Aerosol–cloud drop concentration closure for clouds sampled during the International Consortium for Atmospheric Research on Transport and Transformation 2004 campaign


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This study analyzes 27 cumuliform and stratiform clouds sampled aboard the CIRPAS Twin Otter during the 2004 International Consortium for Atmospheric Research on Transport and Transformation (ICARTT) experiment. The data set was used to assess cloud droplet closure using (1) a detailed adiabatic cloud parcel model and (2) a state-of-the-art cloud droplet activation parameterization. A unique feature of the data set is the sampling of highly polluted clouds within the vicinity of power plant plumes. Remarkable closure was achieved (much less than the 20% measurement uncertainty) for both parcel model and parameterization. The highly variable aerosol did not complicate the cloud droplet closure, since the clouds had low maximum supersaturation and were not sensitive to aerosol variations (which took place at small particle sizes). The error in predicted cloud droplet concentration was mostly sensitive to updraft velocity. Optimal closure is obtained if the water vapor uptake coefficient is equal to 0.06, but can range between 0.03 and 1.0. The sensitivity of cloud droplet prediction error to changes in the uptake coefficient, organic solubility and surface tension depression suggest that organics exhibit limited solubility. These findings can serve as much needed constraints in modeling of aerosol-cloud interactions in the North America; future in situ studies will determine the robustness of our findings.


1. Introduction

Most of the uncertainty in anthropogenic climate change is associated with aerosol–cloud interactions [Lohmann and Feichter, 2004; Andreae et al., 2005]. Explicitly resolving cloud formation, microphysical evolution and aerosol-precipitation interactions in Global Climate Models (GCMs) is a challenging computational task [Khairoutdinov et al., 2005; Randall et al., 2003]; parameterizations are used instead. In terms of predicting droplet number, empirical correlations are often used [e.g., Jones et al., 1994; Guthepe and Isaac, 1996; Boucher and Lohmann, 1995; Lohmann and Feichter, 1997; Kiehl et al., 2000; Menon et al., 2002; Brasseur and Roeckner, 2005], which relate an aerosol property (usually total number or mass) to cloud droplet number concentration, \( N_d \). The data is usually obtained from observations. Although simple and easy to implement, correlations are subject to substantial uncertainty [Kiehl et al., 2000]. Prognostic parameterizations of aerosol–cloud interactions have also been developed [Lohmann et al., 1999, 2000; Ghan et al., 2001a, 2001b; Rotstyn and Penner, 2001; Peng et al., 2002; Nenes and Seinfeld, 2003; Fountoukis and Nenes, 2005] in which \( N_d \) is calculated using cloud-scale updraft velocity, aerosol size distribution and composition. These approaches are based on the “parcel” concept of 1-D Lagrangian numerical cloud models [e.g., Jensen and Charlson, 1984; Considine and Curry, 1998; Nenes et al., 2001]. Although inherently
better than correlations, prognostic parameterizations are still subject to uncertainties in the subgrid (i.e., cloud-scale) updraft velocity [e.g., Menon et al., 2002], aerosol size distribution and composition [e.g., Rissman et al., 2004], aerosol “chemical” effects and changes in droplet growth kinetics [e.g., Nenes et al., 2002].

The ultimate test for prognostic parameterizations and cloud models is the comparison of their predictions against comprehensive in situ data. When done for cloud droplet number, this procedure is termed “cloud droplet closure study,” in which a discrepancy between \( N_d \) predicted by models and measured in situ is usually determined. Hallberg et al. [1997] report ~50% disagreement between predicted and observed \( N_d \) for continental stratocumulus clouds. Chuang et al. [2000] studied marine and continental stratus clouds sampled during the second Aerosol Characterization Experiment (ACE-2) and found a large discrepancy (about a factor of 3) between predictions and observations for updraft velocity range expected for stratocumulus clouds. Snider and Brenguier [2000] and Snider et al. [2003] found up to 50% discrepancy between predicted and measured droplet concentrations for ACE-2 and marine stratocumulus clouds. Part of this discrepancy was attributed to the usage of ground-based observations in the closure. Conant et al. [2004] achieved remarkable closure, to within 15%, for cumulus clouds of marine and continental origin sampled during the NASA Cirrus Regional Study of Tropical Anvils and Cirrus Layers—Florida Area Cirrus Experiment (CRYSTALFACE). Meskhi (2005) also found excellent agreement between predicted and measured \( N_d \) (<30%) for the stratiform cloud data gathered during Coastal Stratocumulus Imposed Perturbation Experiment (CSTRIPE, Monterey, California, July 2003). In general, cloud droplet closure has been successful for clouds formed in clean air masses, and to a lesser degree for polluted clouds. It is however unclear if the latter results from limitations in the observations or in the theory used for predicting cloud droplet number.

