Comparison of surface rainfall retrievals from the TRMM microwave radiometer and the Kwajalein radar

Min-jeong Kim

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science

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Min-jeong Kim

and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
examining committee have been made.

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Date: ________________________
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Comparison of surface rainfall retrievals from the TRMM microwave radiometer and the Kwajalein radar

by Min-jeong Kim

Chair of Supervisory Committee:

This study evaluated the ability of the GPROF (V.5) algorithm, which is the passive microwave rainfall retrieval algorithm of the TRMM program, to retrieve surface rainfall at resolutions down to 0.1° by examining the effects of the surface type, the melting layer effect, the impact of 85-GHz channels, the sufficiency of vertical hydrometeor profiles in the database by examining the effects of the surface type, the melting layer, the impact of 85-GHz channels, and the sufficiency of vertical hydrometeor profiles in the database by comparisons with KR observations.

Comparisons of the GPROF retrieved rainfall with KR observations show that GPROF overestimated surface rainfall by 17.4 % at rainrates less than 5 mm/h, underestimated rainfall by 6.7 % at rainrates between 5 mm/h and 11 mm/h, and overestimated rainfall by 12 % at rainrates greater than 11 mm/h. Power spectral density comparison between GPROF and KR rainmaps shows that the GPROF retrieved rainmaps are less spatially variable at wavelengths less than 54-km in the mean and greater than 33-km within one standard deviation suggesting GPROF rainy areas are smoother and bigger than those observed by KR.
No single factor stands out as a dominant improvement in the GPROF modifications. All of the following were introduced into the revised algorithm in this study.

- This study employed the oceanic GPROF algorithm over the whole Kwajalein validation site.

- The current GPROF algorithm neglects the melting layer over stratiform precipitation. This study employs Klaassen’s (1990) melting layer parameterization in the GPROF algorithm. This melting layer correction reduced the GPROF retrieved rainfall amount by 8% and reduced positive bias at light rainrates.

- To reduce the effect of uncertainty caused by the poor correlation between upper level ice amount and surface rainfall, this study only estimated the convective area fraction from 85-GHz brightness temperatures and neglect 85-GHz brightness temperature in the GPROF database for rainfall retrieval. The general distribution of rainfall and rainy area was not changed while heavy rainfall overestimated by the original GPROF algorithm in convective region was successfully reduced.

- As sigma gets larger in Bayesian calculation, more dissimilar profiles are weighted into the final structure and the retrieved results become accurate. This sigma value depends on the uncertainty of the GPROF database and should vary depending on the rainrates. Instead of using a fixed sigma value as in the original GPROF, this study employed various sigma values depending on the rainrates. This modification reduced the biases both at light and heavy rainrates and resulted in more consistent rainfall retrievals with KR observations.
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Chapter 1

INTRODUCTION

1.1 Rainfall measurements over the ocean

Challenges  Three-fourths of the energy that drives atmospheric circulation is latent heat released by precipitation. Despite its importance, precipitation is one of the most difficult atmospheric parameters to measure due to large variability in space and time. Two thirds of the earth’s surface is covered by oceans. It is especially difficult to measure precipitation over oceans because surface-based observations such as radars and rain gauges are rare. The shortage of rainfall observations over oceans has been an obstacle for atmospheric research.

Solutions and limitations  Rainfall measurements from space offer a solution to this limitation. Large numbers of infrared and passive microwave techniques using satellite data have yielded diverse rain estimates to fulfill this demand for the past several decades (Wilheit et al. 1977, Kummerow and Weinman 1988, Spencer et al. 1989, Petty and Katsaros 1990, Kidder and Barret 1990, Smith et al. 1992, Kummerow and Giglio 1994). However, due to limitations like the sensor’s footprint size and insufficient sampling, the satellite rain products were made mainly at a coarse resolution (1° or coarser) for the purpose of large-scale atmospheric research. Providing high-resolution rainfall products for mesoscale atmospheric research has also been a concern of the satellite remote sensing community. This study will evaluate the
Recent trend and motivation  Recently, a concern of the mesoscale meteorological community has been the benefits of increasing horizontal resolution in numerical weather models and as computer power has increased. The National Centers for Environmental Prediction (NCEP) plans to increase the horizontal resolution of Eta Model to less than 10 km over the next few years. Mass et al.(2002) demonstrated clear improvements in the forecasts as the grid spacing was decreased from 36-km to 12-km over western Washington state using University of Washington real-time MM5 forecasts.

