Master’s thesis on the topic:
Impact of Cloud Particle Habit on Cloud Radar Retrieval
Abstract

The application of physically realistic cloud microphysics, including cloud particle shape specific scattering properties and cloud particle size distribution are an important factor to achieve realistic Radar retrievals, based on radiative transfer simulations. Furthermore, a sound representation of cloud microphysics is also essential for improving future climate predictions. Radar observations of 35 GHz and 95 GHz frequency in combination with in situ measurements of hydrometeor content, obtained during the “Joint flight” measurement campaign in October 2016 are utilized to study the impact of different scattering properties. The focus is set on the influence of these properties, organized into so called cloud particle habits, on retrieved Radar hydrometeor content. For the evaluated Radar cross-section, it was possible to identify cloud particle habits that both agreed with the in situ measurements and resulted in coinciding hydrometeor content values for the two utilized Radar frequencies. Among these cloud particle habits, the cloud particle habit mix of single crystals and aggregates of large columns, as well as single bullet-rosette type cloud particle habits exhibit the best agreement. From the theoretical analysis of the “Joint flight” context, as well as the evaluation of cloud particle images obtained during the campaign, these habits are also expected to be present during the observed situation. Additionally, these habits improve the Radar retrieval outcome in comparison to, for this scenario, less realistic cloud particle habits. Even though the observed cross-section evidently does not consist of solely one cloud particle habit, some of the cloud particle habits are generally able to exhibit the average conditions of the entirety of all present cloud particles. For future applications of the retrieval algorithm the choice of a clear representative cloud particle habit remains challenging without the availability of any in situ measurements and requires the attention of further research. Yet, it is possible to rule out distinct unrealistic cloud particle habits and prevent large errors in retrieved hydrometeor content with a dual-frequency Radar approach.
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Chapter 1

Introduction

As stated in the “Intergovernmental Panel on Climate Change” [IPCC (2001)], the strongest uncertainties in climate research occur in the field of cloud related radiative forcing feedback. To reduce these uncertainties, accurate and highly resolved information on cloud properties is required. Radar (Radio Detection And Ranging) observations enable a detailed insight into the vertical structure of cloud microphysics as they provide a fine vertical resolution. Still, in order to access most of this information, a retrieval needs to be performed on the Radar observations. Radar retrievals of reasonable cloud properties are not only believed to improve passive remotesensing retrievals of larger spatial coverage, but eventually today’s climate models as well [Moore et al. (2001)]. However, the retrieval of accurate cloud properties from Radar observations proves to be very challenging. In general, the hydrometeor content, for example ice, snow or liquid water content, is retrieved from Radar observations. In contrast to several retrieval methods introduced in the past the new retrieval algorithm presented in this study incorporates complex radiative transfer simulations and applies inverse theory. The Atmospheric Radiative Transfer Simulator (ARTS\(^1\)) [Buehler et al. (2018)] utilized for this purpose takes a great amount of microphysical cloud properties like particle size distribution (PSD) and scattering properties into account. Hence, the assumption on realistic microphysical cloud properties is essential to achieve reasonable retrieval results. By implication, reasonable retrieval results also provide information about the microphysical cloud properties. However, it should be noted that also multiple constellations of particle size distribution and scattering properties can result in reasonable values of hydrometeor content, yet due to unphysical relationships.

In order to evaluate the performance of the retrieval results, the degrees of freedom within the retrieval must be reduced, requiring the availability of observational data. The “Joint flight” measurement campaign provides a large amount of observations well suited to both test and evaluate the new retrieval approach. The almost simultaneously acquired cloud Radar observations of 35 GHz and 95 GHz frequency pose a strong advantage in testing the algorithm, as one degree of freedom is eliminated. Past studies [i.e. Sekelsky et al. (1999), Kneifel et al. (2011), Kulie et al. (2014)] often used a trippel-frequency approach to eliminate an additional

\(^{1}\)Utilized Version: 2.3.839
Chapter 1. Introduction

degree of freedom and gain information on both particle shape and PSD. As the "Joint Flight” only provides two different RADAR frequencies such an analysis is not possible. Instead, the evaluation of the retrieval results benefits from in situ measurements of hydrometeor content and PSD. By restricting the PSD, only assumptions about the scattering properties need to be made. Even though images providing an overview on the rough particle shapes during the observed situation were taken during the "Joint flight”, the scattering properties required for the radiative transfer simulations remain unknown. Fortunately, a new scattering database [Eriksson et al. (2018)] including a broad range of different realistic cloud particle habits provides the scattering properties for the utilized RADAR frequencies. Thus, it is possible to test the retrieval outcome for several cloud particle habits and evaluate the results in context of the measured in situ hydrometeor content. Similar studies on the impact and performance of individual cloud particle habits from several scattering databases have been performed on passive remote sensing retrievals [see Eriksson et al. (2015)] but are still pending for active RADAR retrievals.

The overall goal of this study is to identify, whether the new RADAR retrieval set up results in reasonable hydrometeor content values for each tested cloud particle habit. The observational data provided by the “Joint flight” measurement campaign offers two approaches to evaluate the performances for each test case. Intuitively, the direct comparison of retrieved and in situ measured hydrometeor content comes to mind. Yet, also the differences in between the retrieval results from the two RADAR of different frequency can give information on the quality of the retrieval. RADAR of different frequency exhibit deviations in measured RADAR reflectivity, due to a different scattering response to cloud particles within the observed volume which exceed a certain diameter. This effect is described in more detail in Section 3.1. As a consequence, two major hypotheses must be checked in order to evaluate the new approach of hydrometeor content retrieval from RADAR observational data. The retrieved hydrometeor content tested for a specific cloud particle habit is reasonable if its value of retrieved hydrometeor content is

1. able to represent the real (in situ) atmospheric state of hydrometeor content.

2. next to identical for using two RADARS of different frequency.

The “Joint flight” measurement campaign, including the description of the utilized datasets and instruments is displayed in Chapter 2. Further, the new RADAR retrieval set up, its requirements and its corresponding background theory are described in Chapter 3. The general findings of the “Joint flight” measurement campaign and the retrieval results as well as the evaluation of the impact of the individual cloud particle habits on the retrieval are displayed in Chapter 4. Finally, the key findings and suggestions for future improvements are discussed in Chapter 5.
Chapter 2

The Joint Flight Campaign

As a part of the North Atlantic Waveguide and Downstream Impact Experiment (NAWDEX) [Schaefler et al. (2017)], three aircrafts equipped with several in situ and remote sensing instruments, conducted measurements simultaneously along a coinciding path for the sake of observing cloud physical properties on the 14th October 2016. The potential such a “Joint flight” holds is great. For example, it is possible to evaluate the retrieved cloud properties of remote sensing instruments with those measured in situ. Additionally, the retrievals of two or more instruments of the same kind can be evaluated among themselves. In case of this study two Radars of different frequencies are compared. An extensive amount of the data collected by several instruments during the “Joint flight” is used in order to achieve the results presented in this study. Of particular importance hereby are the active remote sensing observations, collected by two Radar of different frequencies. Both the High Altitude and Long Range Research Aircraft (HALO) as well as the French Falcon 20 (FF20) were equipped with a Radar, which are further described in Section 2.1.1 and 2.1.2, respectively. Equally important are the in situ measurements, which were collected by the Facility for Airborne Atmospheric Measurements (FAAM). Figure 2.1 shows the coinciding path of the three aircrafts.

Figure 2.1: Joint Flight campaign on Modis corrected reflectance of NASA’s Aqua satellite on 2016-10-14, 12:30 UTC [https://worldview.earthdata.nasa.gov/, accessed 2018-02-28]
Chapter 2. The Joint Flight Campaign

The following sections will briefly describe the instruments and observed datasets utilized for this study. The evaluation of the synoptic situation as well as both the in situ and remote sensing observations obtained during the “Joint flight” are further documented in Chapter 4.

2.1 Remote Sensing

The active remote sensing observations form the methodological basis of this study. They originate from two cloud profiling Radar (CPR) of 35 GHz and 95 GHz frequency, respectively. In contrast to lower frequency precipitation Radar they are optimized to obtain information about the vertical structure of ice and mixed clouds. Both Radar measure profiles of Radar reflectivity along their flight path. The resulting Radar cross-sections are collocated and transformed to match the same horizontal and vertical grid. For observed cross-section, HALO and FF20 show overlapping Radar footprints. Also in terms of time collocation, HALO and FF20 are next to synchron (HALO: 9:51 - 10:16 UTC; FF20: 9:50 - 10:21 UTC). These cross-sections are discussed in detail in Section 4.2. A technical description of the two individual Radar is given in the following sections.

2.1.1 35 GHz HAMP Radar

During the campaign, the HALO carried along the HALO Microwave Package (HAMP) [Mech et al. (2014)]. Besides passive microwave radiometers covering 26 frequencies, HAMP contains a MIRA-36 CPR [Melchionna et al. (2008)], which operates at a frequency of 35.6 GHz. This Ka-band Radar has a reduced attenuation with respect to cloud particles compared to the more frequently operated W-band Radar [Mech et al. (2014)]. The HAMP Radar is calibrated against the spaceborne CloudSat Radar and Radar reflectivity values are corrected with respect to a 8 dBZ systematic offset. The technical specifications for the HAMP Radar during the Joint Flight campaign are summarized in Table 2.1.

2.1.2 95 GHz RASTA Radar

The Radar system installed on the FF20, called the Radar Aéroporté et Sol de Télédétection des Propriétés Nuageuses (RASTA) is run at a frequency of 95 GHz (W-band) during the Joint Flight campaign. The RASTA Radar is equipped with a multibeam antenna system covering three viewing angles, however, only the nadir pointing one is evaluated in this study. Like the HAMP Radar, RASTA is calibrated against the CloudSat Radar. In past case studies RASTA has shown great differences in sensitivity which is observed to be lower compared to other Radar i.e. the CloudSat Radar [Bouniol et al. (2008)]. The study by Bouniol et al. (2008) also showed that RASTA does not experience as strong multiple scattering enhancement within dense parts of an observed cloud as it is the case for the CloudSat Radar. In a similar fashion to the HAMP Radar further technical specifications for the RASTA Radar during the Joint Flight campaign are summarized in Table 2.1.
Table 2.1: HAMP and RASTA Radar specifications [Mech et al. (2014), Bouniol et al. (2008)]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>HAMP Radar</th>
<th>RASTA Radar</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>35.56 GHz</td>
<td>95.04 GHz</td>
<td>GHz</td>
</tr>
<tr>
<td>Peak power</td>
<td>30 kW</td>
<td>1.8 kW</td>
<td>kW</td>
</tr>
<tr>
<td>Pulse width</td>
<td>200 ns</td>
<td>400 ns</td>
<td>ns</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>5 kHz</td>
<td>25 kHz</td>
<td>kHz</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>-30 dBZ</td>
<td>-15 dBZ</td>
<td>dBZ</td>
</tr>
<tr>
<td>Data Window</td>
<td>0 to 13 km</td>
<td>0 to 11 km</td>
<td>km</td>
</tr>
<tr>
<td>Antenna Size</td>
<td>1 m</td>
<td>0.45 m</td>
<td>m</td>
</tr>
<tr>
<td>Integration Time</td>
<td>1.0 s</td>
<td>0.25 s</td>
<td>s</td>
</tr>
<tr>
<td>Vertical Resolution</td>
<td>30 m</td>
<td>60 m</td>
<td>m</td>
</tr>
<tr>
<td>Beam width</td>
<td>0.6 °</td>
<td>0.7 °</td>
<td>°</td>
</tr>
<tr>
<td>Cross-track Resolution</td>
<td>130 m</td>
<td>100 m</td>
<td>m</td>
</tr>
<tr>
<td>Along-track Resolution</td>
<td>ca. 300 m</td>
<td>ca. 250 m</td>
<td>m</td>
</tr>
<tr>
<td>Most probable error</td>
<td>1.3 dBZ</td>
<td>1.3 dBZ</td>
<td>dBZ</td>
</tr>
</tbody>
</table>

2.2 In situ

Additionally to remote sensing Radar observations, this study takes advantage of in situ observations collected by several different instruments during the “Joint flight” campaign on the 14th October 2016. The most intuitive usage of those observations is to validate the results of this study. However, an additional benefit for the retrieval is gained with the availability of in situ observations. The presented retrieval approach requires information about the atmospheric state. The reasons for that are described in detail in Section 3.2.3. For example, instead of using a general modeled mid-latitude temperature and humidity profile in situ measurements enable more precise estimates. In the following sections the in situ instruments, the variables they measure as well as their benefits to this study are briefly described.

2.2.1 Dropsonde

Several dropsondes were released by all three airplanes along the analysed flight paths. The Vaisala RD94 model dropsondes used along the “Joint track” were released from the FAAM\(^1\). Their locations are marked in Figure 2.1. Each dropsonde measures the air temperature, humidity and GPS information (latitude, longitude and altitude) at discrete points of pressure coordinates. Also, windspeed and winddirection are derived from the GPS information.

For this study, the atmospheric profiles of temperature and relative humidity are interpolated in between the dropsondes along the observed Radar cross-sections corresponding to the collocated Radar-grid. These cross-sections are used to describe the atmospheric state in terms of temperature and humidity, needed as input for the forward simulation, described in Section 3.2.

2.2.2 FAAM Cloud Probes

During the “Joint flight” experiment the FAAM decended into the cloud profiled by both the RASTA as well as the HAMP Radar (10:43 - 11:01 UTC). Equipped with three kinds of cloud probes in situ measurements of ice water content, particle size distribution and high resolution ice particle images were collected. Simultaneously the FAAM measured auxiliary parameters, like for example temperature $T$, relative humidity $RH$ and pressure $p$. The following Section briefly describes the variables of each cloud probe as well as its role for this study.

Nevzorov Cloud Probe

The Nevzorov hot-wire cloud probe consists of two sensors, which are designed to measure total (ice and liquid) and liquid water content. Both sensors consist of a collector and reference winding shielded from cloud particles [Korolev et al. (1998)]. Its approximate sensitivity is estimated to be $10^{-6}$ kg/m$^3$ and its maximum accuracy to be approximately 20%, especially concerning small frozen hydrometeors. From total ice water content (TWC) and liquid water content (LWC) the ice water content (IWC) can be estimated:

$$IWC = TWC - LWC$$

As IWC is the main result of the hydrometeor content retrieval described in this study, the Nevzorov observations can be used to qualitatively validate the results of this study. Additionally, the Nevzorov IWC is used as input to a one moment scheme to calculate the PSD of cloud particles, considering many different ice cloud particle shapes (Section 3.2.2). These estimated PSD can then be evaluated against in situ measurements of PSD, described below.