In this study we assess aerosol-cloud drop number closure using (1) a detailed cloud parcel model [Nenes et al., 2001] and (2) the parameterization of Nenes and Seinfeld [2003] with recent extensions by Fountoukis and Nenes [2005] (hereinafter referred to as “modified NS” parameterization). The observations used in this study were collected on board the Center for Interdisciplinary Remotely Piloted Aircraft Studies (CIRPAS) Twin Otter aircraft (http://www.cirpas.org) during the NASA International Consortium for Atmospheric Research on Transport and Transformation experiment (ICARTT). A unique feature of this data set is the sampling of highly polluted cloudy air within the vicinity of power plant plumes. Closure with the parcel model tests our predictive understanding of cloud droplet formation under extremely polluted conditions, while using the parameterization assesses its performance and quantifies the uncertainty arising from its simplified physics.

2. In Situ Observation Platform and Analysis Tools

During ICARTT, the Twin Otter realized twelve research flights in the vicinity of Cleveland and Detroit (Figure 1), several of which sampled cumuliform and stratiform clouds. Seven flights are considered in this study. The cloud sampling strategy involves several under-cloud “passes” to characterize the aerosol size distribution and chemical composition, followed by in-cloud “legs” to sample the cloud microphysics, chemistry and turbulence.

2.1. Description of Airborne Platform

Table 1 summarizes the instruments and measured quantities aboard the CIRPAS Twin Otter aircraft. A Dual Automatic Classifier Aerosol Detector (DACAD [Wang et al., 2003]) was used to measure dry aerosol size between 10 and 800 nm. The DACAD consists of two scanning Differential Mobility Analyzers (DMAs) operating in parallel, one at a “dry” relative humidity (RH) less than 20%, and another at a “humid” RH of ~75%. From the dry-wet size distributions, the size-resolved hygroscopicity is obtained. Aerosol chemical composition (sulfate, nitrate, ammonium, and organics) was measured in real time by an Aerodyne Aerosol Mass Spectrometer (AMS [Bahreini et al., 2003; Jayne et al., 2000]). Concurrently, aerosol inorganics (\( \text{NO}_x \), \( \text{SO}_x \), \( \text{NH}_4 \)) and some organics (oxalate)
were measured with a Particle-into-Liquid Sampler (PILS [Sorooshian et al., 2006a]). Updraft velocities were obtained from a five-hole turbulence probe, a Pitot-static pressure tube, a C-MIGITS GPS/INS Tactical System, GPS/inertial navigational system (INS), and the Novatel GPS system.

Droplet number concentrations were measured with a Cloud and Aerosol Spectrometer (CAS) optical probe [Baumgardner et al., 2001], and the Forward Scattering Spectrometer Probe (FSSP [Brenguier et al., 1998; Jaenicke and Hanusch, 1993]). The FSSP measures droplets ranging from 1.5 to 37 μm diameter. As with any optical counter, the FSSP is subject to numerous uncertainties such as variations of the size calibration and of the instrument sampling section, nonuniformity in light intensity of the laser beam, probe dead time and coincidence errors [Baumgardner and Spowart, 1990; Brenguier, 1989]. The FSSP is most accurate for measurements of $N_d$ below 200 cm$^{-3}$ [Burnet and Brenguier, 2002]. At high droplet concentrations, $N_d$ can be noticeably underestimated when measured with the Fast-FSSP [Burnet and Brenguier, 2002]. The CAS measures droplet sizes from 0.4 to 50 μm in 20 size bins using a measurement principle similar to that of the FSSP, but improved electronics relaxes the requirement for dead time and coincidence corrections [Burnet and Brenguier, 2002]. A Passive Cavity Aerosol Spectrometer Probe (PCASP) was also flown, which is an optical probe that measures particles between 100 and 2500 nm.