Considering this recent trend and the shortage of observations over oceans, satellite retrieved products should be a data source with a high enough resolution to support this trend. The motivation of this study is to evaluate the estimation of rainfall from space with a resolution ($\sim 0.1^\circ$).

1.2 TRMM satellite and its instruments

TRMM satellite  The purpose of TRMM is to measure precipitation with an array of different instruments over the tropics, of which the surface is largely covered by ocean. The Tropical Rainfall Measuring Mission (TRMM) satellite has a non-sunsynchronous orbit with a low altitude (350 km and 402.5 km before and after changing the altitude in August 2001) and low inclination ($35^\circ$) (Kummerow et al. 1998). The instruments on the TRMM satellite are the TRMM Microwave Imager (TMI), the Precipitation Radar (PR), and the Visible and Infrared Scanner (VIRS). The Lightning Imaging Systems (LIS) and the Clouds and Earth’s Radiant Energy
Figure 1.1: Precipitation instruments on the TRMM satellite (From Kummerow et al. 1998)

Figure 1.1: Precipitation instruments on the TRMM satellite (From Kummerow et al. 1998)

System (CERES) provide ancillary information (Fig. 1.1).

**TRMM Microwave Imager (TMI)** The TMI, on which this study is focused, is a nine-channel passive microwave radiometer based upon the Special Sensor Microwave/Imager (SSM/I) which has been in operation aboard the Defense Meteorological Satellite Program (DMSP) satellites since 1987 (Kidder and Vonder Harr 1995). The characteristics of TMI are summarized in Table 1.1.

In Table 1.1, the beamwidth is defined as twice the angle between the direction of maximum power and the direction at which the power is half the maximum value
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<td></td>
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<tr>
<td>per beamwidth</td>
<td>4</td>
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<td>2</td>
<td>1</td>
<td>1</td>
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<tr>
<td>Temperature</td>
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<tr>
<td>Sensitivity (K)</td>
<td>0.63</td>
<td>0.54</td>
<td>0.50</td>
<td>0.47</td>
<td>0.71</td>
<td>0.36</td>
<td>0.31</td>
<td>9.52</td>
<td>0.93</td>
</tr>
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</table>

(Fig. 1.2(a)). The instantaneous field of view (IFOV) is the footprint resulting from the intersection of TMI antenna beamwidth and the earth’s surface (Fig. 1.2(b)). For the TMI, the IFOV in the cross-track (down-track) direction is called the IFOV-CT (IFOV-DT). The effective field of view (EFOV) is the effective area swept by the antenna beam during the integration time.

**Why focus on the TMI?** The TMI contributes the following benefits to the TRMM satellite. It gives us information about the frozen hydrometeors in the upper levels of the cloud because the high frequency channels of microwave radiometer are
Figure 1.2: Plot illustrating the beamwidth and IFOV
very sensitive to ice scattering. The swath width of TMI is three times wider than that of PR, providing better sampling. VIRS uses visible and infrared wavelengths, at which clouds are opaque and the rainfall must be estimated indirectly from the cloud top information. However, cloud droplets weakly interact with microwave radiation, whereas precipitation drops interact strongly with microwave radiation (Kidder and Vonder Haar 1995). In addition to these methodological advantages, the possibility of linking TMI to other radiometers is an advantage since several satellite borne radiometers with additional channels and similar or higher resolution than the TMI are planned to be launched in future. For example, the Aqua satellite which carries the Advanced Microwave Scanning Radiometer for EOS* (AMSR-E) was launched recently (May 2002). The AMSR-E has 12 channels at 6.9, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz vertically and horizontally polarized. In addition, the National Polar-orbiting Operational Environmental Satellite System (NPOESS) and the Global Precipitation Measurement (GPM) which is a follow-on and expanded mission of TRMM, will launch satellites carrying radiometers similar to the TMI after 2006.

Unfortunately, the TMI has much bigger footprint sizes than the other TRMM sensors such as the PR (4.3 km) and VIRS (2 km). In addition, rainfall retrieval from the TMI suffers uncertainties from several sources, which will be introduced in Section 1.5.2.