Cloud Imaging Probe

Four single particle optical array cloud imaging probes (CIP) with gray-scale imaging capability are mounted on the FAAM\textsuperscript{2}. Cloud particle sizes are recorded on array images with a 15 µm (CIP-15) or 100 µm (CIP-100) pixel width, respectively. The resolution spans from 15 µm to 930 µm for the CIP-15 and from 100 µm to 6200 µm for the CIP-100. To create an image, a diode laser illuminates a diode array. Whenever a cloud particle is caught in between the laser beam and the diode array, it’s shadow is captured on the diode array and the signal is read and saved as an image. Afterwards, the diode array is refreshed. The CIP contains an internal processor which analyses the particle sizes by image and then stores the cumulative number of particle sizes in 62 bins.

The number density sorted by maximum particle size can be used to determine the general PSD of ice particles for the observed cloud. Subsequently, a rough evaluation of the PSD utilized as input for the retrievals can be made.

Chapter 3

Retrieval of Hydrometeor Content

Several cloud hydrometeor retrievals were introduced in the past. Some of the established cloud property retrievals are solely based on empirical hydrometeor content and equivalent radar reflectivity ($Z_e$) relationships [see i.e. Sassen et al. (2002), Sayres et al. (2008)]. Some methods additionally include a temperature dependency [i.e. Liu and Illingworth (2000)]. The disadvantage of such empirical retrievals is the reliance on large amounts of in situ measurements. The pool of those in situ measurements is usually small, bearing the risk of limiting the retrievals validity to certain regions or cloud types. Additionally, the empirical relation is usually optimised for radar observations of a specific frequency, as $Z_e$ is not always perfectly equivalent for radar of different frequency. This effect is further discussed in the following section.

Apart from empirical approaches, Austin et al. (2009) developed an algorithm based on Benedetti et al. (2003) to retrieve cloud properties with the help of inverse theory. They introduce a simple forward model to estimate the PSD of cloud hydrometeors. Here, the PSD is a function of temperature dependent parameters that are retrieved by an optimal estimation method (OEM) [Rodgers (2000)]. Radar reflectivity (measurement) and hydrometeor content (state) are calculated by different moments of the PSD, namely the 6th (Rayleigh scattering) and the 3rd (volume), respectively. Austin et al. (2009) assume a solid sphere as ice particle shape and uses the knowledge about its scattering properties to estimate $Z_e$. For cloud particles with large diameters, they use a correction function to compensate for non-Rayleigh scattering. The parameters which minimise the difference between the simulated and the measured $Z_e$ are estimated in the process and the hydrometeor content can be calculated from the 3rd moment.

The retrieval method displayed in this study exhibits similarities to the approach of Austin et al. (2009) in some aspects. Like Austin et al. (2009) the OEM approach is chosen to solve the inverse problem. However, in contrast to Austin et al. (2009) the hydrometeor content is directly retrieved. In this case the more complex forward model ARTS is used. ARTS is capable of directly simulating radar observations from state (here the hydrometeor content) by estimating the radiative transfer of the radar beam through the atmosphere. Here, the OEM is used to determine the hydrometeor content that minimizes the cost function between measurement and simulation. Additionally, more realistic assumptions considering the particle shape are tested.
Chapter 3. Retrieval of Hydrometeor Content

Figure 3.1: Requirements and processes of hydrometeor content retrieval: Radar observational data (Section 3.1), Forward Simulation and its requirements (Section 3.8), Optimal Estimation Method and its requirements (Section 3.3), Retrieved Hydrometeor Content (Chapter 4)

Figure 3.1 shows the general requirements and processes of the retrieval to estimate the sought hydrometeor content and will be further discussed in the course of this chapter.

3.1 Radar Observations

To estimate the hydrometeor content at any given height an observation of some kind is required. By the help of in situ measurements the hydrometeor content is directly obtainable, but usually these measurements are sparse and not comprehensive enough. Remote sensing observations on the other hand are in general able to cover a larger section of the atmosphere. This study concentrates on Radar observations of active remote sensing nature. The benefit to passive remote sensing instruments is the direct access to the fine vertical resolution of the Radar, which enables an advanced insight into cloud physical properties.

In contrast to optical instruments like Lidar (Light Detection And Ranging) and ceilometer, the Radar is not as easily attenuated by most cloud and precipitation particles, dependent on its frequency. Therefore, it is in most cases able to observe the whole atmospheric cloud profile. Here, only observations of mobile airborne Radar are used. These are less influenced by ground scattering effects compared to local ground stationed Radar. Additionally, when operated from
an airplane, the **Radar** is able to measure a great amount of cloud and precipitation particles, before the signal interacts with heavy precipitation, pollen or insects. The **Radar** signal usually extinguishes when interacting with an accumulation of such objects. [Fukao and Hamazu (2014)] The **Radar** generates a beam of electromagnetic (EM) waves of a fixed frequency $\nu$. The spectral range of **Radar** spans from several MHz to about 100 GHz. Within the **Radar** frequency range, **Radar** beam and cloud or precipitation particles interact primarily by scattering. The detectable particle size is hereby dependent on the **Radar** frequency. With a higher frequency (smaller wavelength $\lambda$) a **Radar** is able to detect smaller particles [Fukao and Hamazu (2014)]. The frequencies of 35 GHz and 95 GHz ($\lambda_{35} = 0.86$ cm and $\lambda_{95} = 0.32$ cm) are well suited to observe particles of typically found sizes in ice and mixed clouds [Fabry (2015)].

Figure 3.2 displays the dependency of the received **Radar** signal on range and time the transmitted **Radar** signal travels through the atmosphere. In terms of range the profile of **Radar** reflectivity is measured on a fine vertical grid. The position of an observed target on such a grid is defined by distance $r$. It can be calculated from the lapse time $t$ it takes the **Radar** beam to travel through the atmosphere [Fabry (2015)]:

$$ r = \frac{ct}{2} \tag{3.1} $$

The speed of light is denoted by $c$. The **Radar** does not send out a continuous signal, but pulses lasting usually a few hundred ns. This time interval is called the pulse width $\tau$. In between the
pulses the Radar “listens” for usually a few hundred µs. Here, pulse repetition time \( T \) is the term for combined pulse width \( \tau \) and “listening time”. From the pulse width \( \tau \) the vertical resolution \( \Delta r \) can be estimated using an equation similar to Eq. 3.1 (by exchanging \( t \) with \( \tau \)). Only the returned pulse itself can be identified, not any exact part of the pulse. The maximum detectable range \( r_{\text{max}} \) is dependent on \( T \). Thus, \( r_{\text{max}} \) can as well be determined in a similar matter as Eq. 3.1 (by exchanging \( t \) with \( T \)). The Radar is not able to distinguish from where a returning signal originates if \( T \) is exceeded. As shown in Figure 3.2, if \( t \) of the Radar signal exceeds \( T \) (in this case case \( t_3 \)) the received power \( P_r \) will be accounted to the \( P_r \) of a pulse subsequent to the one the signal originated from. As the power density of the received Radar signal is anti-proportional to \( r^2 \), the Radar signal returning from a range larger than \( r_{\text{max}} \) will only contribute one quarter of its original value to the subsequent measurement of \( P_r \) [Fabry (2015)]. As the Radar observations utilized for this study correspond to \( r_{\text{max}} \) (\( r_{\text{max, HAMP}} = 30 \text{ km}, r_{\text{max, RASTA}} = 12 \text{ km} \)) larger than the flight altitude (see Table 2.1) this effect does not need to be accounted for.

The intensity of the radiation back-scattered from cloud particles within the volume probed by the Radar is defined as “Radar reflectivity” (\( \eta \)). It is a measure for the entirety of the back-scattered Radar signal dependent on the back-scattering cross-section \( \sigma_b(D) \) corresponding to all particles present within the unit volume. Within the Rayleigh scattering regime \( \eta \) is defined as follows [Fabry (2015)]:

\[
\eta = \frac{\pi^5|K|^2}{\lambda^4} \int_0^\infty D^6 N(D) dD
\]  

(3.2)

With the dielectric constant \( K \) of ice and the cloud particle number density \( N(D) \).

Nevertheless, Radar observations are usually expressed in terms of equivalent Radar reflectivity \( Z_e \) instead of \( \eta \). As \( \eta \) is specific to the individual Radar, \( Z_e \) is applied to achieve coinciding values for Radar of different frequency only dependent on the scatterer’s properties. [Fabry (2015)]

\[
Z_e = \int_0^\infty D^6 N(D) dD
\]  

(3.3)

Generally, while in the Rayleigh regime, \( Z_e \) is proportional to the 6th moment of the scatterer’s diameter \( D \), as \( \sigma_b(D) \) is proportional to \( D^6 \). Therefore, the unit of \( Z_e \) is \( \text{mm}^6 \text{m}^{-3} \). Accordingly, a cloud particle of 1 mm diameter per unit volume [\( m^3 \)] results in an equivalent Radar reflectivity of \( 1 \text{ mm}^6 \text{m}^{-3} \) [Fabry (2015)].

The expected received power \( P_r \), measured by the antenna of the individual Radar is defined by the Radar equation, here based on Probert-Jones (1962) and Fukao and Hamazu (2014).

\[
P_r = \frac{P_t G^2 \lambda^2}{(4 \pi)^3 r^4} V \eta
\]  

(3.4)

\( P_r \) is a function of \( r \) (distance of the Radar to the scatterers). As peak transmitted power \( P_t \) of the Radar signal is approximately distributed over the area of a sphere with the radius \( r \) (weighted by the antenna gain \( G \)) both on the way towards the scatterers as well as on its way back, \( P_r \) is anti-proportional to \( r^4 \). However, the radar resolution volume \( V \) (volume the Radar penetrates...
at distance \( r \) must be taken into account.

\[
V = r^2 \cdot \frac{c \tau}{2} \cdot \frac{\pi \Theta^2}{8 l n(2)} \tag{3.5}
\]

With the Radar beam width \( \Theta \).

Substituting Equation 3.2, 3.3 and 3.5 into Equation 3.4 as described above \( P_r \) is found to be anti-proportional only to \( r^2 \). Yet, most importantly a dependency of \( Z_e \) on \( P_r \) is found corresponding to both Radar specific constants as well as medium specific constants.

\[
P_r = \frac{\pi^2 c}{1024 l n(2)} \cdot \frac{P_l G^2 \Theta^2 \tau}{\lambda^2} \cdot \frac{K^2 Z_e}{\text{Medium}} \cdot \frac{1}{r^2} \tag{3.6}
\]

\( Z_e \) itself is a constant corresponding to the medium, as it depends on the scatterers diameters. It is usually processed Radar intern by solving Equation 3.6 for \( Z_e \). As a function of \( r \) (and \( P_r \)), \( Z_e \) is then given as measurement output for the individual Radar.

While observing the same cloud, \( Z_e \) is invariant for any Radar of different frequency, as long as the interaction of the Radar beam with the scatterers is within the Rayleigh scattering regime. Yet, if the back-scattering of a Radar beam happens within the Mie scattering regime the back-scattering cross-section \( \sigma_b(D) \) is not proportional to \( D^6 \) anymore, but to a lower exponent. Then, \( P_r \) and consequently \( Z_e \) are reduced. With increasing Radar frequency, smaller particle diameters \( D \) already respond to scattering taking place in the Mie-regime. Consequently, of two Radar observing the same volume with particles of the same \( N(D) \), the one with the higher frequency will correspond to a smaller \( Z_e \) provided some scattering happens in the Mie regime. As scattering within the Mie regime is largely dependent on the shape of the cloud particles present in the observed Volume, this effect can be utilized to actually validate the performance of the retrieval. This is done in Section 4.5.2.

The range of \( Z_e \) usually spans over orders of magnitude for most cloud observations. Therefore, \( Z_e \) is often depicted in units of decibels (dBZ) [Fabry (2015)]:

\[
dBZ = 10 \cdot \log_{10}(Z_e) \tag{3.7}
\]

From now on the term Radar reflectivity will exclusively be expressed in dBZ.

Finally, the most important features to understand the basics of Radar observational data, are defined. The following section focuses on a way to find a connection between Radar observations and the sought hydrometeor content, namely the forward simulation.
3.2 Forward Simulation

Remote sensing observations, including active Radar measurements provide only indirect information about the atmospheric state. The signal measured by the Radar is dependent on multiple elements of atmospheric state ($\vec{b}$) and not solely on the retrieval quantity $\vec{x}$ (state vector), in this case the hydrometeor content. If all necessary atmospheric state variables $\vec{x}$ and $\vec{b}$ are known, the measurement vector $\vec{y}$ can be calculated on the basis of radiative transfer simulations. In addition, the expected measurement noise $\vec{\varepsilon}$ must be taken into account. In general, a complex forward model $f$ is used to calculate the radiative transfer through the atmosphere. Based on Rodgers (2000) $\vec{y}$ is estimated as follows:

$$\vec{y} = f(\vec{x}, \vec{b}) + \vec{\varepsilon}$$ (3.8)

The retrieval of $\vec{x}$ requires the inversion of Equation 3.8. Here, the inverse problem is ill-posed, as multiple atmospheric states could result in the same measurement vector $\vec{y}$. As a result, the inversion of Equation 3.8 not trivial. The approach to solve the inverse problem is chosen to be the OEM, which is further described in Section 3.3. However, before the inverse of Eq. 3.8 can be found it is important to fully set up the forward model as it provides the essential link between Radar observations and sought hydrometeor content. Another important step is to define the variables incorporated in $\vec{b}$.

The forward model $f$ used to perform the forward simulations for this study is the radiative transfer model ARTS [Buehler et al. (2018)]. Due to its modular design, ARTS is able to simulate a large variety of remote sensing instruments and is easy to extend, with Radar being one of the latest implementations.