### 2.2. Cloud Parcel Model

The numerical cloud parcel model used in this study [Nenes et al., 2001, 2002] simulates the dynamical balance between water vapor availability from cooling of an ascending air parcel and water vapor depletion from condensation onto a growing droplet population. The model has successfully been used to assess cloud droplet closure in cumulus during CRYSTAL-FACE [Conant et al., 2004] and has been used in numerous model assessments of aerosol-cloud interactions [e.g., Nenes et al., 2002; Rissman et al., 2004; Lance et al., 2004]. The model predicts cloud droplet number concentration and size distribution using as input the cloud updraft velocity, aerosol size distribution and chemical composition. “Chemical effects,” such as surface tension depression [Shulman et al., 1996; Facchini et al., 1999], partial solubility or the presence of film-forming compounds [Feingold and Chuang, 2002; Nenes et al., 2002; Rissman et al., 2004; Lance et al., 2004] can also be easily considered; their effect on droplet closure will be assessed through sensitivity analysis.

### 2.3. Droplet Formation Parameterization

The modified NS parameterization [Fountoukis and Nenes, 2005] is one of the most comprehensive, robust and flexible formulations available for global models. The calculation of droplet number is based on the computation of maximum supersaturation, $s_{max}$, within an ascending air parcel framework. The parameterization provides a computationally inexpensive algorithm for computing droplet number and size distribution and can treat externally mixed aerosol subject to complex chemical effects (e.g., surface tension effects, partial solubility, changes in water vapor uptake). The parameterization’s excellent performance has been evaluated with detailed numerical cloud parcel model.
simulations [Nenes and Seinfeld, 2003; Fountoukis and Nenes, 2005] and in situ data for cumuliform and stratiform clouds of marine and continental origin [Meskhidze et al., 2005]. Formulations for sectional [Nenes and Seinfeld, 2003] or lognormal [Fountoukis and Nenes, 2005] aerosol have been developed. The latter (lognormal) formulation is used in this study.

3. Observations and Analysis

3.1. Description of Research Flights

Ten Seven flights are analyzed in this study, in which 27 clouds are profiled (Table 2). The clouds formed downwind of power plants, Cleveland and Detroit. Three research flights (IC3, 5, and 12) sampled clouds downwind of the Conesville power plant (Figure 1a), one flight (IC6) sampled clouds downwind of the Monroe power plant (Figure 1a), two flights (IC 9, 10) sampled southwest of Cleveland (Figure 1a) and one flight (IC11) sampled clouds southwest of Ontario (Figure 1a). Flight IC3 was the first to probe the Conesville power plant plume; its visible impact on local clouds (Figure 1b) motivated two more research flights (IC5 and 12) that fully characterized the plume and its influence on clouds. Backward Lagrangian trajectory analysis computed from the NOAA-HYSPLIT model (http://www.arl.noaa.gov/ready/hysplit4.html) suggests that during flights IC3 and IC9, the air mass sampled was transported by northerly winds (Figure 2a). The air sampled in all other flights originated in the boundary layer and was transported by westerly winds (Figure 2b). Prevailing wind directions, cloud types and other characteristics for each cloud case are given in Table 2.

3.2. Cloud Droplet Number and Updraft Velocity Measurements

[i] The observed cloud droplet spectra are carefully screened to eliminate biases in \( N_d \). Dilution biases are avoided by considering only measurements with effective droplet diameter greater than 2.4 \( \mu m \) and geometric standard deviation less than 1.5 [Conant et al., 2004]. A lack of a drizzle mode (liquid water) present, i.e., negligible concentrations of droplets larger than 30 \( \mu m \) (typically 0–0.2 cm\(^{-3} \)) suggest that collision-coalescence and drizzle formation were not important for the clouds sampled. Particles below 1 \( \mu m \) are either evaporating or unactivated haze and not counted as droplets.

For flights before 13 August, the CAS suffered from a saturation bias for concentrations above 1500 cm\(^{-3} \). About 3% of the data set was subject to this bias and was disregarded from this study. The CAS was also found to overcount droplets smaller than 6 \( \mu m \) but reliably counted droplet larger than 6 \( \mu m \). This problem is addressed by disregarding the 1–6 \( \mu m \) CAS data and replacing them with FSSP data corrected for dead time and coincidence errors [Burnet and Brenguier, 2002]. Droplet concentration uncertainty was assessed by comparing FSSP and CAS concentrations in the 6–10 \( \mu m \) range; the former was to be about 40% lower than the latter. As all known sources of bias are accounted for in the FSSP correction, we assume that the difference between the two probes (40%) expresses an unbiased uncertainty (±20%) in observed droplet concentration for the whole data set and droplet size range.