1.3 Physical background for microwave remote sensing

1.3.1 Brightness temperature

According to Planck’s law, the radiance emitted at a wavelength, \( \lambda \) by a blackbody is given by

*Earth Observing System
\[ B_\lambda(T) = \frac{2hc^2\lambda^{-5}}{\exp\left(\frac{hc}{\lambda kT}\right) - 1} \] (1.1)

where \( h \) is Planck’s constant, \( k \) is Boltzmann’s constant, \( T \) is the absolute temperature of a blackbody, and \( c \) is the speed of light. For wavelengths long enough that \( \lambda \gg \lambda_c = \frac{hc}{kT} \), the Planck function is approximated by

\[ B_\lambda(T) = 2kc\lambda^{-4}T \] (1.2)

This is known as the Rayleigh-Jeans approximation. For typical atmospheric temperatures, \( \lambda_c \sim 50 \mu m \). Thus, in the microwave portion of the spectrum (\( \lambda \geq 1000 \mu m \)), radiance is simply proportional to temperature and it is customary to divide the satellite observed radiance values by \( 2kc\lambda^{-4} \) and to refer the parameter as the “brightness temperature” (Stephens 1994).

### 1.3.2 Radiative transfer equation

The radiation beam along the slant path, \( ds \), can be extinguished by absorption and scattering. On the other hand, it is strengthened by the emission and radiation which is multiply scattered from all other directions into the beam.

\[ dI = -k_{ext}Ids + jds, \] (1.3)

where \( I \) is radiation intensity (radiance, \( W/m^2Sr^{-1} \)), \( k_{ext} \) is the extinction coefficient \( (m^{-1}) \) of the medium and \( j \) represents the source function.

\( k_{ext} \) is defined as

\[ k_{ext} = k_a + k_s \] (1.4)

where \( k_a \) is the absorption coefficient expressed by
\[ k_a = k_a^{\text{water vapor}} + k_a^{\text{cloud water}} + k_a^{\text{rain}} + k_a^{O_2} \quad (1.5) \]

and \( k_s \) is the scattering coefficient of rain and ice expressed by

\[ k_s = k_s^{\text{rain}} + k_s^{\text{cloud ice}} + k_s^{\text{frozen hydrometeor}} \quad (1.6) \]

If we define \( S = \frac{\hat{i}}{k_{\text{ext}}} \) then

\[ dI = -k_{\text{ext}}(I - S)ds \quad (1.7) \]

In a horizontally stratified atmosphere, it is convenient to define \( z \) as vertical to the plane of stratification. For a radiometer with viewing angle of \( \theta \) with respect to nadir, the radiative transfer equation becomes

\[ \cos \theta \frac{dI}{k_{\text{ext}}dz} = (-I + S) \quad (1.8) \]

where \( I \) is now the radiance in direction \( \theta \).

If we define the optical depth as

\[ \tau = \int_z^\infty k_{\text{ext}}dz' \quad (1.9) \]

and \( \mu = \cos \theta \), then

\[ \mu \frac{dI}{d\tau} = -I + S \quad (1.10) \]

where \( S = S_{\text{emission}} + S_{\text{scattering}} \).

The precipitating cloud is assumed to be horizontally homogeneous in Eq. 1.9. This assumption may be dubious for convective clouds where horizontal and vertical dimensions are comparable. However, as a first approach, this assumption suffices.

The emission component of the source function, \( S_{\text{emission}} \) is a function of temperature and can be defined as
\[ S_{\text{emission}} = (1 - \frac{k_s}{k_{\text{ext}}})B(T) \]  

(1.11)

The scattering component of the source function, \( S_{\text{scattering}} \) is a sum over contribution from all directions. Given a photon that was incident from solid angle \( d\omega' \) about \( \mu' \) and has been scattered, then \( \frac{1}{4\pi}P(\mu', \mu)d\omega' \) is the probability that the photon will reappear in solid angle element \( d\omega \) about \( \mu \). Then Eq. 1.10 is given by

\[
\frac{dI(z, \mu)}{d\tau} = -I(z, \mu) + (1 - a)B(T) + \frac{1}{4\pi} \int_{4\pi} aI(z, \mu')P(\mu', \mu)d\omega'
\]  

(1.12)

where \( a = \frac{k_s}{k_{\text{ext}}} \) is referred to as the single scattering albedo.

The first term on the right-hand side of Eq. 1.12 represents the effects of absorption and emission when a beam of radiation travels upward through an atmospheric layer in the direction of a satellite. The second term shows the radiation emitted by the atmospheric layers including precipitation, cloud, and atmospheric gases. The third term on the right represents the scattering of radiation by atmospheric particles. Using the Rayleigh-Jeans approximation given in Eq. 1.2, \( I \) in Eq. 1.12 is expressed in brightness temperature.

