and $k$ account together for only about 15% of the total variance for $c_F > 0.8$ so that the error budget is almost entirely driven by uncertainties in the three input parameters $c_F$, $W$, and $\tau$.

### 3.7. Comparison of Microwave and Near Infrared Estimates

[39] The near infrared data and the microwave data provide observations of cloud liquid water path based on entirely different physical principles. Table 1 compares the estimates of $W$ derived from passive microwave data and MODIS near infrared data for all stratus boundary clouds for the five different investigation areas. Note that the near infrared estimates presented in Table 1 employ equation (6) (assuming an adiabatically stratified cloud) and thus differ by the aforementioned factor of 0.83 from the standard MODIS products that uses equations (4) (assuming a vertically homogeneous cloud).

[40] The ratio between the near infrared and microwave estimates in Table 1 is in range between 0.92 and 1.06 with a mean value of 0.99 ± 0.06, thus highlighting the validity of the adiabatic stratification assumption of boundary layer clouds. While the possibility still exists that both the near infrared and microwave estimates of liquid water path are off by the same factor, this would require correlated errors between the microwave instrument and MODIS. While it is ultimately impossible to fully exclude the existence of such correlated error source, the good agreement between the two different data sets indicates that at least, on average, neither data set is systematically biased at around the average values of $W$.

[41] In addition to the derivation of $W$ itself, the above framework also allows the derivation of an estimate of the effective radius at cloud top ($r_{\text{eff}, \text{TOP}, \text{MW}}$) from combined passive microwave observations of $W$ and MODIS observations of the optical thickness $\tau$ using equations (5), (3), and (8). While the effective radius derived directly from MODIS ($r_{\text{eff}, \text{NIR}}$) is not entirely independent from $r_{\text{eff}, \text{TOP}, \text{MW}}$, this estimate circumferes the use of the near infrared liquid water absorption channels of MODIS and it appears worthwhile to compare the two different estimates (see Table 1). The only additional assumption that needs to be made in the retrieval of cloud effective radius from microwave and near infrared data is that the effective radius and volume mean radius at cloud top are related via the aforementioned parameter $k$, which is set fixed to a value of 0.8. Both estimates agree well with an about 5% systematic difference, which supports the choice of $k = 0.8$.

[42] Figure 4 exemplarily shows a comparison of data density plots and histograms of both $W$ and $r_{\text{eff}}$ for the two different methods discussed above for region SAM. The histograms of both quantities match well, with a somewhat more skewed distribution of both $W$ and $r_{\text{eff}}$ for the near infrared estimates than for the microwave estimates. The data density plots show that while, on average, the bias between the two effective radius estimates is only $-0.2 \mu m$, the region with the highest data density (around $12 \mu m$) shows a bias of about $1 \mu m$ with the near infrared estimate being higher than the microwave estimate. Accounting for this deviation in $k$ would yield a $k = 0.78$ which is still well within the assumed range of uncertainty of ±0.1.

[43] The data density plot of $W$ highlights that, on average, cloud liquid water path agrees well between the two different estimates, but that for low values of $W$ the microwave systematically overestimates $W$ whereas for higher values it understimates $W$ compared to the near infrared estimate. The positive bias in the estimate of $W$ at the low end can clearly be attributed to systematic errors in the microwave retrieval (see above discussion on various error sources). For the systematic deviations at the high end, it is at this point unclear what the dominant source of error is.

### 4. Results

#### 4.1. Global Analysis

[44] Figure 5 (top left) shows the global distribution of the two and a half year average retrieved cloud droplet number concentration of maritime boundary layer clouds in a $1 \times 1^\circ$ grid. Only grid points with more than 10 days with a low cloud fraction higher than 80% within the observation period are shown. Those areas are located in the subtropical subsidence areas off the coasts of the continents between roughly 15$N$ (S) and 45 $N$(S). Note that we restrict the investigation here to ±60° latitude, so that arctic stratus clouds are not included. Cloud droplet number concentration is, in general, highly variable with maximum values close to the continents and significantly lower over the remote oceans. Maximum values of more than 200 cm$^{-3}$ occur close to the coast downwind of the major continents.
Figure 5 (top right) shows the average cloud droplet number concentration for stratiform clouds that are likely to be drizzling. Drizzle was separated from nondrizzle observations by employing the aforementioned relation between drizzle and $H^3/N$ (see section 3.2) with a threshold of 0.4 m$^{-6}$ above which clouds are assumed to contain drizzle. These clouds have a significantly lower cloud droplet number concentration, although the general feature of higher cloud droplet number concentration closer to major landmasses can still be identified. Finally, Figure 5 (bottom left/bottom right) give the relative fraction of areas with low/high likelihood of drizzle, defined for each grid-box as the number of observations without/with drizzle divided by the total number of observations times one hundred. In particular, almost all clouds are likely to contain drizzle over the southern remote oceans. Note that the observations taken by Aqua are around the early afternoon when solar heating is highest and cloud liquid water path typically lowest. At nighttime, liquid water path (and thus $H$) are higher which increases the risk of drizzle even more.