In order to simulate active measurements such as Radar with ARTS some simplifications are applied. Most importantly, multiple scattering is omitted and only single scattering is considered. The effect of multiple scattering is only of secondary order and a valid assumption for Radar simulations, except for very intense ice clouds (from the ARTS User Guide [Eriksson and Buehler (2017)]). The pulse of EM-waves transmitted by the Radar is described by a monochromatic pencil beam. In contrast to passive measurement simulations, where attenuation of radiation is of primary concern, active Radar observations are predominantly concerned with the backscattered radiation ($s_b$) and only to some extent with the attenuation due to cloud particles. For Radars used in this study the Radar beam is transmitted from the same position as it is received. Even though the observations concerned are taken from a moving aircraft the radar signal travels much faster in comparison. Notably, $s_b$ is displayed at discrete points of distance $r$ from the receiver, estimated from travelling time $t$ of the signal as defined by Equation 3.1. Moreover, the measurement grid resolution is given by $\Delta r$, estimated from the Radar pulse width $\tau$ (Section 3.1). For active instruments, ARTS only performs forward simulations concerning $s_b$ and atmospheric extinction. The latter is for example corresponding to atmospheric gases ($N_2$, $O_2$, $O_3$, $H_2O$), expressed by the volume mixing ration (VMR) included in $\vec{b}$. The estimation of VMR is further
3.2. Forward Simulation

described in Section 3.2.3. Within ARTS $s_b$ is estimated as follows [Eriksson and Buehler (2017)]:

$$s_b = T_h Z_b T_a s_t$$  \tag{3.9}

The Stokes vector $s_t$ characterizes the emitted intensity and polarisation of the Radar signal. The matrices $T_a$ (away direction) and $T_h$ (home direction) characterize the transmission from receiver to the point of scattering and back and account for atmospheric attenuation. The backscattering properties of the entirety of scattering elements (cloud hydrometeors) are defined by the bulk phase matrix $Z^b$ for the backward direction (scattering angle $\Omega=180^\circ$):

$$Z^b = \sum_i (n_i Z^b_i)$$  \tag{3.10}

Each scattering element $i$ (individual cloud hydrometeor of certain diameter) is accompanied by a particle number density $n_i$ and an individual back-scattering cross-section $Z^b_i$. The sum of their products defines the bulk back-scattering properties of all cloud particles in the observed volume. As of yet, both $Z^b_i$ and $n_i$ can not be directly derived from the Radar observations. Actually, they are elements of the unknown atmospheric state vector, dependent on the cloud particle shape and the PSD, respectively. Hence, in order to estimate $Z^b_i$ an assumption on the particle shape is necessary in order to proceed. For this study the scattering properties are taken from a scattering database, which is described in detail in Section 3.2.1. An assumption for $n_i$ is gained through the usage of a PSD parameterization, described in Section 3.2.2. The remaining elements of $\vec{b}$ are further described in section 3.2.3.

3.2.1 Scattering Database

Common hydrometeor content retrieval errors often result from uncertainties in particle shape, size, orientation and phase [Eriksson et al. (2015)]. The scattering properties of an ice particle are dependent on these ice particle properties. When observing ice clouds, it should be noted that a great variety of different ice particle shapes exists. Here, the meteorological conditions of the atmosphere are of major importance during the formation of the individual ice particle. Especially temperature and ice supersaturation are among the dominant factors. Additionally, pressure and wind shear influence the shape [Nakaya (1951)]. As ice molecules tend to form hexagonal lattice structures, the most common ice particle shapes consist of hexagonal columns, plates, bullets and bullet rosettes or aggregates of these crystals [Macke (1993)]. The back-scattering properties, denoted here as back-scattering efficiency $Q_{back}$, differ between the individual ice particle shapes. Currently, there is no time efficient method to estimate scattering properties for any ice particle shape simultaneously to the retrieval process. Instead, the scattering properties are taken from a scattering database. For this study the scattering database presented by Eriksson et al. (2018) is chosen, as it features several advantages over other databases [i.e. Liu (2008), Hong et al. (2009)]. The performances of these databases are evaluated in detail by Eriksson et al. (2015). The scattering database by Eriksson et al. (2018) is designed to fulfill many applications. It covers
Chapter 3. Retrieval of Hydrometeor Content

the entire microwave region, especially including the Radar frequencies, 35 GHz and 94 GHz, very close to those utilized in this study. Additionally, it contains scattering data covering an enormous amount of cloud particle shapes.

Extinction matrix $\vec{E}$, absorption vector $\vec{a}$ and phase matrix $\vec{Z}$ are provided by Eriksson et al. (2018) for 34 distinct frequencies and three temperatures (190 K, 230 K, 270 K) matching the entire polarisation information of the Stokes vector $s_t$. The method Eriksson et al. (2018) use to estimate $\vec{E}$, $\vec{a}$ and $\vec{Z}$ is the Discrete Dipole Approximation (DDA) [Ekelund et al. (2017)], which is not further described here, but can be reviewed from Draine and Flatau (1994).

To estimate $Z^b_i$ in order to solve Equation 3.10 the backwards direction ($\Omega = 180^\circ$) of $\vec{Z}$ corresponding to the $i^{th}$ cloud particle with a temperature ($T$) and maximum diameter ($D_{\text{max}}$) is needed:

$$Z^b_i = \vec{Z}(\Omega = 180^\circ, T_i, D_{\text{max}_i})$$  \hspace{1cm} (3.11)

However, $Z^b_i$ is unique, depending on the choice of the cloud particle shape. As there are next to infinite different ice particle shapes, a method of shape classification has to be introduced first in order to narrow down shapes to select from. Generally, ice hydrometeors can be divided in two main categories: single crystals with a $D_{\text{max}}$ usually below 200 $\mu$m and aggregates with a $D_{\text{max}}$ usually above 200 $\mu$m [Ekelund et al. (2017)]. Still, there are great differences in cloud particle shape within both of these categories. Therefore, the ice hydrometeors are organized into so called “habits” by Eriksson et al. (2018). Each habit contains a series of ice hydrometeors of different $D_{\text{max}}$ that roughly share the same standard mass-size relationship:

$$m = \alpha D_{\text{max}}^\beta$$  \hspace{1cm} (3.12)

where $\alpha$ and $\beta$ are parameters defined for each cloud particle habit individually. In total, the scattering database by Eriksson et al. (2018) provides 33 different ice hydrometeor habits of realistic optical properties. These cloud particle habits cover a broad range of shapes typically observed in the atmosphere. Habit mixes which consist of different ice hydrometeor shapes for certain $D_{\text{max}}$ intervals are also introduced. Here, single crystals for small and aggregates for larger $D_{\text{max}}$ are chosen. For each cloud particle habit Eriksson et al. (2018) only provide scattering properties for totally random orientated ice particles, though further orientations (e.g. azimuthally random) are planned in future extensions of the database. Hence, this study only considers totally random orientation.

**Cloud Particle Habit**

Now, the primary task is to choose a habit which fits the overall conditions present during the “Joint flight” measurement campaign. Direct measurement information on the ice hydrometeor shapes is sparse, or rather its derivative from thousands of photos is exceeding the scope of this thesis. Instead of evaluating only one cloud particle habit, which might be reasonable under the given conditions but most probably does not fully represent the unknown atmospheric state, the
3.2. Forward Simulation

Figure 3.3: Cloud particle Habits chosen from scattering database by Eriksson et al. (2018) for testing of retrieval algorithm: (a) IconSnow, (b) SectorSnowflake, (c) ColumnType1, (d) LargeColumnAggregate, (e) EvansSnowAggregate, (f) 6-BulletRosette, (g) Perpendicular4-BulletRosette, (h) Flat3-BulletRosette, (i) LargePlateAggregate, (j) LargeBlockAggregate, (k) PlateType1, (l) IconCloudIce, (m) 8-ColumnAggregate, (n) GemGraupel, (o) IconHail and (p) IceSphere_Id24.

retrieval is tested for several different habits.

From aircraft [Zhang et al. (2013)] and balloon [Orikasa et al. (2013)] borne observations the most frequently classified single ice particle shapes in midlatitude clouds are found to be columns, bullet rosettes and plates. Hence, these habits are included as test cases within the retrieval. Yet, irregular shapes dominated the observations. Additionally, it should be noted that the clouds observed during these campaign were mainly of cirrus type. Another approach to identify possible habits to test for is to use a proxy ice particle habit that has been proven to exhibit average conditions in previous retrieval studies. Geer and Baordo (2014) found that for passive remote sensing retrievals the sector snowflake as well as the bullet rosette type habits minimise the average deviations from direct hydrometeor content observations. Even though these habits perform well for passive observations a likewise behaviour for Radar observations can not be assumed and will therefore be tested.

For the observed scene during the “Joint Flight” the cloud top temperature was below -40°C. Bailey and Hallett (2009) state that under these conditions a mix of columnar and platelike polycrystals as well as bullet- and mixed rosettes is to be expected, even within the usually plate dominated growth regime between -40°C and -20°C. For temperatures exceeding -20°C also more complex ice crystals like snowflakes are possible. Hence, the collection of habits chosen for testing includes bullet rosettes, single columns, plates and snowflakes as well as aggregates of columns, plates, snowflakes and blocks. Additionally, the retrieval is tested for hail and graupel, as their occurrence is likely within a lower, more dense part of the cloud. For reference the retrieval is also tested for a simple ice sphere habit, as this shape is often used as an approximation for past Radar retrievals i.e. the one introduced by Austin et al. (2009). This study does not aim on finding the dominant habit within the observed cloud, but instead narrow down possible characteristics in shape parameter and scattering properties that represent those of the real state. The cloud particle habits chosen for this study are shown in Figure 3.3. Furthermore, the most
important specifications of these cloud particle habits and habit mixes are documented and can be reviewed in Appendix A, Table A.1 and Table A.2. Also, their back-scattering properties are shown in Figure A.2, A.3 and A.4.

Finally, $Z_i^b$ (Equation 3.10) can be accessed within the scattering database, dependent on tested cloud particle habit and size in terms of diameter $D_{\text{max}}$ of the particles within the observed volume. Still, in order to close Equation 3.10 the number of cloud particles corresponding to each size ($n_i$) needs to be defined. This number can be estimated from the PSD of the cloud particle habit.

### 3.2.2 Particle Size Distribution

As the outcome of the cloud hydrometeor retrieval is dependent on the assumed $n_i$ (Equation 3.10), it is important to choose a corresponding PSD that captures the present conditions during the radar observations. There are several established parametrizations for the PSD [i.e. McFarquhar and Heymsfield (1997), Field et al. (2007), Seifert and Beheng (2006), Milbrandt and Yau (2005)]. Each of them relies on the information of one or more moments of the size dimension, in most cases $D_{\text{max}}$ and in fewer cases volume equivalent diameter ($D_{\text{veq}}$). All of the mentioned PSD schemes are based on empirical cloud observations. The most common one moment schemes presented by McFarquhar and Heymsfield (1997) and Field et al. (2007) use ice or rather snow water content (IWC/SWC) as input. The estimated PSD is therefore directly dependent on the atmospheric state variable $\vec{x}$ and handled as such. Two moment schemes like those presented by Seifert and Beheng (2006) and Milbrandt and Yau (2005) use an additional moment, namely the number density, as input. Unfortunately, of those PSD parametrizations only the one of Field et al. (2007) is applicable under the given conditions. The PSD parametrization by McFarquhar and Heymsfield (1997) is restricted to the tropics, but the radar data utilized for this study is exclusively observed in the mid latitudes. Furthermore, both two moment schemes are not applicable for OEM calculations within ARTS yet. With only one PSD parametrization at hand it is important to evaluate its quality concerning the true atmospheric state. Fortunately, in situ measurements of PSD and IWC were simultaneously conducted during the "Joint flight" campaign. They do not cover the whole radar cross-section but can be used as reference for the true atmospheric state in comparison to the PSD estimated from the parametrization by Field et al. (2007). The in situ PSD information is received from the two CIP described in Section 2.2. The PSD based on Field et al. (2007) is estimated for every tested habit. Here, the habit specific parameters $\alpha$ and $\beta$ and IWC measured by the Nevzerov cloud probe (Section 2.2) are required as input for the ARTS internal method "F07" to estimate the PSD corresponding to each in situ measurement point. By utilizing in situ measured IWC as input, the resulting PSD is comparable to the in situ measured PSD. In order to compare the measured and the simulated PSD for each size bin, the average over all simulated and in situ measured number densities is calculated. The in situ measurements as well as the simulated PSD are given in terms of $D_{\text{max}}$. Yet, in terms of cloud particle mass $D_{\text{veq}}$ is a more intuitive measure of diameter than $D_{\text{max}}$. Hence, a
3.2. Forward Simulation

conversion of the PSD corresponding to $D_{\text{eq}}$ is calculated and displayed in Appendix A, Figure A.1. Still, as the $\alpha$ and $\beta$ parameters of the state are unknown and their derivation is non trivial, the transformation of the PSD into the $D_{\text{eq}}$ space can only be done for each individual habit specific $\alpha$ and $\beta$. The comparison within the $D_{\text{max}}$ space therefore provides similar information, but only the measured PSD is needed for comparison.

Figure 3.4 shows the result of the bin-wise averaged in situ and simulated PSD. Additionally, the 25 and 75% percentiles of the in situ PSD are displayed. The average number densities, corresponding to the cloud particle habits chosen for testing, lie within the 25 and 75% percentiles of the in situ measured average number density for every bin size and cloud particle habit. The overall shape of the PSD is also comparable. In between $10^2$ and $10^3$ $\mu$m the simulated PSD show a flattening, which can also be seen within the in situ measured PSD, though not as strongly. Within this $D_{\text{max}}$ interval the in situ PSD intersects with almost all simulated PSD, except the compact and sphere-like growing ones. The same applies for $D_{\text{max}}$ larger than $10^3$ $\mu$m, except now the simulated PSD are steeper than the in situ PSD. For $D_{\text{max}}$ smaller than $10^2$ $\mu$m the in situ number densities are underestimated by all cloud particle habit specific PSD. It should be noted that the CIP is less accurate towards the minimum detectable $D_{\text{max}}$ (15 $\mu$m) and should be evaluated with caution. The PSD corresponding to the compact cloud particles habits GemGraupel, IconHail and IceSphere underestimate the in situ PSD for every size bin. Additionally, the PSD corresponding to the LargeColumnAggregate, the EvansSnowAggregate and the BulletRosette type cloud particle habits overestimate the in situ PSD for $D_{\text{max}} > 2 \cdot 10^2$ $\mu$m.

In summary, the simulated PSD corresponding to the tested cloud particle habits are reasonably

![Particle Size Distribution](image)

Figure 3.4: Bin-wise average of Field et al. (2007) simulated for each tested cloud particle habit, in situ measured PSD and bin-wise 25 and 75% percentiles of in situ measured PSD.
close to the in situ measured PSD and can thus be considered as representative for the true atmospheric state. Nevertheless, some of the cloud particle habits should be observed with caution.

Apart from atmospheric state variables directly connected to $\vec{x}$, i.e. the PSD, the forward model requires additional atmospheric state variables contained in $\vec{b}$.

### 3.2.3 Boundary Conditions

The auxiliary or boundary input parameters are needed for several applications within the forward simulation. The forward simulation is performed on profiles of the atmospheric state variables. The dimension of the input parameters is therefore "height". All variables contained in $\vec{b}$ are derived from in situ measurements in order to be as close to the true atmospheric state as possible. To estimate the cloud particle phase ensuring to discard Radar reflectivity values corresponding to the liquid phase, the temperature ($T \text{ [K]}$) is required. Additionally, $T$ is needed to estimate the back-scattering efficiency value from the corresponding temperature grid of $Z^b_i$. To estimate the two-way attenuation of gases included in $T_a$ and $T_h$ the VMR is needed. The VMR is estimated from relative humidity ($RH \text{ [%]}$) profiles to account for the amount of water vapour present in the atmosphere. $T$ and $RH$ cross-sections are estimated by interpolation of the dropsonde measurements unto the Radar grid as described in Section 2.2.