The observed cloud droplet concentrations for each flight are presented in Table 2. Average \( N_d \) varied from 320 cm\(^{-3} \) to 1300 cm\(^{-3} \) and as expected, correlated with...
cloud updraft velocity, \( w \); clouds with \( N_d > 1000 \, \text{cm}^{-3} \) typically had \( w > 1 \, \text{m s}^{-1} \), \( N_d \sim 500–1000 \) for \( w \sim 0.5 \, \text{m s}^{-1} \) and \( N_d \sim 300–500 \) for \( w \sim 0.25 \, \text{m s}^{-1} \). High droplet concentration (even for clouds with low updraft velocity) is indicative of the high aerosol loading in almost all clouds profiled.

As expected, updraft velocity varied significantly in each cloud (even at cloud base); we chose to fit observations to a mass-flux-weighted Gaussian probability density function (pdf), as discussed by Meskidze et al. [2005] and Conant et al. [2004]. Aircraft turns were eliminated from our analysis and the pdf in the measurements were shifted to have a mean of zero (consistent with the assumption of a slowly evolving boundary layer). Table 2 shows the values of average updraft velocity (closest to cloud base) and its standard deviation. Average cloud updraft velocity (at cloud base), \( w_u \), varied between 0.12 (±0.13) and 1.89 (±0.73) m s\(^{-1}\). \( w_u \) and its standard deviation, \( \sigma_{w_u} \), were highly correlated (Figure 3); typical of stratocumulus clouds, \( \sigma_{w_u} \) is significant and comparable to the mean updraft velocity.

### 3.3. Aerosol Size Distribution and Composition

Flight legs were first conducted below cloud base to characterize aerosol composition and size distribution, followed by constant-altitude transects through the cloud; a final pass was done at the cloud top (at 300–1000 m). The vertical profiles and horizontal transects are used to deduce cloud spatial extent and height. The under-cloud aerosol size distributions are averaged and fit to three (or four) lognormal modes (depending on the observations) using least squares minimization. Average total aerosol concentration ranged from 4200 cm\(^{-3}\) to 13300 cm\(^{-3}\); the distribution information for each cloud case is summarized in Table 3.

Whenever available (flights IC3, IC5, IC6), AMS measurements were used to describe the dry aerosol composition. The AMS always detected significant amounts of organics, constituting 35–85% of the total aerosol mass. Highest organic mass fractions were observed outside of power plant plumes (Table 3). The ammonium-sulfate molar ratio obtained both by the PILS and the AMS was larger than 2 for most flights (ranging from 2.0 to 3.7), except for IC5, where the ratio was 1.75. This suggests that the aerosol was
neutralized in all flights except IC5. Lack of size-resolved composition precludes the detection of acidity changes throughout the aerosol distribution, but any gas phase ammonia (for all flights except IC5) would quickly condense and neutralize acidic particles formed from in-cloud production of sulfate. The PILS analysis showed small amounts of nitrate and oxalate, the latter being generated by in-cloud oxidation of organic precursors [Sorooshian et al., 2006b]. It is unclear whether particulate nitrate is associated with aerosol phase organics. When combined, nitrate and oxalate did not exceed 2% of the total (soluble + insoluble) aerosol mass and were excluded from our analysis; a small change in the soluble fraction would not significantly impact droplet concentrations [Rissman et al., 2004]. Table 3 presents the aerosol size distribution and composition for each cloud case considered in this study.

Additional compositional insight (and its spatial variability) can be obtained from the DACAD; the hygroscopic growth factor (wet over dry aerosol diameter) during flight IC3 was ~1.17, (compared to 1.44 for pure ammonium sulfate at 77% relative humidity), characteristic of carbonaceous material with low sulfate content. Ageing of the plume downshow showed an increase in hygroscopicity, consistent with condensation of sulfates on the aerosol. The influence of the power plant plume could be detected for more than 20 miles downwind of the plant (Figure 4). Representative examples of measured and fitted size distributions are shown in Figure 5; the discrepancy for CCN-relevant size range (larger than 30 nm) is generally small, less than 10%.