4.2. Remote Oceans

Table 2 presents the mean droplet number concentrations for the five major remote ocean basins. These numbers are average values for ocean areas at least 1500 km away from any continent. The two northern ocean areas and the south Atlantic show a higher average droplet number concentration than the south Pacific and Indian Ocean. Highest average droplet number concentrations are found over the north Atlantic, with droplet number concentrations of 118 cm$^{-3}$ for nonprecipitating cases. Over the southern oceans, the droplet number concentration is below 80 cm$^{-3}$, on average, even for nondrizzling clouds. Similarly, the fraction of clouds that are likely to contain drizzle is highest in the southern oceans, with up to 89% of the clouds over the remote southern oceans likely to contain drizzle. Those clouds also have a significantly reduced cloud droplet number concentration between 30 cm$^{-3}$ and 50 cm$^{-3}$. In contrast, only about 56% are likely to be precipitating for the northern ocean.

The numbers shown in brackets in Table 2 give the estimate of $N$ if the relation $k = k(N)$ derived from Lu and Seinfeld [2006] is used in the estimation process. Using this relation generally leads to a slightly higher estimate of $N$ with larger relative increases for smaller droplet number concentrations. Differences in the estimate of $N$ can be more than 10% and also lead to a reduced likelihood of drizzle. While these changes in the estimate of $N$ are typically smaller than the long-term variability in $N$ (as expressed in terms of the standard deviations in Table 2), especially under pristine conditions, the particular choice of $k$ might have a significant impact on the estimation of $N$. A better determination of $k$ and of its potential dependency on other observables therefore seems to be highly desirable.

4.3. Regional Results

Table 3 summarizes the results for the five areas shown in Figure 1. The highest cloud droplet number concentration is found in northeast Asia (NEA) with on average 133 cm$^{-3}$. Contrarily, the lowest numbers are found
Table 2. Statistics of Cloud Droplet Number Concentration for Remote Ocean Areas With at Least 1500 km Distance to the Next Major Landmass

<table>
<thead>
<tr>
<th>Area</th>
<th>$N$ All, cm$^{-3}$</th>
<th>$N$ No Drizzle, cm$^{-3}$</th>
<th>$N$ Drizzle, cm$^{-3}$</th>
<th>Fraction Drizzle, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Atlantic</td>
<td>89(99) ± 27</td>
<td>118(120) ± 23</td>
<td>50(56) ± 10</td>
<td>56(48) ± 20</td>
</tr>
<tr>
<td>South Atlantic</td>
<td>67(77) ± 29</td>
<td>93(96) ± 17</td>
<td>34(39) ± 7</td>
<td>64(59) ± 30</td>
</tr>
<tr>
<td>North Pacific</td>
<td>64(74) ± 22</td>
<td>84(88) ± 19</td>
<td>38(44) ± 9</td>
<td>57(49) ± 27</td>
</tr>
<tr>
<td>South Pacific</td>
<td>40(49) ± 16</td>
<td>69(74) ± 15</td>
<td>32(38) ± 7</td>
<td>86(82) ± 23</td>
</tr>
<tr>
<td>South Indian</td>
<td>42(51) ± 18</td>
<td>76(80) ± 14</td>
<td>32(38) ± 7</td>
<td>79(72) ± 21</td>
</tr>
</tbody>
</table>

The values given are two and a half year mean value with one standard deviation. Results are presented for all stratiform boundary layer cloud cases and separated in clouds with high/low likelihood of drizzle. The values in parentheses give the estimates that are derived using the parameterization of $k$ derived by Lu and Seinfeld [2006]. Standard deviations for the estimates using Lu and Seinfeld [2006] are almost identical to the standard deviations for $k = 0.8$ and are not reported.