### 3.2.4 Conversion to Measurement Unit

Now, all variables needed as input to the forward simulations, in order to estimate $s_b$ are defined. Nevertheless, the Radar specific unit must be determined. From $s_b$ the Radar reflectivity can be calculated as follows [Eriksson and Buehler (2017)]:

$$Z_e = \frac{4\lambda_r}{\pi^4 |K|^2} p \cdot s_b \quad (3.13)$$

where $p$ is a vector utilized to weight the polarization response of the Radar receiver. In this case only the first component, namely the intensity of the stokes vector, is considered.

The forward simulation is now entirely set up in the context of the "Joint flight" measurement campaign. The following Section will proceed in describing the method used to perform the inversion of Equation 3.2.

### 3.3 The Optimal Estimation Method

There are a several methods to retrieve the atmospheric state vector $\vec{x}$ from the measurement vector $\vec{y}$. For estimating the hydrometeor content from the Radar observation the optimal estimation method (OEM) is chosen here. Several passive remote sensing observation retrievals already use this method, so choosing OEM here can facilitate combined retrievals in the future.
3.3. The Optimal Estimation Method

3.3.1 Linear Optimal Estimation Approach

OEM uses the information provided by the forward simulation (Section 3.2) in combination with the measurement and an a priori \((\vec{x}_a)\) information. The a priori represents the knowledge about the atmospheric hydrometeor content prior to the retrieval. The choice for the value of \(\vec{x}_a\) is further discussed in Secion 3.3.3. The optimal estimate \(\hat{x}\) of the hydrometeor content \(\vec{x}\) is found for a certain combination of both \(\vec{x}\) and \(f(\vec{x})\) that minimises the cost function \(\chi^2\) [Rodgers (2000)].

\[
\chi^2 = (\vec{y} - f(\vec{x}))^T S_y^{-1} (\vec{y} - f(\vec{x})) + (\vec{x} - \vec{x}_a)^T S_a^{-1} (\vec{x} - \vec{x}_a)
\]  

(3.14)

Here, the impact of \(\vec{y}\) and \(\vec{x}_a\) is dependent on their corresponding covariance matrices \(S_y\) and \(S_a\), also further described in Section 3.3.3. If the measurement uncertainty of \(\vec{y}\) provided by \(S_y\) is large the measurement is less weighted and the resulting \(\hat{x}\) leans more towards \(\vec{x}_a\) in the retrieval process and vice versa. The cost function \(\chi^2\) is derived with the Bayesian Approach which can be reviewed in detail from Rodgers (2000). The state vector reaching the highest probability given the measurement vector \((P(\vec{x} | \vec{y}))\) is defined as the best estimate \(\hat{x}\). As by definition \(\chi^2 = -2ln(P(\vec{x} | \vec{y}))\), \(\chi^2\) is minimised by maximising \(P(\vec{x} | \vec{y})\). In order to find the minimum of \(\chi^2\), the partial derivative \(\frac{d\chi^2}{dx}\) = 0 must be solved for \(\vec{x}\). This requires the estimation of the partial derivative \(\frac{d(f(\vec{x}))}{dx}\) as well as the direct inversion of the forward model. Both are not possible to estimate, as the inverse problem is ill-posed and non-linear. However, even though the radiative transfer is non-linear, the forward model can be linearized locally around an atmospheric state \(\vec{x}_0\) with only minor errors being expected. Linearizing Equation 3.8:

\[
\vec{y}|_{\vec{x}_0} = K|_{\vec{x}_0}(\vec{x} - \vec{x}_0) + \vec{y}_0 + \epsilon
\]  

(3.15)

With the Jacobi Matrix \(K\) as the partial derivative \(\frac{d(f(\vec{x}))}{dx}\) around the linearization point \(\vec{x}_0\). The rows of \(K\) (Jacobians) describe how the measurement, in this case the Radar Reflectivity in a certain height, changes with varying hydrometeor content. Mathematically, the Jacobians are weighting functions over the hydrometeor content along the whole profile. In the case of Radar the weight lays almost exclusively on the the height the Radar signal originates from, as only single scattering is concerned in the radiative transfer simulations.

In contrast to the non-linear forward model it is possible to invert the linearization of \(f(\vec{x})\). Therefore, the partial derivative of Equation 3.14 can be solved for \(\vec{x}\):

\[
\hat{x} = \vec{x}_a + (K^T S_y^{-1} K + S_a^{-1})^{-1} K^T S_y^{-1} (\vec{y} - K \vec{x}_a)
\]  

(3.16)

With \(\hat{x}\) as the best estimate for \(\vec{x}\). Here, the linearization of \(f(\vec{x})\) is performed around \(\vec{x}_a\). Equation 3.16 states that \(\hat{x}\) is equal to \(\vec{x}_a\), which is corrected by the covariance matrices weighted measurement vector \(\vec{y}\). As a gradient the Jacobians determine the direction along which \(\vec{x}_a\) is corrected. The disadvantage of a linear approach to the optimal estimation solution is that the linearization point has to be close to the true state. Otherwise, the Jacobians at the linearization point can
deviate greatly from those close to the true state. This results in erroneous optimal estimates. To overcome these errors a non-linear approach has to be applied.

### 3.3.2 Non-linear Optimal Estimation Approach

The non-linear approach to find the optimal estimate $\hat{x}$ involves to continuously update the linearization point and the corresponding Jacobians in an iterative process. Even though the non-linear approach is computationally very expensive for each iteration since the entire radiative transfer and the responding Jacobians have to be updated, the retrieval is considerably improved. During the course of this study, the Levenberg-Marquardt OEM algorithm [Rodgers (2000)] was chosen to retrieve $\hat{x}$ over the Gauß-Newton algorithm [Rodgers (2000)]. Latter was less prone to converge, meaning that for many iterations no local minimum of $\chi^2$ was found. For the Levenberg-Marquardt algorithm Equation 3.16 is altered in the following way [Rodgers (2000)]:

$$x_{i+1} = x_i + [(1 + \gamma)S^{-1}a + K^T S^{-1}y_k]^{-1}[K^T S^{-1}y (y - f(x_i))] - S^{-1}(x_i - x_a)$$  (3.17)

During each iteration step $i$ the best estimate of that step ($x_{i+1}$) is originating from the best estimate of the preceding iteration step ($x_i$) around which the forward model is linearized. In contrast to the Gauß-Newton algorithm the Levenberg-Marquardt algorithm incorporates the damping factor $\gamma$. For the first iteration step $\gamma$ is set to be large (in this case $\gamma_0 \sim 10^4$). The step-size towards the next $x_{i+1}$ is therefore small. Here, the Levenberg-Marquardt algorithm is dominated by the method of steepest descent. If $\chi^2$ is decreased in the following iteration, the value of $\gamma$ is also reduced. If $\gamma$ is decreased, the size-step is increased. Hence, if the retrieval is tending towards minimising $\chi^2$ it is allowed to proceed faster. If, on the other hand, $\chi^2$ is increased, $\gamma$ is as well increased and the size step is decreased. This prevents the method from diverging. Only when $\chi^2$ is reduced $x_i$ is updated by $x_{i+1}$.

In order to prevent the iterative process to run exceed a certain amount of iterations a termination criterion has to be applied. A threshold in relative change of $\chi^2$ in between the iterations is chosen. If the relative change is below 0.1% the iteration process is considered as converged. If not converged after a certain amount of iterations (in this case 10) the process is terminated as well.

### 3.3.3 A priori, First Guess and Covariance Matrices

To initialize the OEM an a priori profile of the atmospheric state variable, in this case IWC, has to be committed. For the iterative Levenberg-Marquardt approach an additional “first guess” denoted here as the first linearization point $x_0$ is needed. The a priori is a representation of the knowledge about the atmospheric state and should prevent the retrieval from going towards an unphysical solution. The algorithm by Liu and Illingworth (2000) already provides a rough estimate on the order of magnitude and the overall shape of the sought profile corresponding to the measured RADAR signal. Additionally, it is very easy to apply. An advantage over other
empirical approaches is that Liu and Illingworth (2000) provide functions for both utilized Radar frequencies. For the “first guess” a profile close to the true atmospheric is required to shorten the computational time. Hence, both the a priori profile, as well as \( x_0 \) are chosen to be derived from the established empirical retrieval function introduced by Liu and Illingworth (2000).

\[
IWC = a \cdot Z_V^b
\]  

(3.18)

With \( a = 0.137 \cdot 10^{-3} \) and \( b = 0.64 \) for the 95 GHz Radar (estimated for 94 GHz by Liu and Illingworth (2000)) and \( a = 0.097 \cdot 10^{-3} \) and \( b = 0.59 \) for the 35 GHz Radar. The error estimate given by Liu and Illingworth (2000) states an uncertainty of 20% for an IWC \( \sim 10^{-5} \text{ kg/m}^3 \) and 30% for an IWC \( \sim 10^{-4} \text{ kg/m}^3 \). This error estimate is applied to construct the diagonal of the a priori covariance matrix \( S_a \) corresponding to the estimated a priori profile. The measurement covariance matrix \( S_y \) on the other hand is constructed from the measurement uncertainty of 1.3 dBZ for both utilized Radar along the diagonal. The measurement uncertainty is also displayed in Table 2.1.

### 3.3.4 Error Sources

In addition to the errors expected from imprecise input variables to the forward simulation, some errors were identified within the OEM process itself. By examining the forward simulated profiles in comparison to the measured ones, a smoothing error was discovered at the cloud edges. This effect arises from the discrepancy that the hydrometeor content is estimated between the retrieval grid points while the Radar reflectivity is given on them.

As described above the OEM did not always converge. This was especially the case when using the Gauß-Newton approach. However, also for the Levenberg-Marquard approach a small amount of profiles did not converge, especially if the profile contained large dBZ values. A decrease in vertical resolution to a 60 m bin width (vertical resolution of RASTA, see Table 2.1) reduced the number of non-converging profiles. The remaining profiles, though small in number, are set to NaN.

With all necessary input parameters at hand the hydrometeor content (IWC in this case) is estimated from the Radar reflectivity values observed during the “Joint flight” measurement campaign, using the non-linear OEM approach. As described in Section 3.2, the retrieval is tested for several different cloud particle habits. For each habit the same basic atmospheric state in terms of temperature and relative humidity profile (Section 3.2.3) is applied. The PSD (Section 3.2.2) and the back-scattering properties (Section 3.2.1), which are dependent on the cloud particle diameter, are specific for each individual cloud particle habit. The OEM estimates an IWC for which the balance of PSD and amount of back-scattering, result in a simulated Radar reflectivity equal or very close to the original measured Radar reflectivity. The results of all tested cloud particle habits are evaluated in the context of the “Joint flight” campaign in the following chapter.
Chapter 4

Analysis and Evaluation of Retrieved Hydrometeor Content in Context of the Joint Flight Measurement Campaign

In order to evaluate the hydrometeor content from the observed RADAR cross-sections it is of major importance to achieve an overview on the situation on which the retrieval is tested on. Therefore, the synoptic situation is analysed first, as it gives insight to the large scale processes present during the measurement campaign. This is followed by the evaluation of the RADAR observations and in situ measurements obtained, as they give a great amount of small scale information to the situation present during the Joint flight.

4.1 Synoptic Situation

From the 500hPa geopotential map shown partly in Figure 4.1 (full map and the analytical weather map displayed in Appendix B, Figure B.1 and B.3) a “cut-off” low pressure system originating from Greenland with an occluded front, located at the south-western tip of Ireland, can be identified on the 14th of October 2016. Additionally, a high pressure system over Scandinavia dominated the synoptic situation in the measurements area. Central European air-masses, advected by the geostrophic wind in between the above mentioned pressure systems caused the formation of clouds over the Northern sea and the Atlantic north of Scotland towards Island, visible in both VIS [Figure 4.1: Partial 500hPa Geopotential map of the measurement area on the 14th October 2016, 12UTC, [http://www.wetterzentrale.de/ accessed 2018-06-11]]

(Figure 2.1) and IR (Figure B.4) satellite images. The advected air-masses are lifted above a layer of cold air in the measurement area, which can be observed in the 850hPa temperature map (Figure B.2). This causes adiabatic cooling and condensation. The resulting clouds can possibly be associated with Nibostratus type originating from thickening Altostratus type clouds [WMO (1975)].

4.2 The Joint Flight Observational Context

One of the great advantages of Radar observation over passive remote sensing observations is that Radar reflectivity is measured on a vertical grid instead of on a frequency grid. Consequently, it is possible to make some basic statements about the observed situation, even before a retrieval of IWC is performed. Figure 4.2 shows the Radar reflectivity cross-section observed by the HAMP and the RASTA Radar, accompanied by the path of descent of the FAAM aircraft, as well as the path of the utilized dropsondes. The Radar observations show evidence of a cloud

![Figure 4.2](image)

Figure 4.2: Cross-section of Radar reflectivity measurements of the HAMP 35 GHz Radar and the RASTA 95 GHz Radar along the “Joint Flight” track. The dropsonde (dotted blue, orange, green and red lines) as well the descent of the FAAM aircraft (grey line, dotted: whole descent / dashed: analysed measurements) are displayed accordingly.
4.2. The Joint Flight Observational Context

pattern that spans over several latitudes (ca. 330 km). Here, the low sensitivity of the RASTA Radar, described by Bouniol et al. (2008), is clearly visible in comparison to the HAMP Radar measurements. Only the denser core of the observed cloud is captured by the RASTA Radar. Using the HAMP Radar signal the cloud height is estimated to reach over 8 km altitude and is especially extensive between 57 °N and 59 °N.

Lidar measurements, additionally obtained from the FF20 during the Joint flight, also indicate a cloud height larger than 8 km altitude, but with an expansion beyond 59 °N. A possible layer of super-cooled water is suspected around 59 °N, shielding the Radar signal from penetrating further down into the cloud. [from personal communication during the "HALO topical workshop"1 16th-17th November 2017, Hamburg]

At lower altitudes, strong precipitation events can be identified frequently along the whole horizontal range of the observed cross-section. Presumably additional precipitation occurred between 57.5 °N and 58 °N, but the Radar signal is attenuated by the dense cloud above, therefore no explicit statement can be made.