3.4. Cloud Droplet Closure: Parcel Model

[18] The average updraft velocity, \( w_u \), is used to compute \( N_d \), this was shown by Meskhidze et al. [2005] to give optimal closure for cumulus and stratocumulus clouds. \( w_u \) is defined as, 

\[
\frac{w_u}{\psi_w} = \frac{\int w p(w)dw}{\int p(w)dw},
\]

where \( p(w) \) is the vertical velocity probability density function (pdf). For a Gaussian pdf with standard deviation \( \psi_w \) and zero average velocity, 

\[
p(w) = \frac{1}{\sqrt{2\pi}\psi_w} \exp\left(-\frac{w^2}{2\psi_w^2}\right),
\]

\[
w_u = -\frac{w_o}{(2\pi)^{1/2}} \int_0^\infty \exp(-x)dx \frac{1}{0.5} \left(\frac{2}{\pi}\right)^{1/2} \psi_w \approx 0.8\psi_w
\]
as calculated from equation (1), is identical to the “characteristic” velocity found by Peng et al. [2005] used for assessing cloud droplet closure for stratocumulus clouds sampled in the North Atlantic Ocean. Equation (1) is also reflected in the updraft velocity observations (Figure 3); \( \sigma_z \), which is roughly half of \( \psi_w \), yields after substitution into equation (1) \( \sigma_z \approx 0.63 \psi_w \), which is consistent with the slope of Figure 3.

The undercloud temperature, pressure and relative humidity describe the precloud thermodynamic state of the atmosphere and are used as initial conditions for the parcel model. Aerosol observations and cloud updraft velocity are obtained from Tables 2 and 3.

It is assumed that the aerosol is internally mixed and composed of two compounds: ammonium sulfate (with density \( \rho_{\text{sulf}} = 1760 \text{ kg m}^{-3} \)) and organic (with density \( \rho_{\text{org}} = 1500 \text{ kg m}^{-3} \)). The “organic” density is slightly larger than the 1200–1250 \( \text{kg m}^{-3} \) value of Turpin and Lim [2001] proposed for Los Angeles to account for ageing and the presence of some crustal species. For flights which AMS data were not available (i.e., IC9, IC10, IC11, IC12), the “insoluble” volume fraction, \( V_{\text{ins}} \), was inferred by subtracting the ammonium sulfate volume, \( V_{\text{sulf}} \) (obtained from PIRS measurements) from the total aerosol volume, \( V_{\text{total}} \) (obtained from size distribution measurements). The mass fraction of the insoluble material, \( m_{\text{ins}} \), is then calculated as,

\[
 m_{\text{ins}} = \frac{\rho_{\text{org}} V_{\text{ins}}}{\rho_{\text{sulf}} V_{\text{sulf}} + \rho_{\text{org}} V_{\text{ins}}} 
\]

The assumption that only inorganics contribute soluble mass relevant for CCN activation appears to be reasonable in CCN closure studies conducted in North America [e.g., Medina et al., 2007; Broekhuizen et al., 2005]. The importance of both assumptions in cloud droplet number prediction is discussed in section 3.5.

The mass water vapor uptake (condensation) coefficient, \( a_c \), needed for computing the water vapor mass transfer coefficient [Fountoukis and Nenes, 2005] is currently subject to considerable uncertainty. Li et al. [2001] have shown that if uptake is controlled by the accommodation of water vapor molecules onto droplets, \( a_c \), can range from 0.1 to 0.3 for pure water droplets, from 0.04 to 0.06 for aged atmospheric CCN [Shaw and Lamb, 1999; Pruppacher and Klett, 2000; Chuang, 2003; Conant et al., 2004], while a recent work suggests that it should be close to unity for dilute droplets and pure water [Laaksonen et al., 2004]. However, ambient CCN at the point of activation are concentrated solutions composed of electrolytes and (potentially) organic surfactants,
Figure 6. Cloud droplet number closure using the parcel model. The conditions for predicting $N_d$ are summarized in Tables 2 and 3.

which, together with other kinetic processes (e.g., solute dissolution [Asa-Awuku and Nenes, 2007]), can slow water uptake and growth kinetics; this would give an apparent uptake coefficient much less than unity (even if $a_c$ were unity). Because of this, and following the suggestions of Shaw and Lamb [1999] and Conant et al. [2004], we consider a “base case” value of $a_c$ equal to 0.06. The data set (Tables 2 and 3) is used to determine a “best fit” value for $a_c$ and constrain its uncertainty (section 3.5).