Figure 5. Two and a half year (July 2002 to December 2004) average cloud droplet number concentration $N$ for (top left) all stratiform boundary layer cloud cases, (top right) only clouds with high likelihood of drizzle, (bottom left) only those with low likelihood of drizzle, and (bottom right) fraction of clouds with high likelihood of drizzle. Note the different scales of the color bars.
Table 3. As Table 2 but for the Five Different Areas Shown in Figure 1

<table>
<thead>
<tr>
<th>Area</th>
<th>N All, cm$^{-3}$</th>
<th>N No Drizzle, cm$^{-3}$</th>
<th>N Drizzle, cm$^{-3}$</th>
<th>Fraction Drizzle, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAF</td>
<td>95(103) ± 23</td>
<td>127(128) ± 30</td>
<td>45(51) ± 9</td>
<td>40(33) ± 10</td>
</tr>
<tr>
<td>SAF</td>
<td>95(103) ± 19</td>
<td>113(117) ± 29</td>
<td>34(39) ± 6</td>
<td>22(18) ± 9</td>
</tr>
<tr>
<td>NAM</td>
<td>96(104) ± 26</td>
<td>120(121) ± 36</td>
<td>37(44) ± 7</td>
<td>29(22) ± 8</td>
</tr>
<tr>
<td>SAM</td>
<td>77(84) ± 36</td>
<td>101(103) ± 39</td>
<td>34(40) ± 7</td>
<td>34(31) ± 11</td>
</tr>
<tr>
<td>NEA</td>
<td>129(135) ± 23</td>
<td>151(151) ± 42</td>
<td>55(64) ± 24</td>
<td>23(18) ± 3</td>
</tr>
</tbody>
</table>

on average in the South America (SAM) region. Subsequently, a more detailed analysis of three of the five areas highlighted in Figure 1 will be performed.

4.3.1. South America (SAM)

[40] Figure 6 shows a two and a half years time series of 10 day averages of droplet number concentration, cloud effective radius, geometrical height, and cloud liquid water path (from both MODIS and AMSR) for the region SAM. In this region the average cloud droplet number concentration does not show any major disturbances with an average value of 101 cm$^{-3}$ (see Table 3). Note that there is a strong horizontal gradient with an increase of $N$ toward the coast of South America (see Figure 5). The effective radius and cloud geometrical thickness both show a weak annual cycle with highest effective radii and cloud geometrical thickness around July (southern winter). The correlation between the effective radius and either geometrical height or liquid water path is in the order of 0.6, while the correlation between $N$ and any of the aforementioned quantities is only about 0.1. Variability in stratiform boundary layer clouds off the coast of South America is therefore mostly driven by changes in terms of cloud geometrical thickness under constant conditions in terms of the availability of cloud condensation nuclei. The apparent annual cycle in cloud geometrical thickness is most likely simply forced by the different solar illumination conditions with a minimum of solar forcing triggering thicker clouds in the southern winter. Note that both remote sensing estimates of $W$ show a well correlated annual cycle of liquid water path, but the MODIS estimate of the annual cycle of liquid water path appears slightly stronger with maximum deviations of around ±10 g/m$^2$ between the two estimates.

4.3.2. North America (NAM)

[50] Figure 7 shows the same time series for the NAM region. In contrast to SAM, the time series for NAM shows a much higher variability in $N$, with lowest 10 day average values around 80 cm$^{-3}$ and highest values around 250 cm$^{-3}$. Estimates of $N$ are highly negatively correlated with the effective radius (correlation coefficient $-0.82$) indicating that in this area the variability of cloud condensation nuclei has a strong impact on the average size of the cloud particles. Both cloud geometrical thickness and liquid water path exhibit a similar annual cycle as in the SAM area, however shifted by six months with maximum geometrical thickness in the northern winter. The correlation between effective radius and geometrical height or liquid water path is similar to the correlation found in SAM (0.6). Consequently, because of the high negative correlation between $N$ and $r_{eff}$, $N$ is slightly negatively correlated with liquid water path ($-0.45$). For NAM we thus find that the cloud geometrical thickness, as well as cloud liquid water path, exhibit a similar annual cycle as the in region SAM. However, the cloud microphysics (expressed in $N$) is much more variable. This variability occurs on much shorter timescales than the annual variability of liquid water path, indicating the importance of the particular synoptic situation on cloud microphysics. Our analysis showed a similar behavior for both the north Africa (NAF) and NEA areas (not shown here) indicating that the variability of cloud microphysics is strongly driven by synoptic-scale events on the Northern Hemisphere.

4.3.3. South Africa (SAF)

[51] Figure 8 shows the same time series for the SAF region. In this region, $N$ shows a very distinct behavior with very pronounced maxima around July, coinciding with the dry biomass burning season in southern Africa (July–October). The SAF region lies at the northwestern edge of the South African gyre, under almost constant easterly winds that transport heavily polluted air over the Atlantic Ocean (see, for example, Sinha et al. [2003] for more details). The pronounced maxima of $N$ are highly correlated with very small effective radii (correlation $-0.93$) and only weakly correlated with variations in $H$ (correlation coefficient 0.33). Both cloud geometrical thickness and liquid water path do not exhibit a strong annual cycle.