The so called "Bright band", which is the thin, horizontal aligned Radar signature of increased dBZ, is visible just below 2 km altitude above the precipitation, especially prominent in the HAMP observations. The “Bright band” appears approximately where the vertical temperature profile reaches 0 °C and a layer of melting ice particles is present. The melting process starts at the surface of the ice particle, propagating towards its center. The thermodynamic process of phase and therefore dielectric constant K change leads to an increase in Radar reflectivity. When a particle is fully liquified it collapses and its diameter is largely reduced. Hence, the Radar reflectivity is again reduced. [Fabry (2015)]

The Radar reflectivity [dBZ] measured by HAMP and RASTA, displayed in Figure 4.2, is not only different in terms of sensitivity, but also deviates in between the dBZ values. To compare the Radar reflectivities of HAMP and RASTA directly they are visualized using a heatmap (Figure 4.3). Only data points for which RASTA exceeds its sensitivity dBZ are considered for comparison, thus only core cloud measurements are taken into account from both Radar. A cross-section similar to Figure 4.2, where the dBZ values are correspondingly masked, can be observed within Appendix B, Figure B.5. In Figure 4.3 the most frequent combinations of RASTA and HAMP Radar reflectivities are marked in the darkest shades of red, while less frequent, or non-existent combinations go towards the brighter shades of red or white, respectively. As described in Section 3.1, the most frequent combinations of RASTA and HAMP Radar reflectivities would be aligned along the equivalent Radar reflectivity line (here grey dashed) if scattering only happens within the Rayleigh regime. For the case study at hand most dBZ values measured by RASTA correspond to higher dBZ values measured by HAMP. For increasing dBZ values the difference between HAMP and RASTA measured dBZ values also increases. Hence, strong evidence of scattering happening within the Mie regime is given. Only for the smallest dBZ values measured by RASTA the dBZ values measured by HAMP are close to equivalent. For

lower dBZ values an even closer dBZ value relation between RASTA and HAMP is expected. However, this can not be shown here due to the relative low sensitivity of RASTA. From the in situ measurements of IWC and temperature profile shown in Figure 4.4 relatively similar conclusions about the atmospheric situation to those of the Radar observation can be derived. The cloud top height is observed above 8 km altitude, due to a clear measured IWC signal up to these heights. As shown in Figure 4.2 the airplane approached the cloud from the south and entered it horizontally at the observed IWC altitude threshold (Figure 4.4) just above 8 km. Hence, the maximum cloud top height is expected at an even higher altitude. The dropsonde measurements indicate that for the maximum cloud top height a temperature below -40 °C can be assumed along the whole extension of the cross-section. Additionally, a temperature inversion can be identified from the dropsonde measurements. The inversion height observed from the dropsonde temperature profiles is subsiding in northerly direction. The maximum measured IWC is observed closely above the melting layer just below 2 km altitude, which is displayed by both “Bright Band” as well as the in situ measured temperature changes towards 0 °C and higher temperatures. The in situ measured IWC is increasing in downward direction from a height of approximately 7 km towards the melting layer height. However, an exception just below 5 km altitude exists where the IWC strongly decreases and strongly increases again a few hundred meters below. Presumably the FAAM aircraft left the cloud at that point. From the cross-section shown in Figure 4.2 the observed dBZ values also decrease northwards of FAAM path, however not as prominent along the direct path (Figure 4.4). During the temporal delay (ca. 20 minutes, see Chapter 2) between the Radar observations and the FAAM descent, the cloud was possibly transported northwards. The tilt observed for the dropsonde descents indicates a positive $v$-component of the wind (coming from the south). This assumption is in
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Figure 4.4: In situ temperature and IWC, measured by dropsondes and nevzorov probe, respectively and Radar reflectivity values [dBZ], observed along the FAAM decent

Line with expected south-western geostrophic winds. Apart from this large collocation error, the Radar reflectivity profiles measured by both HAMP and RASTA along the FAAM decent already share coinciding features with the in situ measured IWC profile. In general, the measured dBZ values are increasing with decreasing altitude below approximately 7 km, until reaching its maximum value just above the expected melting layer. Notably, the HAMP Radar reflectivity is increasing much stronger than the RASTA Radar reflectivity, as expected. Below 2 km altitude both observed Radar reflectivities decrease rapidly. This is most likely due to a dense layer of ice and melting ice particles causing the Radar signal to attenuate. Even though the FAAM descended further, Radar reflectivity values corresponding to temperatures above 0 °C are not taken into account for the retrieval (see Appendix B, Figure B.5) and are therefore not displayed in Figure 4.4.

Not only the IWC, but also the cloud particle shape is of great interest for this thesis. Therefore, a sample of cloud particle images taken along the FAAM descent is displayed in Figure 4.5. Additionally to the weak representation of the large amount of images, the interpretation of these images is rather subjective and must be observed with caution. Nevertheless, some general assumptions of the cloud particle shape at different altitudes is possible.

The examination of the CIP-15 images reveals the presence of small bullett rosette type cloud particles within the 5-7 km altitude region. Within this region these bullett rosette type cloud particles increase in size with decreasing altitude. As the IWC, shown in Figure 4.4, also increases with decreasing altitude within this altitude region, it is expected that the PSD is shifted to larger D_{max} here. Following Bailey and Hallett (2009), for temperatures below -20 °C which are measured above 5 km altitude (Figure 4.4) the bullet rosette type is an expected cloud particle
Figure 4.5: Sample CIP-15 ice particle images at distinct heights of the observed profile of in situ measurements

habit. Even though not clearly distinguishable from the CIP-15 images, the bullett rosettes are in theory accompanied by columnar and platelike polycrystals for the observed temperatures above 5 km altitude [Bailey and Hallett (2009)]. Notably, the circular features visible on the image slides (Figure 4.5) at higher altitudes are small cloud particles which are out of focus. Between 4 km and 5 km altitude even larger particles are present. In addition to aggregate type cloud particle, rosette like shaped cloud particles are observed. However, latter are not necessarily of rosette type. From the ice particle classification by Lindqvist et al. (2012) also column aggregate type cloud particles fit the rather blurry two dimensional particle observations. Following Bailey and Hallett (2009), accumulations of plates and columns are expected within the temperature range between -20 °C and -15 °C observed between 4 km and 5 km altitude (Figure 4.4).

In the altitude region between 2 km and 4 km the distribution of different cloud particle shapes is more extensive. Aggregate type cloud particles, large dendric polycrystals, sector plates as well as different kinds of irregular shapes are distinguishable on the CIP-15 images. With the evaluation of the sample CIP-15 cloud particle images, the situation observed during the Joint flight is fully described. Now, the retrieved IWC from the different test cases needs to be set into context of the observations collected during the Joint Flight campaign described above. Corresponding to the hypotheses introduced in Chapter 1, this is achieved by using error metrics which display the deviations of retrieval and measurement and in between the two frequency retrievals. The applied error metrics are described in the following Section.


4.3 Error Statistics

The error metrics chosen to evaluate the IWC retrieved from HAMP and RASTA Radar observations tested for several cloud particle habits are the systematic offset (BIAS) and the standard deviation of the error (SDE). These error metrics are well established and therefore beneficial for past and future comparisons. In the field of Meteorology the variable IWC is generally displayed within the $\log_{10}$ space, as it usually ranges over several orders of magnitude. By testing several different cloud particle habits it is expected that the resulting IWC values also differ within amounts of magnitudes from each other and the in situ measurements. The error metrics are therefore also applied to the $\log_{10}$ space. The differences at each point $i$ of the profile/cross-section of two IWC sources $A$ and $B$ within the $\log_{10}$ space are calculated as follows:

$$
\log_{10}(\tilde{IWC}_{A,i}) - \log_{10}(\tilde{IWC}_{B,i}) = \log_{10} \left( \frac{IWC_{A,i}}{IWC_{B,i}} \right) \tag{4.1}
$$

The $\tilde{IWC}$ represents the dimensionless IWC, which is normed by the unit. The index $i$ corresponds to a specific point in height and latitude of the in situ profile or Radar cross-section, respectively. The $\text{BIAS}_{log_{10}}$ or the average over the profile/cross-section of differences is therefore defined as:

$$
\text{BIAS}_{log_{10}}(A, B) = \frac{1}{N} \sum_{i=1}^{N} \log_{10} \left( \frac{IWC_{A,i}}{IWC_{B,i}} \right) \tag{4.2}
$$

The $\text{BIAS}_{log_{10}}$ is a measure of systematic offset in terms of magnitude between the two IWC sources $A$ and $B$. If the first hypothesis introduced in Chapter 1 is evaluated, $A$ and $B$ correspond to IWC retrieved from either 35 GHz or 95 GHz Radar observations and in situ measured IWC, respectively. If the second hypothesis introduced in Chapter 1 is evaluated, $A$ and $B$ correspond to retrieved IWC from 35 GHz and 95 GHz Radar observations, respectively. A $\text{BIAS}_{log_{10}}$ close to zero denotes agreeing performance between $A$ and $B$. A negative or positive $\text{BIAS}_{log_{10}}$ implies that $A$ is over- or underestimated by $B$. The $\text{SDE}_{log_{10}}$ or the standard deviation over the profile/cross-section of differences is derived analogously to the $\text{BIAS}_{log_{10}}$ in the $\log_{10}$ space.

$$
\text{SDE}_{log_{10}}(A, B) = \sqrt{\frac{1}{N - 1} \sum_{i=1}^{N} \left[ \log_{10} \left( \frac{IWC_{A,i}}{IWC_{B,i}} \right) - \text{BIAS}_{log_{10}}(A, B) \right]^2} \tag{4.3}
$$

The $\text{SDE}_{log_{10}}$ is a measure of variability in between the differences of the profile or cross-section in terms of magnitude around the $\text{BIAS}_{log_{10}}$ corrected profile or cross-section. It is expected, that the base value of $\text{SDE}_{log_{10}}$ is primarily influenced by differences due to collocation effects. However, secondary enhancement effects could be of concern.

Comparability of the different cloud particle test cases is now available in terms of systematic offset ($\text{BIAS}_{log_{10}}$) and random deviation ($\text{SDE}_{log_{10}}$). In order to gain a deeper understanding of the causes for the resulting error metrics a classification of cloud particle habits is introduced which takes the habit specific characteristics into account.
4.4 Classification of Cloud Particle Habits

Cloud particle habits can be distinguished by their mass-size dimension relationship and their scattering properties. The mass-size dimension relationship of a cloud particle habit is defined by its $\alpha$ and $\beta$ parameters (see Section 3.2.1). Small $\alpha$ and $\beta$ contribute to ice particles with a comparable low density, which already grow rapidly in diameter when their mass is slightly increased. These habits, further denoted as “fluffy”, are chosen for this study to correspond to $\alpha < 10^{-1}$ and $\beta < 2.2$ and are displayed in red from now on. $\alpha$ and $\beta$ of medium value contribute to ice particles of a density still relatively low, but their growth rate in terms of diameter is not as rapidly as for the “fluffy” habits when their mass is increased. These habits, further denoted as ”medium”, are chosen to correspond to $10^{-1} < \alpha < 10$ and $2.2 < \beta < 2.6$ and are displayed in blue from now on. Finally, large $\alpha$ and $\beta$ contribute to ice particles with high density and sphere-like growth. These habits, further denoted as “compact”, are chosen to correspond to $\alpha > 10$ and $\beta \approx 3$ and are displayed in green from now on. The values of $\alpha$ and $\beta$ corresponding to each habit are displayed in Appendix A, Table A.1 and A.2 and Figure A.5.

Concerning the scattering properties of the different habits a classification is met with more difficulties. In contrast to the mass-size parameter classification, the scattering properties of a cloud particle habit cannot be as easily defined by given parameters. In general, back-scattering properties are displayed in terms of back-scattering efficiency $Q_{\text{back}}$, which is directly accessible from the utilized scattering database (Section 3.2.1). $Q_{\text{back}}$ can be reviewed for the utilized frequencies and habits from Eriksson et al. (2018).

As described in Section 3.1, differences in Radar reflectivity in between different Radar frequencies occur for scattering corresponding to the Mie-regime. To catch the impact of Mie scattering and be able to compare the utilized frequencies in terms of volume equivalent diameter $D_{\text{veq}}$, the back-scattering properties are classified in terms of Rayleigh-normed back-scattering efficiency $\tilde{Q}_{\text{back}} = Q_{\text{back}} / Q_{\text{back,rayleigh}}$. With $Q_{\text{back,rayleigh}}$ as the back-scattering efficiency corresponding to a theoretical Rayleigh sphere, further described in Appendix A, Section A.2. $\tilde{Q}_{\text{back}}$ for both utilized frequencies and each cloud particle habit is additionally displayed in Figure A.2, A.3 and A.4 and evaluated for classification.

Cloud particle habits are marked with dark shades, if their $\tilde{Q}_{\text{back}}$ is decreasing for comparably low $D_{\text{veq}}$ and is comparable low in terms of value within the Mie-regime. Bright shades, on the other hand, correspond to cloud particle habits, for which $\tilde{Q}_{\text{back}}$ is found to correspond just the opposite way. In terms of back-scattering the cloud particle habits are found to behave differently in between the above defined mass-size classification. Therefore the habits are separately classified within each mass-size class. If the above defined error metrics (Section 4.3) are analysed, cloud particle habits, within the same mass-size class, that are classified to exhibit similar back-scattering properties, are marked with the same shade. For the remaining analyses a continuous brightness scale was proven to be easier to distinguish.

The exact classification of each cloud particle habit is summarized in Appendix A, Table A.3 and is displayed in Figure A.5.
4.5 Evaluation of Retrieved Hydrometeor Content

The primary goal in evaluating the retrieved IWC is to distinguish if any of the chosen settings (habit test cases) for the retrieval provide physically reasonable results. Due to access to direct in situ measurements of IWC and Radar observations of different frequencies both hypotheses formulated in Chapter 1 can be examined in the following sections.

At first however, a general overview over the differences in retrieved IWC for each habit test case is presented. This is achieved by estimating the habit specific dBZ-IWC relationship between the retrieved IWC and the measured Radar reflectivity. It should be noted that for all tested cloud particle habits the retrieved IWC scatters up to half an order of magnitude for each dBZ value. Thus, the dBZ-IWC relationship is represented by an average IWC, calculated from all IWC values corresponding to a certain dBZ bin. Conveniently, the empirical retrieval approaches introduced in Chapter 3 can easily be displayed in a similar format. Especially a comparison to the approach introduced by Liu and Illingworth (2000), which has been used to estimate the a priori and “first guess” to initialize the retrieval (Section 3.3.3), is of interest. Yet, most importantly, the dBZ-IWC relationship helps to explain features observed in the in situ and dual-frequency evaluation and is therefore displayed for each habit and both Radar in Figure 4.6. For most Radar reflectivity values the lowest IWC values are for the most part observed for the “compact” habit test cases. Of these habits, the denser ones, corresponding to a comparably large $Q_{\text{back}}$ sometimes deep within the Mie scattering regime (brightest shades), contribute the lowest IWC for most dBZ values. Coinciding findings in terms of back-scattering response are evident for the “medium” habit test cases, though minor exceptions are to be noted. For the

![Figure 4.6: Relationship between measured dBZ and retrieved IWC, averaged for bins of 1 dBZ corresponding to the different habit test cases and the two utilised Radar frequencies](image)

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“fluffy” habit test cases the reverse applies. Depending on the specific habit, the “medium” habit test cases correspond to intermediate or even comparably large IWC for each Radar reflectivity value. Here, the EvensSnowAggregate stands out, as its average IWC exceeds the ones of all other tested cloud particle habits by up to one order of magnitude.