[22] Figure 6 shows the cloud droplet number closure for all 27 clouds analyzed in this study. The parcel model predictions of $N_d$ are close to the 1:1 line of perfect agreement with observations. In most cases, predictions are within 25% of the observations (average error 3.0 ± 15.4%; average absolute error 12.8 ± 8.7%), which is considerably less than the estimated $N_d$ uncertainty of ~20%.

3.5. Cloud Droplet Closure: Modified NS Parameterization

[23] Evaluation of the modified NS parameterization is carried out via a closure study, using the procedure outlined in section 3.3. The results are shown in Figure 7; on average, the modified NS parameterization was found to reproduce observed $N_d$ with the same accuracy as the parcel model (average error 1.5 ± 17.9%; average absolute error 13.5 ± 11.5%). There is no systematic bias between the modeled and the observed $N_d$. This is remarkable, given that highly polluted clouds formed from CCN containing large amounts of organics have long been considered a challenge for any parameterization and parcel model [e.g., Conant et al., 2004]. This study, combined with the work of Meskhidze et al. [2005] clearly show that the modified NS parameterization can accurately and robustly predict the process of cloud droplet activation and reliably be used in GCM assessments of the aerosol indirect effect.

3.6. Sources of Uncertainty and Sensitivity Analyses

[24] Despite the excellent closure, it is important to identify key contributors to $N_d$ error (defined as the difference between predicted and measured $N_d$ normalized to measured $N_d$). This is done by examining the correlation of $N_d$ error with key parameters affecting $N_d$, being (1) total aerosol number, (2) accumulation mode aerosol number, (3) average cloud base updraft velocity, (4) cloud base updraft velocity variance, (5) observed cloud droplet number, and (6) aerosol sulfate mass fraction. The first two parameters are used as a proxy for pollution. The next two parameters are used as a proxy for cloud dynamics, which strongly impact cloud droplet number and its sensitivity to “chemical effects” [e.g., Nenes et al., 2002; Rissman et al., 2004]. Sulfate mass fraction itself is a proxy for “chemical effects,” as low sulfate is usually correlated with high organic content, which in turn may be water-soluble and contain surfactants. Finally, observed cloud droplet number is used to explore whether the $N_d$ observations are subject to some concentration-dependant bias (section 3.2). Table 4 presents the results of the correlation analysis. When the whole data set is considered, $N_d$ error only correlates significantly with $w_u$ (R^2 in Table 4 is for $w_u < 1$ m s\(^{-1}\)) and its variance. There is practically no correlation of droplet error with $w_u$ when it is above 1.0 m s\(^{-1}\) (roughly 50% of the data set). The correlation of error with updraft is stronger as the $w_u$ decreases; this is expected as vertical velocity uncertainty becomes substantial for low updrafts. Lack of droplet error correlation with chemical composition variations is consistent with Rissman et al. [2004], who show droplet number is most sensitive to variations in updraft velocity under conditions of low supersaturation (i.e., strong competition for water vapor from high aerosol concentration and low updraft velocity). When considering subsets of data, updraft velocity still correlates with droplet error (Table 4), more weakly (R^2 = 0.2) for power plant flights alone (IC3,5,6,12) and more strongly (R^2 = 0.5) for non-power-plant plume flights (IC9,10,11). The strength of correlation is expected, as power plant clouds are more vigorous (56% have $w_u > 1$, 6% have $w_u < 0.25$), than non-power-plant clouds (55% have $w_u > 1$, and 27% with $w_u < 0.25$).

[25] For power plant flights alone, droplet error also correlates with aerosol number. This is likely from the temporal averaging of the aerosol size distribution; an averaged distribution cannot account for the spatial heterogeneity of the aerosol (hence droplet number) in the vicinity of power plant plumes. Therefore droplet error does not arise...
from the presence of very high aerosol concentrations at cloud base, but variations thereof. The observations support this hypothesis; $N_d$ error decreases as the plume ages and dilutes to the polluted (but homogeneous) background aerosol. Despite the correlation, the droplet number variability is still small compared to the highly variable aerosol near the vicinity of a power plant plume (Figure 4) for two reasons: droplet number variability is inherently less than the CCN variability [Sotiropoulou et al., 2006], and clouds may not respond to aerosol variations when they take place at small particle sizes and $s_{\text{max}}$ is not sufficiently high to activate them. The latter can be seen in Figure 4; most of the aerosol variability is seen in small diameters (＜60 nm), while droplets formed upon CCN with diameter greater than 70 nm (simulations suggest that $s_{\text{max}} \sim 0.085\%$). For non-power-plant plume flights (IC9,10,11), cloud droplet error correlates with cloud droplet number (but not sulfate fraction or aerosol number), which suggests the presence of minor biases in the $N_d$ observations, which however are not significant enough to affect closure.