[52] This seems to indicate a strong impact of biomass burning on droplet number concentrations in this region with a sharp increase in droplet number concentration and a corresponding lower droplet effective radius due to more heavily polluted air. Another possible explanation would be smoke layers in the free troposphere that do not interact with the boundary layer clouds but are misinterpreted by the MODIS algorithm as water clouds with a small effective radius. In this case MODIS would interpret smoke layers falsely as liquid water and would hence overestimate the liquid water path compared to AMSR which is insensitive against aerosols. Figure 9 shows the difference in AMSR minus MODIS liquid water path versus cloud droplet number concentration for region SAF. The periods with high droplet number concentration show a higher AMSR liquid water path than MODIS, which is inconsistent with a possible misinterpretation of smoke clouds by MODIS. The correlation between the differences in $W$ and $N$ is +0.26, thus only weak and of the opposite sign than would be expected in case of a misinterpretation of aerosols as clouds by MODIS. Therefore the dramatic increase in observed $N$ during the biomass burning season appears to be real.

[53] Finally, it is interesting to note that in all of the five coastal areas the fraction of clouds with possible drizzle is...
much lower than over the remote oceans. On average, only between 20% and 40% exceed the drizzle threshold we chose in this study.

5. Conclusions

Cloud droplet number concentration of marine stratiform boundary layer clouds shows a very distinct global distribution and is highly variable both spatially and temporally. Especially leeward of the continents, droplet number concentrations are in general high and the downwind transport of polluted air appears to be a major factor affecting the microphysical state of the boundary layer clouds. It is shown that on the long-term average maritime boundary layer clouds even over the remote oceans of the Northern Hemisphere have a higher droplet number concentration than on the Southern Hemisphere. While a linkage between human activities and changes in cloud microphysics cannot be established from this study alone, the results found in this investigation may serve as a tool to

Figure 6. Time series of cloud droplet number concentration (N), cloud top effective radius ($r_{\text{eff}}$), cloud geometrical thickness ($H$), and cloud liquid water path ($W$) for area SAM. Average values are obtained for clouds with low likelihood of drizzle only.
validate, for example, global circulation models that simulate the cloud aerosol interactions as well as transport of pollution.

[55] A first attempt at the identification of drizzle from remote sensing data has been made. While uncertainties in the identification of drizzle remain, recent studies of boundary layer clouds suggest that the likelihood of drizzle can be estimated from cloud geometrical thickness and cloud droplet number concentration. Using a conservative threshold for the onset of drizzle in maritime boundary layer clouds, it is found that over the remote southern oceans up to 90% of the clouds are likely to be precipitating, while close to major land areas drizzle rates are significantly reduced. Clouds that are more likely to contain drizzle on average show a significantly reduced cloud droplet number concentration. Ultimately, a well calibrated method to remotely sense drizzle intensity might lead to a quantification of latent heat release (and to a better estimate of the autoconversion threshold) and thus important pieces of information contributing to the energy budget of the boundary layer.

[56] Another related issue that could not been addressed in this investigation is the diurnal cycle of maritime boundary layer clouds. In the tropics and subtropics, maritime
boundary layer clouds exhibit a strong diurnal cycle of cloud liquid water path. While from NASA’s Aqua satellite no information about the diurnal cycle of cloud microphysical properties can be derived, recent advances in geostationary satellite observations might allow to estimate diurnal variability in cloud droplet number concentration. Those variations might be related to drizzle formation or changes in maximum updraft velocities and resulting changes in maximum supersaturation. Contrarily, if the cloud droplet number concentration was only governed by the initial aerosol spectrum, a diurnal cycle would only occur in cloud geometrical thickness and not in cloud droplet number concentration. Those questions could partly be answered using a similar methodology as presented here but for geostationary satellite data, such as the data provided by the SEVIRI instrument on Meteosat-8.

As a byproduct of this investigation, it has been demonstrated that the cloud liquid water path of maritime boundary layer clouds is likely to be stratified adiabatically and that the classical retrieval of effective radius and optical thickness might be used to derive cloud droplet number concentration of maritime boundary layer clouds.

This investigation suggests that in particular two aspects of maritime boundary layer clouds can be further
Figure 9. Cloud droplet number concentration versus AMSR-MODIS difference in liquid water path for the 10-day average data shown in Figure 8.

studied using remote sensing observations. Firstly, the albedo effect of variable cloud droplet number concentration can be deduced from the Clouds and the Earth’s Radiation Budget Experiment (CERES [Wielicki et al., 1996]), which is also flown on NASA’s Aqua satellite. These data together with the results presented in this investigation will allow to quantify the impact of variability of cloud droplet number concentration on the shortwave albedo. Secondly, existing long-term satellite climatologies such as the PATMOS data set [Thomas et al., 2004] provide up to 20 years of satellite observations of effective radius and cloud optical thickness and might allow to study human-induced changes in cloud microphysics over the world oceans.

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References


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