Not only in terms of back-scattering response, but also overall dBZ-IWC relationship, the “fluffy” habits stand out with rather low IWC values for low dBZ values and high IWC values for large dBZ values. One exception is the ColumnType1 habit, which is more similar to some of the “medium” habits in terms of dBZ-IWC relationship. Hence, the steepest slope in dBZ-IWC relationship is found for the rather “fluffy” habit test cases like IconSnow and SectorSnowflake. The more “compact” habit test cases show a comparably flat dBZ-IWC relationship for HAMP (over whole dBZ value range) and RASTA (up to 10 dBZ).

The habit test cases of “medium” mass-size relationship are relatively similar to the more “compact” habits except for the EvensSnowAggregate and the LargeColumnAgrregate, in terms of dBZ-IWC slope. Especially for HAMP retrieved IWC at higher dBZ, both habit test cases show a comparably flatter dBZ-IWC relationship.

In general, for each tested habit the dBZ-IWC relationship is found to be steeper for the RASTA retrieved IWC than for the HAMP retrieved IWC, especially for higher dBZ values. Additionally, the average IWC value corresponding to a certain dBZ bin is equal or higher for the RASTA retrieval, compared to the HAMP retrieval.

As a matter of course, the dBZ-IWC relationship used for initiating each retrieval test case [Liu and Illingworth (2000)] is altered strongly within the retrieval process. In comparison to the tested habits the approach by Liu and Illingworth (2000) results in higher IWC for both frequencies and each dBZ bin, except for the EvansSnowAggregate test case. The slope of the empirical approach by Liu and Illingworth (2000) is comparable to the “medium” and “compact” habits for lower dBZ values, but not as steep for higher dBZ values. Further empirical retrieval approaches are displayed in Appendix B, Section B.3, Figure B.6. Additionally, their specifications are documented in Table B.1 for further inspection. Like Liu and Illingworth (2000) these empirical approaches correspond to rather large IWC for each dBZ bin compared to the tested habits. Though, of the empirical approaches i.e. the one by Atlas et al. (1995) shows a relatively similar dBZ-IWC relationship as i.e. the BulletRosette type habits and the ColumnType1.

With the general relation between IWC as well as the Radar reflectivity and differences in between the tested habits analysed, the next step focuses on setting these findings in context of the “Joint Flight” measurement campaign. As differences in IWC in between the habit test cases is found to vary in orders of magnitudes, an estimate about the true amount of IWC is needed to rule out unphysical habits. The intuitive approach to gain this estimate is from the measured in situ IWC.
4.5. Evaluation of Retrieved Hydrometeor Content

4.5.1 Evaluation in Context of In Situ Observations of IWC

In order to compare retrieved IWC from the Radar cross-section and in situ measured IWC only the cross-section grid points nearest to the FAAM descent are selected. Both in situ and retrieved IWC are averaged corresponding to the Radar vertical grid. Subsequently, the error metrics are applied to the resulting profiles of IWC. Thus, one respective value of $B\text{IAS}_{\log_{10}}$ and $S\text{DE}_{\log_{10}}$ is obtained for each profile retrieved for the 16 different habit test cases and the empirical approaches. Figure 4.7 shows the $B\text{IAS}_{\log_{10}}$ and $S\text{DE}_{\log_{10}}$ to the in situ measured IWC of all tested habits and empirical retrieval approaches, scattered for the two Radar frequencies. Additionally,

![Graph showing BIAS and SDE for in situ IWC and IWC retrieved from 35 GHz and 94 GHz Radar observations.](image-url)

*Figure 4.7: BIAS and SDE between in situ IWC and IWC retrieved from 35 GHz and 94 GHz Radar observations, tested for 16 different cloud particle habits and the empirical retrieval approaches.*

a comparison between profiles of IWC retrieved from HAMP and RASTA observations and the in situ measured IWC for each tested habit are shown in Figure 4.8. These profiles provide further insight into erroneous features in addition to the error metrics.

The BIAS$_{\log_{10}}$ (Figure 4.7) closest to zero corresponds to BulletRosette type habits and the LargeColumnAggregate considering both HAMP and RASTA retrievals. The SDE$_{\log_{10}}$ observed for these habits (Figure 4.7) is increased for the RASTA retrieval in comparison to other tested habits. Yet, the SDE$_{\log_{10}}$ increase is only small in comparison to the collocation induced base SDE$_{\log_{10}}$. For most cloud particle habit test cases the same applies for the HAMP retrieval. Thus, the primary focus of habit internal evaluation is set to the BIAS$_{\log_{10}}$.

The comparable small average deviation (BIAS$_{\log_{10}}$) from the in situ observations of the BulletRosette type test cases supports the findings of Geer and Baordo (2014). Furthermore, these findings are also in line with previous measurement campaigns [Zhang et al. (2013), Orikasa et al. (2013)] and with the (theoretical) occurrence of ice particle shapes derived from temperature profiles [Bailey and Hallett (2009)]. The BIAS$_{\log_{10}}$ of BulletRosette type habits and the LargeColumnAggregate is slightly positive for both Radar retrievals, except for the 6-BulletRosette retrieval from the RASTA observations. The Flat3- and 4-BulletRosette have a larger BIAS$_{\log_{10}}$ for the HAMP retrieval, while for LargeColumnAggregate the BIAS$_{\log_{10}}$ is of comparable value for both Radar retrievals.

For the habit test cases, which correspond to a BIAS$_{\log_{10}}$ comparably close to zero, a comparably small deviation from the in situ measurements is also observed for the profile comparison (Figure 4.8), especially between 5-6 km and 3-4 km altitude. The large deviations between retrieved and in situ measured IWC between 4-5 km altitude can be explained by the Radar and in situ collocation error described in Section 4.2. Between 5-6 km altitude also the ColumnType1 habit is in overall agreement with in situ measured IWC for both Radar retrievals. The LargeColumnAggregate is a habit mix with single large columns corresponding to the smallest cloud particle diameters. Because the PSD is shifted towards smaller diameters for lower IWC values, the similarity between ColumnType1 and LargeColumnAggregate at that height is likely. In terms of BIAS$_{\log_{10}}$ the ColumnType1 habit also displays values comparably close to zero.

Below 3 km altitude the in situ IWC and IWC retrieved from RASTA observations for BulletRosette type habits are still in well agreement. The RASTA Radar is known to exhibit only sparse multiple scattering, as described in Section 2.1.2. As single scattering is a requirement of the retrieval setup, the retrieval is expected to perform admirably for the RASTA Radar. The IWC retrieved from the HAMP observations on the other hand overestimates the in situ measured IWC. This overestimation contributes to the larger BIAS$_{\log_{10}}$ of the HAMP retrieval compared to the RASTA retrieval. In literature there is no mention of a reduction in multiple scattering enhancement for the HAMP Radar. It is possible that a small part of the overestimation results from increased dBZ values due to multiple scattering enhancement. Yet, this can not be proven.

The in situ measured IWC is also overestimated by the IWC retrieved from HAMP observations below 3 km for the LargeColumnAggregate test case, however of all habits corresponding to a
4.5. Evaluation of Retrieved Hydrometeor Content

Figure 4.8: Profile of retrieved IWC from RASTA and HAMP for all habit test cases and empirical approaches in comparison to in situ measured IWC
BIAS$_{\log_{10}}$ close to zero this one is the smallest.

Strikingly, the above described cloud particle habits (LargeColumnAggregate and BulletRosette type habits) are relatively similar in terms of mass-size dimension relationship, as well as scattering properties. Thus, it is reasonable that with the assumption of random orientation, small cloud particles of BulletRosette type, Column and ColumnAggregate show coinciding behaviour. In context of the remarkably well performance of the LargeColumnAggregate and BulletRosette type habits it should be noted that these habits showed larger discrepancies towards the in situ measured PSD than most other tested habits. Still, for all other cloud habit test cases the estimated BIAS$_{\log_{10}}$ to the in situ IWC deviates stronger from zero. Except for the EvensSnowAggregate test case, those tested habits tend to underestimate the in situ measured IWC. The underestimation is stronger for the RASTA than for HAMP retrieval. This is no surprise, as the IWC retrieved from the RASTA observations was generally found to be smaller than the IWC retrieved from HAMP observations.

The BIAS$_{\log_{10}}$ of the PlateType1, LargePlateAggregate, LargeBlockAggregate, IconCloudIce and SectorSnowflake habit test cases are relatively similar. In terms of scattering classification these habits all correspond to a relatively large $Q_{\text{back}}$ within the Mie-regime, especially in comparison to the LargeColumnAggregate (see Figure A.2). These cloud particle habits only show a slightly bigger but negative offset compared to the in situ IWC than for example the BulletRosette type habits. Nevertheless, no altitude region exists for which the retrieved and in situ measured IWC are in likewise good agreement to the BulletRosette or LargeColumnAggregate test case (Figure 4.8). For example, at higher altitudes ($\gtrsim$ 5 km) the in situ IWC is underestimated by the IWC retrieved for the SectorSnowflake from both HAMP and RASTA. At lower altitudes ($\lesssim$ 3 km) the in situ IWC is underestimated by the IWC retrieved from RASTA, but overestimated by the IWC retrieved from HAMP. In between ($\sim$ 3-5 km) IWC retrieved from both HAMP and RASTA over- and underestimates the in situ measured IWC in a seemingly random fashion. Hence, laying focus on the SectorSnowflake, predicted by Geer and Baordo (2014) as a habit with average properties, fulfills these expectations in terms of BIAS$_{\log_{10}}$ at least for the HAMP Radar retrieval. Yet, if observed per profile the SectorSnowflake actually performs poorly, as described above. While the RASTA retrieval systematically underestimates the in situ IWC for the most part (negative BIAS$_{\log_{10}}$ and small SDE$_{\log_{10}}$), the HAMP retrieval displays under- and overestimations for small and large dBZ values, respectively, leading to a small BIAS$_{\log_{10}}$, but also comparably large SDE$_{\log_{10}}$ (see Figure 4.7). The rather steep dBZ-IWC relationship observed in Figure 4.6 explains these prominent over- or underestimations for the HAMP retrieval.

The overall retrieved IWC and therefore the BIAS$_{\log_{10}}$ further decreases (stronger underestimation of the in situ measured IWC) for more “compact” habits (8-ColumnAggregate, GemGraupel, IconHail and IceSphere). The dBZ-IWC relationship of the “compact” habits (Figure 4.6) stronger scattering within the Mie-regime was found to correspond to lower retrieved IWC for the main part of the dBZ range. Notably, $Q_{\text{back}}$ is larger for the more “compact” habits, especially for large $D_{\text{eq}}$. 
4.5. Evaluation of Retrieved Hydrometeor Content

The IceSphere, often used as an approximation for the cloud particle shape in previous radar retrievals [e.g. Stephens et al. (2008)], exhibits the largest systematic deviations from the in situ measured IWC. Interestingly, an increased negative $\text{BIAS}_{\text{log}_{10}}$ is also observed for the rather “fluffy” cloud habit IconSnow test case. The IWC retrieved for the “compact” habit test cases systematically underestimates the in situ measured IWC at almost all altitude levels. Only between 2-3 km the IWC retrieved from the HAMP observations are in relatively well agreement with the in situ measured IWC.

In contrast to most habits tested with the new retrieval algorithm the $\text{BIAS}_{\text{log}_{10}}$ (Figure 4.7) corresponding to IWC estimated for the majority of the empirical retrieval approaches implies an overestimation of the in situ measured IWC. In most cases the $\text{BIAS}_{\text{log}_{10}}$ is also strongly increased for the HAMP in comparison to the RASTA retrieval. This was to be expected as most of these approaches have been implemented specifically for application to 94 GHz frequencies. Solely the approach by Liu and Illingworth (2000) which provides separate parameters for the 35 GHz retrieval shows agreeing $\text{BIAS}_{\text{log}_{10}}$ values for both HAMP and RASTA retrieval. However, of the empirical approaches, the one introduced by Atlas et al. (1995) is the only one yielding a comparable $\text{BIAS}_{\text{log}_{10}}$ for both HAMP and RASTA, as the well performing habits. Its corresponding $\text{SDE}_{\text{log}_{10}}$ (Figure 4.7) on the other hand is increased in comparison to those habits. In fact, most empirical approaches show a large $\text{SDE}_{\text{log}_{10}}$ compared to all tested habits, especially for the RASTA retrieval. Hence the overall shape of the in situ profile is not well captured by the empirical approaches, even though the $\text{BIAS}_{\text{log}_{10}}$ is in some cases similar. The approaches by Sayres et al. (2008) and Schneider and Stephens (1995) for example exhibit a relatively low $\text{BIAS}_{\text{log}_{10}}$ at least for RASTA retrieval, yet also an especially increased $\text{SDE}_{\text{log}_{10}}$.

In conclusion, an overall agreement between retrieved IWC and in situ measured IWC is evident for several different tested cloud particle habits. These habits also improve empirical retrieval approaches in terms of $\text{BIAS}_{\text{log}_{10}}$, but especially in terms of $\text{SDE}_{\text{log}_{10}}$. However, differences in between retrieved IWC by HAMP and RASTA, especially at lower altitude levels, are observed for single profiles. The problem is, even if an IWC close to the in situ observations is retrieved from a single radar observation, the combination of input PSD and scattering properties can not be considered valid, yet. To determine whether the tested cloud particle habit is physically reasonable, the IWC in between the two radar retrievals of different frequency must also be in well agreement as described in Section 3.1. Additionally, due to the limited amount of in situ measured data points represented by a single profile, a larger scale evaluation is needed. Therefore, the following section focuses on the intercomparison of HAMP and RASTA retrieved IWC.
4.5.2 Evaluation in Context of Dual Frequency RADAR Approach

The $\text{BIAS}_{\log_{10}}$ in between the IWC retrieved from HAMP and RASTA RADAR observations is used to determine if the habit specific scattering properties and mass-size relationship are physically realistic. Caution must be exercised in the interpretation of the $\text{BIAS}_{\log_{10}}$ as its meaning now changed in regard to the in situ comparison. As described in Section 3.1, RADAR reflectivity of two RADAR of different frequency is only equivalent for the Rayleigh scattering regime. When the scattering detected by a RADAR occurs within the Mie-regime, the measured RADAR reflectivity will deviate for different frequencies. Each tested cloud particle habit corresponds to individual scattering properties and PSD. Even if one of the RADAR retrievals results by chance in an IWC close to the real state, a second RADAR of a different frequency will most probably not be able to retrieve a likewise coinciding IWC. The $\text{BIAS}_{\log_{10}}$, as a measure of systematic offset, is well suited to reveal unphysical assumptions within the retrieval. The $\text{SDE}_{\log_{10}}$ is expected to mainly be a measure of differences due to collocation errors. Each tested cloud particle habit as well as each tested empirical method is scattered corresponding to its $\text{BIAS}_{\log_{10}}$ and $\text{SDE}_{\log_{10}}$ between HAMP and RASTA retrieval and is shown in Figure 4.9. Here, the whole observed cross-section is taken into account. Every retrieved IWC value exceeding $10^{-9}$ kg/m$^3$ for both HAMP and RASTA is evaluated (the retrieval corresponds to the masked data, as displayed in Figure B.5).