[26] Droplet number error also arises by assuming that aerosol chemical composition is invariant with particle size (section 3.3). Broekhuizen et al. [2005], Medina et al. [2007] and Sotiropoulou et al. [2006] have shown that this assumption for polluted areas can result in up to 50% error in CCN predictions. If our data set is subject to similar uncertainty, the resulting $N_d$ error should range between 10 and 25% [Sotiropoulou et al., 2006], well within the observational uncertainty. If organics partially dissolve and depress droplet surface tension, $N_d$ can become less sensitive to variations in chemical composition [Rissman et al., 2004].

[27] Figure 8 presents the sensitivity of droplet number prediction error, averaged over the data set, to the uptake coefficient, $a_c$. Figure 8 displays the $N_d$ standard deviation only for the parcel model, as the parameterization exhibits roughly the same behavior. The sensitivity analysis was done using the parcel model and activation parameterization, and assuming that the organic fraction is insoluble. Assuming that the droplet number prediction error is random, our simulations indicate that the “best fit” value of $a_c$ (i.e., the value which the average $N_d$ error is minimal and its standard deviation lies between the measured droplet uncertainty range) is 0.06, which is in agreement with values obtained from the Conant et al. [2004] and Meskhidze et al. [2005] closure studies. Assuming a 20% uncertainty in observed $N_d$ (and neglecting the $N_d$ error standard deviation) constrains $a_c$ between 0.03 and 1.0 (Figure 8). Peng et al. [2005] also obtain good closure using a much different $a_c$ (=1) in their analysis; this does not suggest that the closure is insensitive to $a_c$, but rather that updraft velocity and droplet number measurements require reduction in their uncertainty (Figure 8) to further constrain $a_c$.

[28] Finally, we assess the sensitivity of droplet closure to “chemical effects” (i.e., solubility of the organic fraction and depression of surface tension); the focus is to assess whether different values of the uptake coefficient and organic solubility (compared with the “base case” simulations for $a_c = 0.06$) can yield good closure. In the sensitivity analysis, the dissolved organic was assumed to have a molar volume of 66 cm$^3$ mol$^{-1}$ and a Van’t Hoff factor of 1, which is consistent with a lower limit of properties derived from the activation of water-soluble organic carbon extracted from biomass burning samples (A. Asa-Awuku, Georgia Institute of Technology, personal communication, 2006). Organic solubility varied from 10$^{-4}$ to 1 kg kg$^{-1}$; when surface tension is allowed to decrease, we use the correlation of Facchini et al. [1999], assuming 8 mols of carbon per mol of dissolved organic [Nenes et al., 2002]. We also consider two values of the uptake coefficient, 0.06 and 1.0. Simulations indicate (Figure 9) that organic solubility less than 10$^{-3}$ kg kg$^{-1}$ is not enough to affect CCN (thus droplet number) concentrations. All the organic dissolves during activation when its solubility is larger than 10$^{-2}$ kg kg$^{-1}$; this leads to an average increase

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**Table 4. Correlation of Droplet Number Error With Important Aerosol-Cloud Interaction Properties**

<table>
<thead>
<tr>
<th>Observed Property</th>
<th>Whole Data Set</th>
<th>Non-Power-Plant</th>
<th>Power Plant Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total aerosol number</td>
<td>0.002</td>
<td>0.018</td>
<td>0.111</td>
</tr>
<tr>
<td>Accumulation mode aerosol number</td>
<td>0.002</td>
<td>0.043</td>
<td>0.198</td>
</tr>
<tr>
<td>Cloud updraft velocity</td>
<td>0.358</td>
<td>0.500</td>
<td>0.209</td>
</tr>
<tr>
<td>Updraft velocity standard deviation</td>
<td>0.150</td>
<td>0.383</td>
<td>0.066</td>
</tr>
<tr>
<td>Cloud droplet number</td>
<td>0.067</td>
<td>0.343</td>
<td>0.014</td>
</tr>
<tr>
<td>Aerosol sulfate mass fraction</td>
<td>0.025</td>
<td>0.036</td>
<td>0.014</td>
</tr>
</tbody>
</table>