In general, the habit test cases shown in Figure 4.9 display similar characteristics, if they possess similar mass-size parameters and scattering properties. The lowest values of $\text{BIAS}_{\log_{10}}$ are
4.5. Evaluation of Retrieved Hydrometeor Content

dominantly observed for habits with a “medium” α and β, namely LargeColumnAggregate, BulletRosette type habits and EvansSnowAggregate. In terms of scattering properties these habits are corresponding to a comparably low $Q_{back}$ within the Mie-regime. Additionally, they share similar back-scattering property deviations in between 35GHz and 95GHz for small $D_{veq}$. A slightly increased BIAS$_{\log_{10}}$ compared to the above mentioned habits is observed for PlateType1 and IconCloudIce, which are of similar mass-size relationships but correspond to larger $Q_{back}$ within the Mie-regime. A comparable value of BIAS$_{\log_{10}}$ to the IconCloudIce test case is additionally observed for several cloud particle habit test cases corresponding to both “compact” and “fluffy” classification. Further increased BIAS$_{\log_{10}}$ are observed for cloud particle habit test cases of all classifications, mainly corresponding to a larger $Q_{back}$ within the Mie-regime. Here, the largest BIAS$_{\log_{10}}$ is observed for the SectorSnowflake test case.

In summary, a tendency for a smaller BIAS$_{\log_{10}}$ is found for the “medium” class cloud particle habits. Yet, also a response to scattering is found for all mass-size classes in terms of BIAS$_{\log_{10}}$. The SDE$_{\log_{10}}$ as described above, is expected to be primarily related to collocation errors in between the Radar observations. Hence, the collocation error is most probably responsible for the relatively large base value of the SDE$_{\log_{10}}$ compared to the BIAS$_{\log_{10}}$. However, if the collocation error would be the only source, one would expect almost the same SDE$_{\log_{10}}$ for every habit specific retrieval, which is not the case. As described in Section 4.5 the retrieved IWC was found to vary for distinct dBZ values. Hence, a habit specific enhancement of random deviations in between the retrievals from different frequencies is given. Furthermore, a distinct response of the SDE$_{\log_{10}}$ to mass-size classification can be observed. While “compact” habits are of comparably low SDE$_{\log_{10}}$, “fluffy” habits, which show the steepest slope in dBZ-IWC relationship (Figure 4.6), correspond to the largest SDE$_{\log_{10}}$.

In comparison to the cloud particle habits tested with the new retrieval algorithm the BIAS$_{\log_{10}}$ in between HAMP and RASTA shown in Figure 4.9 is larger (except for the SectorSnowflake case) for almost all empirical retrieval approaches applied to the Radar cross section. Only the retrieval approach by Liu and Illingworth (2000) is comparable to the habits corresponding to a relatively small BIAS$_{\log_{10}}$ (Flat3- and Perpendicular4-BullettRosette). Hence, the application of a frequency specific empirical retrieval approach does improve the agreement between retrievals of different frequency.

In terms of SDE$_{\log_{10}}$ most empirical approaches show improved agreement in between HAMP and RASTA retrieval than the tested cloud particle habits. Nevertheless, only the approach by Liu and Illingworth (2000) improves the well performing habits in terms SDE$_{\log_{10}}$ and exhibits a comparably low BIAS$_{\log_{10}}$.

Interestingly, also the empirical retrieval approaches corresponding to the steepest dBZ-IWC relationship (Figure B.6) exhibit the largest SDE$_{\log_{10}}$ and BIAS$_{\log_{10}}$, respectively. Additionally, the value of SDE$_{\log_{10}}$ and BIAS$_{\log_{10}}$ is decreasing with decreasing steepness of the dBZ-IWC relationship of the corresponding empirical approach, excluding the approach by Liu and Illingworth (2000).

With the two hypotheses introduced in Chapter 1 evaluated, the following Chapter discusses the key findings of this study and presents possible improvements to be applied in future studies.
Chapter 5

Conclusions and Outlook

There are multiple cloud particle habits that satisfy both hypotheses introduced in Chapter 1. On the contrary, none of the empirical retrieval approaches evaluated in comparison accomplishes this. Multiple cloud particle habits (i.e. LargeColumnAggregate and BulletRosette type habits) tested with the new retrieval algorithm improve the empirical retrieval approaches considering the in situ BIAS_{log10} and SDE_{log10} but also the dual-frequency BIAS_{log10}. Furthermore, the additional benefit of gaining insight on PSD and scattering properties and hence, presumably cloud particle shape is also denied when using empirical approaches. Thus, the application of a retrieval approach similar to the one introduced in this study is advised for further studies.

From the analysis of the profile of retrieved and in situ IWC as well as the BIAS_{log10} in between the Radar retrieval the LargeColumnAggregate clearly stands out from the other cloud particle habits. Especially for the lower part of the profile the LargeColumnAggregate is in best agreement with the in situ measurements when both Radar retrievals are taken into account. Also the BulletRosette type habit test cases result in relatively low errors in terms of in situ BIAS_{log10}. Remarkably, the BulletRosette type habit was already assumed by several authors [Zhang et al. (2013), Orikasa et al. (2013), Geer and Baordo (2014), Bailey and Hallett (2009)] to perform admirably. Even though declared as different habits, the LargeColumnAggregate as well as the BulletRosette type habit share similar characteristics, especially in terms of mass-size relation, but also in terms of back-scattering properties. Here, the assumption of totally random oriented particles lead to coinciding back-scattering properties between these cloud particle habits. A future sensitivity study might be able to shed some light on the consequences of particle orientation in this context. Such a sensitivity study will be feasible in the near future, as a planned extension of the scattering database by Eriksson et al. (2018) will include scattering properties for azimuthally random oriented particles.

The retrieval of IWC corresponding to LargeColumnAggregate, BulletRosette type habits and additionally to the ColumnType1 are very close to the in situ measured IWC in the upper part of the profile. As a habit mix of LongColumns and LargeColumnAggregates, the LargeColumnAggregate habit mix is able to combine both the shapes of single columns as well as those of the column aggregate. Hereby, the single columns dominating at higher altitudes in the profile
are corresponding to lower IWC whereas the column aggregates dominate the lower part of the observed profile. When accounting for a whole profile in the present case of large clouds, a habit mix is presumably the best choice. This hypothesis should further be checked by direct inter-comparison of retrievals from pure aggregate, single crystal and habit mix.

In accordance to the low BIAS$_{\log_{10}}$ values, evidence of BulletRossettes and LargeColumnAggregates within the altitude regions of sound performance can also be found in sample CIP-15 images (Figure 4.5), though a more detailed analysis in terms of cloud particle shape from the CIP images could prove beneficial for future evaluations. Thus, the utilized setup of Radar retrieval introduced in Chapter 3 is capable of yielding reasonable IWC values along the atmospheric profile as well as for most of the dBZ range. This holds true as long as physically reasonable assumptions on PSD and scattering properties are made. Nevertheless, this study discusses only a single cloud scene within the mid-latitudes. Hence, the retrieval outcome for different cloud particle habits should also be tested for additional cloud types and observations from the tropical and the arctic regions.

Even though the PSD of most tested cloud particle habits does fit the PSD observed for the evaluated scene well, the best performing habits regarding both hypotheses show a poorer agreement towards the in situ measured PSD. As a consequence, a sensitivity study considering different PSD approaches should be applied in further studies, especially if a different scene is evaluated.

With regard to future Radar retrievals it would be desirable to derive a physically reasonable cloud particle habit solely from the given Radar observations due to the probable lack of in situ observations. The cloud observatory on Barbados [Stevens et al. (2016)] is for example a location feasible for future long-term dual-frequency Radar studies. Additionally to a 35 GHz Cloud Profiling Radar a second 94 GHz Radar will be installed by the end of 2018 [from personal communications with Lutz Hirsch$^1$].

However, comparably small BIAS$_{\log_{10}}$ and SDE$_{\log_{10}}$ in between the retrievals of HAMP and RASTA do not necessarily indicate a physically reasonable cloud particle habit. The Evans-SnowAggregate is a good example. Even though the HAMP and RASTA retrieved IWC are relatively similar, the BIAS$_{\log_{10}}$ to the in situ measurements is large. Therefore, caution is advised when choosing a habit without any in situ references to validate it with. Still, from the IWC-dBZ relationship shown in Figure 4.6, the EvansSnowAggregate can clearly be identified as an outliner compared to the other habits. The retrieved IWC is exceeding its pendants by at least half an order of magnitude. This strong difference in retrieved IWC towards the other tested habits is substantial, with respect to mass-size dimension and scattering properties. The main distinction from the other tested habits is that the EvansSnowAggregate is the only aggregate type habit not extended to a habit mix by a single crystal cloud particle habit. Additionally, when transformed corresponding to D$_{\text{eq}}$, the respective PSD$_{D_{\text{eq}}}$ to the EvansSnowAggregate shown in Appendix A, Figure A.1 clearly deviates from the other PSD$_{D_{\text{eq}}}$ in contrast to the PSD$_{D_{\text{max}}}$.

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$^1$Max Planck Institute for Meteorology, Hamburg
underline the necessity of inter-comparison between habit mixes and habits solely consisting of single crystals or aggregates, respectively.

Even though a small $\text{BIAS}_{\log_{10}}$ in between the Radar retrievals does not necessarily indicate a fitting cloud particle habit, a cloud particle habit that results in a large $\text{BIAS}_{\log_{10}}$ in between Radar retrievals of different frequency most probably indicates a discrepancy between the observed and assumed PSD and back-scattering properties. For most cloud particle habit test cases an increased $\text{BIAS}_{\log_{10}}$ in between the Radar retrievals also corresponds to an increased $\text{BIAS}_{\log_{10}}$ to the in situ measurements, especially considering the RASTA retrieval. As described in Section 2.1.2 the RASTA Radar is expected to have a reduced multiple scattering enhancement within dense parts of an observed cloud. As the retrieval setup (Section 3.2) only takes single scattering into account, an increased $\text{BIAS}_{\log_{10}}$ of the RASTA retrieval to the in situ measurements needs to be treated with caution. In order to gain an overview on the impact of multiple scattering on the retrieval outcome of different cloud particle habits, further studies should include a sensitivity study on multiple scattering. As ARTS does contain the Monte-Carlo multiple scattering tool such a study is feasible. Yet, the impact from multiple scattering will most probable not be able to compensate for very large deviations in retrieved IWC. Therefore, a large $\text{BIAS}_{\log_{10}}$ in between the Radar retrievals is still a strong indication for large deviations in retrieved IWC along the profile, even if the in situ $\text{BIAS}_{\log_{10}}$ is comparably small. The ColumnType1 test case is a good example for that. Even though the $\text{BIAS}_{\log_{10}}$ to the in situ measurements is small for both Radar retrievals, it is evident that the retrieved IWC only agrees for both Radar retrievals at the upper part of the profile. In the lower part of the profile the retrieved IWC not only deviates from the in situ measurements, but especially between the Radar retrievals. This effect is found for many of the other habit test cases, i.e. for the SectorSnowflake, LargeBlockAggregate or IceSphere. All these habits correspond to a large $\text{BIAS}_{\log_{10}}$ in between the Radar retrievals. In order to narrow down the physically reasonable cloud particle habits in absence of in situ measurements it is reasonable to rule out those habit test cases with a comparable large $\text{BIAS}_{\log_{10}}$ in between the Radar retrievals. Even though some of the tested habits can be ruled out, it should be noted that a result equally distinct as the one found in this study (LargeColumnAggregate) can not be expected for other cloud scenes.

An additional option to rule out further habit test cases is the application of a third Radar frequency. From three independent Radar frequency observations it is possible to get a rough estimate on all three unknowns connected to the atmospheric state, namely the PSD, the particle shape and the hydrometeor content [i.e. Sekelsky et al. (1999), Kneifel et al. (2011), Kulie et al. (2014)]. Nevertheless, a setup consisting of three Radar is very rare and often only available from short term airplane campaigns or local, ground stationed Radar. Therefore, the triple-frequency approach can most likely just be realized in form of additional case studies. Yet, for a more general inter-comparison of retrievals from different cloud types and climate zones, Radar observations of polar orbiting satellites are probably the best choice. Here, the 94 GHz Radar on bord of the CloudSat satellite comes to mind, but the restriction to one frequency prevents a
statement on the quality of the utilized PSD and cloud particle habit. Still, an evaluation of the CloudSat IWC retrieval product [Austin et al. (2009)] in context of this study is of interest, as it is one of the most prominent Radar retrievals which uses a cloud particle habit (IceSphere) that does not perform well in this study. Unfortunately, no CloudSat retrieval product was available in proximity of the “Joint flight” measurement area, along a path the HALO and the FF20 joined with the CloudSat satellite as well on 14th October 2016. Additionally, the soon to be launched Earth Cloud, Aerosol and Radiation Explorer (EarthCARE) satellite will carry a 94 GHz Cloud Profiling Radar [Illingworth et al. (2015)]. Even though the EarthCARE Radar will also be restricted to one frequency, in advance to CloudSat the EarthCARE satellite will additionally be equipped with a Lidar and a broadband radiometer, holding the advantage of future combined retrievals.

Apart from the CloudSat and EarthCARE Radar the dual-frequency Radar on board of the Global Precipitation Measurement (GPM) Core Observatory (CO) [Hou et al. (2014)], including a Ka-band (35.6 GHz) and a Ku-band (13.6 GHz) Radar, is an option to look into. Here, both the global coverage as well as that the Radar installed on the satellite measure simultaneously, reducing possible collocation errors, are of advantage. Additionally, evaluating the retrieval results for a frequency (Ku-band) lower than both frequencies utilized in this study also proves to be interesting. However, it should be noted that the GPM mission focusses on the observation of precipitation instead of clouds. It is possible that the sensitivities of the Radar are not suited for cloud hydrometeor analysis at all altitude regions of interest. For example, thin clouds or snow events within the arctic regions generally correspond to Radar reflectivities below the GPM Radar detection threshold [Fabry (2015)].

In conclusion, for the specific analysis of the Radar cross-section observed during the “Joint Flight” campaign the Radar retrieval was found to produce reasonable results of IWC, provided the input of PSD and scattering properties is physically reasonable. From the Dual-Frequency inter-comparison as well as in situ comparison a habit fulfilling the overall conditions present during the campaign was found. Still, in order to increase the certainty whether the chosen input parameters (PSD, scattering properties) represent the physical conditions, some additional analysis must be considered. In order to improve passive remote sensing retrievals and eventually climate models the retrieval setup evaluated in this study must prove equally successful in further case and sensitivity studies like those suggested above.
This study utilizes several observational datasets obtained during the “Joint Flight” measurement campaign. The HALO observational data, especially including HAMP Radar observations was provided by Heike Konow\textsuperscript{2}. The FF20 observational data, especially including the RASTA Radar observations was provided by Julien Delanoë\textsuperscript{3}. Finally, the FAAM observational data, especially including dropsonde and cloud probe measurements was provided by Stuart Fox\textsuperscript{4}. Thanks go to Patrick Eriksson\textsuperscript{5}, who provided me with the starting toolkit to perform Radar retrievals with ARTS. I also thank Simon Pfrendschuh\textsuperscript{5} for providing me with his findings on errors encountered when performing Radar retrievals with ARTS. Furthermore, for discussion and inspiration on the evaluation of particle size distribution, I thank Christoph Sauter\textsuperscript{2}. Finally, I thank Marvin Kähnert\textsuperscript{2} for proof-reading this thesis.

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Bibliography


Appendix A

Cloud Particle Habit Properties
### Appendix A. Cloud Particle Habit Properties

**Table A.1: Specifications of tested cloud particle habits and habit mixes [Eriksson et al. (2018)], (“fluffy” and “medium”)**

<table>
<thead>
<tr>
<th>Habit</th>
<th>Type</th>
<th>$D_{\text{max}}$ [μm]</th>
<th>(\alpha)</th>
<th>(\beta)</th>
<th>Shape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector Snowflake</td>
<td>single</td>
<td>20 - 12000</td>
<td>0.00081</td>
<td>1.44</td>
<td></td>
</tr>
<tr>
<td>Column Type 1</td>
<td>single</td>
<td>14 - 8835</td>
<td>0.0380</td>
<td>2.05</td>
<td></td>
</tr>
<tr>
<td>ICON Snow</td>
<td>Habit mix</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short Column</td>
<td>single</td>
<td>17 - 3303</td>
<td>110</td>
<td>3.00</td>
<td></td>
</tr>
<tr>
<td>ICON Snow</td>
<td>aggregate</td>
<td>120 - 20000</td>
<td>0.031</td>
<td>1.95</td>
<td></td>
</tr>
<tr>
<td>Large Column Aggregate</td>
<td>Habit mix</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long Column</td>
<td>single</td>
<td>24 - 4835</td>
<td>34</td>
<td>3.00</td>
<td></td>
</tr>
<tr>
<td>Large Column Aggregate</td>
<td>aggregate</td>
<td>368 - 19981</td>
<td>0.25</td>
<td>2.43</td>
<td></td>
</tr>
<tr>
<td>Evans Snow Aggregate</td>
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<td>0.2</td>
<td>2.39</td>
<td></td>
</tr>
<tr>
<td>6-Bullet Rosette</td>
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<td>16-8905</td>
<td>0.4927</td>
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<tr>
<td>Perpendicular 4-Bullet Rosette</td>
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<tr>
<td>Flat 3-Bullet Rosette</td>
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<td>0.2433</td>
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<tr>
<td>Large Plate Aggregate</td>
<td>Habit mix</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thick Plate</td>
<td>single</td>
<td>16 - 3246</td>
<td>110</td>
<td>3.00</td>
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</tr>
<tr>
<td>Large Plate Aggregate</td>
<td>aggregate</td>
<td>349 - 22860</td>
<td>0.21</td>
<td>2.26</td>
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Table A.2: Specifications of tested cloud particle habits and habit mixes [Eriksson et al. (2018)], ("medium" and "compact")

<table>
<thead>
<tr>
<th>Habit</th>
<th>type</th>
<th>$D_{max} [\mu m]$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>shape</th>
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<td>Large Block Aggregate</td>
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<td>aggregate</td>
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<td>0.3499</td>
<td>2.2657</td>
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<tr>
<td>PlateType1</td>
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<td>13 - 8933</td>
<td>0.7570</td>
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<tr>
<td>IconCloudIce</td>
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<td>13 - 8931</td>
<td>1.59</td>
<td>2.56</td>
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<tr>
<td>8-Column Aggregate</td>
<td>aggregate</td>
<td>19 - 9714</td>
<td>65</td>
<td>3.00</td>
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</tr>
<tr>
<td>GemGraupel</td>
<td>Habit mix</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8-Column Aggregate</td>
<td>aggregate</td>
<td>19 - 9714</td>
<td>65</td>
<td>3.00</td>
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<tr>
<td>GemGraupel</td>
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<td>2.97</td>
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<td>IconHail</td>
<td>Habit mix</td>
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<td></td>
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<td></td>
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<tr>
<td>GemCloudIce</td>
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<td>440</td>
<td>3.00</td>
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<tr>
<td>IconHail</td>
<td>single</td>
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<td>380</td>
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<td>IceSphere</td>
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<td>480</td>
<td>3.00</td>
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</table>
Appendix A. Cloud Particle Habit Properties

A.1 Particle Size Distribution

The PSD $dN/dD_{\text{max}}$ calculated for each cloud particle habit using the F07 approach yields the number density $N$ per volume $[\text{cm}^3]$ and maximum diameter $[\mu\text{m}]$. The volume equivalent diameter $D_{\text{veq}}$ is more intuitive if particles of equal mass are evaluated. The transformation from $dN/dD_{\text{max}}$ to $dN/dD_{\text{veq}}$ for a specific bin $i$ of $D_{\text{veq}}(D_{\text{max}}(i))$ is performed following Petty and Huang (2011).

$$
\frac{dN}{dD_{\text{veq}}(D_{\text{max}}(i))} = \frac{dN}{dD_{\text{max}}(i)} \cdot \frac{dD_{\text{max}}}{dD_{\text{veq}}(D_{\text{max}}(i))} \quad (A.1)
$$

The relation between $D_{\text{max}}$ and $dN/dD_{\text{veq}}$, derived from the mass-size relation (Equation 3.12) and described by:

$$
D_{\text{max}} = \left( \frac{\rho_{\text{ice}} \pi D_{\text{veq}}^3}{6\alpha} \right)^{1/\beta} D_0 \quad (A.2)
$$

$D_0$ is needed as placeholder for the unit. The partial derivative:

$$
\frac{dD_{\text{max}}}{dD_{\text{veq}}} = 3\beta \left( \frac{\rho_{\text{ice}} \pi}{6\alpha} \right)^{1/\beta} \left( D_{\text{veq}} \right)^{(3/\beta - 1)} \quad (A.3)
$$

The resulting PSD for each cloud particle habit is shown in Figure A.1.

![Particle Size Distribution](image_url)

*Figure A.1: F07 Particle Size Distribution corresponding to each tested cloud particle habit, transformed from $dN/dD_{\text{max}}$ to $dN/dD_{\text{veq}}$*
A.2 Scattering Properties

The following figures (A.2,A.3,A.4) display the back-scattering properties in terms of Rayleigh normed back-scattering efficiency $\tilde{Q}_{\text{back}} = Q_{\text{back}} / Q_{\text{back,rayleigh}}$. Here, $Q_{\text{back}}$ corresponding to frequencies (35 GHz and 94 GHz) very close to the utilized Radar frequencies are taken from the database by Eriksson et al. (2018). The back-scattering efficiency of a theoretical Rayleigh-sphere $Q_{\text{back,rayleigh}}$ is calculated as follows:

$$
Q_{\text{back,rayleigh}} = \frac{4\sigma_{\text{back,rayleigh}}(D_{\text{veq}})}{\pi D_{\text{veq}}^2} = \frac{4\pi^4 |K|^2}{\lambda^4} D_{\text{veq}}^{-4} \tag{A.4}
$$

From decreasing $\tilde{Q}_{\text{back}}$ the impact of Mie scattering can be identified. Here, $\tilde{Q}_{\text{back}}$ is displayed in terms of $D_{\text{veq}}$ instead of the more commonly used size parameter $x = \pi D_{\text{veq}} / \lambda$. The range of $D_{\text{veq}}$ for which differences in between the utilized frequencies are encountered contributes to the differences expected in Radar reflectivity (not considering the PSD weight). Additionally, shape induced scattering enhancement within the Rayleigh-regime is revealed (strong i.e. for PlateType1 and IconCloudIce).

Figure A.2: Rayleigh-normed back-scattering efficiency 35 GHz vs. 94 GHz
Figure A.3: Habit specific Rayleigh-normed back-scattering efficiency (“fluffy”; “medium”)
Figure A.4: Habit specific Rayleigh-normed back-scattering efficiency (“medium”; “compact”)
Appendix A. Cloud Particle Habit Properties

A.3 Classification

![Figure A.5: Markers corresponding to classification of cloud particle habits by mass-size (α and β) parameter (color) and by scattering properties (shading)](image)

Table A.3: Classification of Cloud Particle Habits in terms of scattering properties for each mass-size parameter class

<table>
<thead>
<tr>
<th>Habit</th>
<th>scattering classification by $Q_{\text{back}}$</th>
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<tbody>
<tr>
<td>fluffy</td>
<td></td>
</tr>
<tr>
<td>IconSnow</td>
<td>Low within Mie; decreasing for small $D_{\text{eq}}$</td>
</tr>
<tr>
<td>SectorSnowflake</td>
<td>Medium within Mie; local max; decreasing for medium $D_{\text{eq}}$</td>
</tr>
<tr>
<td>ColumnType1</td>
<td>Large within Mie; local max; decreasing for medium $D_{\text{eq}}$</td>
</tr>
<tr>
<td>medium</td>
<td></td>
</tr>
<tr>
<td>LargeColumnAggregate</td>
<td>Very low within Mie; decreasing for small $D_{\text{eq}}$</td>
</tr>
<tr>
<td>EvansSnowAggregate</td>
<td>Very low within Mie; local max; decreasing for small $D_{\text{eq}}$</td>
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<tr>
<td>6-BulletRosette</td>
<td>Low within Mie; decreasing for small $D_{\text{eq}}$</td>
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<tr>
<td>Perp.4-BulletRosette</td>
<td>Low/medium within Mie; decreasing for small $D_{\text{eq}}$</td>
</tr>
<tr>
<td>Flat3-BulletRosette</td>
<td>Low/medium within Mie; decreasing for small $D_{\text{eq}}$</td>
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<tr>
<td>LargePlateAggregate</td>
<td>Low/medium within Mie; decreasing for medium $D_{\text{eq}}$</td>
</tr>
<tr>
<td>LargeBlockAggregate</td>
<td>Low/medium within Mie; decreasing for medium $D_{\text{eq}}$</td>
</tr>
<tr>
<td>PlateType1</td>
<td>Large within Mie; local max; decreasing for large $D_{\text{eq}}$</td>
</tr>
<tr>
<td>IconCloudIce</td>
<td>Large within Mie; local max; decreasing for large $D_{\text{eq}}$</td>
</tr>
<tr>
<td>compact</td>
<td></td>
</tr>
<tr>
<td>8-ColumnAggregate</td>
<td>Large within Mie; decreasing for large $D_{\text{eq}}$</td>
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<tr>
<td>GemGraupel</td>
<td>Large within Mie; decreasing for large $D_{\text{eq}}$</td>
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<tr>
<td>IconHail</td>
<td>Very large within Mie; decreasing for very large $D_{\text{eq}}$</td>
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<tr>
<td>IceSphere_Id24</td>
<td>Very large within Mie; decreasing for very large $D_{\text{eq}}$</td>
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Appendix B

Retrieved Hydrometeor Content in context of the Joint Flight
Appendix B. Retrieved Hydrometeor Content in context of the Joint Flight

B.1 Synoptic Situation

Figure B.1: 500hPa geopotential map from the 14th October 2016 12UTC, [http://www.wetterzentrale.de/, accessed 2018-06-11]

Figure B.2: 850hPa temperature map from the 14th October 2016 12UTC, [http://www.wetterzentrale.de/, accessed 2018-06-11]
B.1. Synoptic Situation

Figure B.3: Surface pressure weather map of DWD from the 14th October 2016 00UTC, [http://www.wetterzentrale.de/, accessed 2018-06-11]

Figure B.4: Infrared Satellite image of Meteosat Prime (0°E) from the 14th October 2016 12UTC, [http://www.wetterzentrale.de/, accessed 2018-06-11]
Appendix B. Retrieved Hydrometeor Content in context of the Joint Flight

B.2 Radar Observations

Figure B.5: Masked cross-section of Radar reflectivity observations of the HAMP 35 GHz Radar and the RASTA 94 GHz Radar along the “Joint Flight” track. The dropsonde (dotted blue, orange, green and red lines) as well the descent of the FAAM aircraft (grey line, dotted: whole descent / dashed: analysed measurements) are displayed accordingly.
### B.3 Empirical dBZ-IWC Dependency

#### Figure B.6: Empirical dBZ-IWC relationship

#### Table B.1: Mass-size relationship parameters a and b to estimate hydrometeor content from different empirical studies.

<table>
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<tr>
<th>Publication</th>
<th>Abbreviation</th>
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<th>b</th>
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<td>Sassen (1987)</td>
<td>Sassen1987</td>
<td>0.12</td>
<td>0.696</td>
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<tr>
<td>Schneider and Stephens (1995)</td>
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<td>0.696</td>
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<tr>
<td>Sassen and Liao (1996)</td>
<td>Sassen1996</td>
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<tr>
<td>Aydin and Tang (1997)</td>
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<td>Liu and Illingworth (2000)</td>
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<td>0.137</td>
<td>0.643</td>
</tr>
<tr>
<td>Liu and Illingworth (2000)</td>
<td>Luillling2000-35GHz</td>
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<td>0.59</td>
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<tr>
<td>Sassen et al. (2002)</td>
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<td>Protat et al. (2007)</td>
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<td>Sayres et al. (2008)</td>
<td>Sayres2008</td>
<td>0.13</td>
<td>0.54</td>
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</tbody>
</table>
Versicherung an Eides statt


__________________________________________  ______________________________________
Christiane Duscha                             Ort, Datum