*The parcel model was used for computing cloud droplet number. Strongest correlations are shown in bold.*

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**Figure 8. Sensitivity of droplet number error (between model and observations) to the value of the water vapor uptake coefficient.**
in droplet number (error) by 10–15%, accompanied with a substantial increase in droplet error variability. If surface tension depression is included, droplet number (error) is on average increased by about 30% compared to the “base case” simulation. Surface tension depression is considered only for simulations with $a_s = 1.0$, as a lower value would yield droplet error outside of the uncertainty range. Using a larger organic molar volume (i.e., molecular weight) would just decrease their effect on CCN activation; a lower molar volume is unlikely, given that a lower estimate was already used. The simulations suggest that combinations of organic solubility, degree of surface tension depression and uptake coefficient can give cloud droplet closure within experimental uncertainty. However, the “base case” conditions give by far the best closure since average droplet error and its variability are within measurement uncertainty (Figure 9). This suggests that “chemical effects” do not considerably influence aerosol activation. The sensitivity analysis above illustrates the importance of reducing the droplet measurement uncertainty. On the basis of Figure 9, a 10% uncertainty would further constrain the extent of “chemical effects” on cloud droplet formation.

4. Summary

This study analyzes 27 cumuliform and stratiform clouds sampled aboard the CIRPAS Twin Otter during the 2004 ICARTT (International Consortium for Atmospheric Research on Transport and Transformation). A unique feature of the data set is the sampling of highly polluted clouds within the vicinity of power plant plumes. In situ observations of aerosol size distribution, chemical composition and updraft velocity were input to (1) a detailed adiabatic cloud parcel model [Nenes et al., 2001, 2002] and (2) the modified NS parameterization [Fountoukis and Nenes, 2005; Nenes and Seinfeld, 2003]; predicted droplet number is then compared with the observations. Remarkable closure was achieved (on average to within 10%) for parcel model and parameterization. The error in predicted cloud droplet concentration was found to correlate mostly with updraft velocity. Aerosol number also correlated with droplet error for clouds affected by power plant plumes (which is thought to stem from spatial variability of the aerosol not considered in the closure). Finally, we assess the sensitivity of droplet closure to “chemical effects.” A number of important conclusions arise from this study:

1. Cloud droplet number closure is excellent even for the highly polluted clouds downwind of power plant plumes. Droplet number error does not correlate with background pollution level, only with updraft velocity and aerosol mixing state.

2. A highly variable aerosol does not necessarily imply a highly variable $N_d$ concentration. The clouds in this study often do not respond to aerosol variations because they take place primarily at small particle sizes, and cloud $s_{\text{max}}$ is not high enough to activate them. Any droplet variability that does arise is inherently less than the CCN variability it originated from [Sotiropoulou et al., 2006].

3. Usage of average updraft velocity is appropriate for calculating cloud droplet number.

4. The water vapor uptake coefficient ranges between 0.03 and 1.0. Optimum closure (for which average $N_d$ error is minimal and its standard deviation is within droplet measurement uncertainty) is obtained when the water vapor uptake coefficient is about 0.06. This agrees with values obtained from previous closure studies for polluted stratus-cumulus [Meskhidze et al., 2005] and marine cumulus clouds [Conant et al., 2004].

5. On average, organic species do not seem to influence activation through contribution of solute and surface tension depression. Optimal cloud droplet closure is obtained if the CCN are approximated by a combination of soluble inorganics and partially soluble organics (less than 1 g kg$^{-1}$ water assuming a molar volume of 66 cm$^3$ mol$^{-1}$ and a Van’t Hoff factor of 1).

6. The cloud droplet activation parameterization used in this study [Nenes and Seinfeld, 2003; Fountoukis and Nenes, 2005] has performed as well as the detailed cloud parcel model. Excellent performance has also been reported by Meskhidze et al. [2005]. Together, both studies suggest that the parameterization can robustly be used in GCM assessments of the aerosol indirect effect.

7. Distinguishing the “chemical effects” on the cloud droplet spectrum requires the observational uncertainty to be of order 10%.

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