The radiance at the top of the atmosphere will be calculated using boundary conditions of the temperature at the surface and between atmospheric layers, assuming that the optical depth is determined by the hydrometeors and gases in the atmosphere. Calculating brightness temperatures from the known hydrometeor profiles is straightforward. However, estimating hydrometeor distributions in the atmosphere from the measured brightness temperatures is more difficult because the radiance, \( I(z_{\text{TOA}}, \mu) \), at the top of the atmosphere (TOA) is a vertical integral of the radiatively active cloud constituents. The vertical distribution of the components in Eq. 1.5 and Eq. 1.6 are poorly resolved without additional input.
1.3.3 Ocean emissivity and emission/scattering effects

According to Eq. 1.12, the observed brightness temperature from a satellite is dependent on the emission from the earth’s surface modified by the intervening atmosphere. The emissivity is a function of the dielectric constant. The emissivity of land surfaces vary according to vegetation and soil moisture and is generally large ($\sim 0.9$). Over the ocean, the emissivity is relatively uniform and low ($\sim 0.5$). That is, the brightness temperature of the ocean viewed by a satellite is much colder than the thermodynamic surface temperature. On the other hand, emission by rain can increase brightness temperature over the ocean. This makes it possible for a microwave radiometer to estimate rainfall over the ocean.

More specifically, the emission effect of liquid phase hydrometeors increases brightness temperatures in the low frequency channels (10 GHz, 19.35 GHz, 21.3 GHz, and 37 GHz) and the scattering effect caused by ice phase hydrometeors decreases brightness temperatures in high frequency channels (37 GHz and 85 GHz). The cold brightness temperature caused by ice scattering is often used to estimate convective precipitation, but its efficiency depends on the correlation between ice aloft and the rain below.

1.4 How do microwave retrieval algorithms work?

1.4.1 Empirical vs. physical methods

Microwave rainfall retrieval algorithms using satellite measured brightness temperatures are generally based on two methods: i.e. empirical and physical.

There are many empirical methods, which calculate a regression to find the relation between observed radiances and ground-based rainfall measurements. The advantage
of empirical methods is that they are simple to calculate and easy to implement. Errors also can be quantified easily and are based upon the best fit between radiance observations and ground-based observations. The major disadvantage of empirical methods is that their applicability beyond the validation site is questionable (Kummerow 1998).

Physical methods employ a radiative transfer model to calculate brightness temperatures at the top of the atmosphere at specified rain rates (Weinman and Guetter 1977; Wilheit et al. 1977, Wu and Weinman 1984; Smith and Mugnai 1988; Kummerow and Weinman 1988).

The advantage of the physical approach is that each assumption can be tested more easily than in the empirical method. Realistic error estimates can also be established for each assumption. However, such error tests have rarely been performed (Kummerow 1998) due to the limited number of observations with which the results can be compared.

The major disadvantage of the physical method is the fact that calculating brightness temperatures requires assuming vertical profiles of hydrometeors. In addition, hydrometeor shapes and sizes with sufficient detail are required for reasonable brightness temperature calculations. This requirement makes a physical algorithm time consuming to implement.

1.4.2 *The Goddard profiling algorithm*

To save computational time and to provide guidance for the vertical distribution of radiatively active cloud constituents, the TMI rainfall retrieval algorithm, referred to the Goddard Profiling (GPROF) algorithm, employs the Goddard Cumulus Ensemble (GCE) model. The model has been run for a variety of tropical soundings to produce simulated hydrometeor profiles. Using vertical profiles of the atmosphere (tempera-
ture, humidity, and surface wind) and the simulated hydrometeor profiles for cloud liquid, cloud ice, rain, snow, graupel, and hail provided by this cloud model, brightness temperatures are calculated by the Eddington radiative transfer model (Wu and Weinman 1984). These calculated brightness temperatures and cloud profiles are averaged over the area which is commensurate with the field of view of TMI at 85 GHz. These averaged brightness temperatures, hydrometeor profiles, and convective area fractions are stored in a lookup database, which is referred to as the GPROF database (section 7.1).

With brightness temperatures and convective area fraction measured with the TMI, the GPROF algorithm generates the best fit hydrometeor profiles by minimizing the difference between observations and profiles stored in GPROF database. The reason for considering convective area fraction is related to the beamfilling effect which will be explained in Section 1.5.2.

A comprehensive description of the GPROF algorithm is presented in Kummerow and Giglio (1994a, b), Kummerow et al. (1998), and Kummerow et al. (2001).

1.5 Objective of this study

1.5.1 Challenge of high-resolution rainfall retrieval from microwave radiometer

Evolution of microwave radiometers For the past several decades, spaceborne microwave radiometers have been improved in terms of the number of channels and the footprint size. The interest in passive microwave rainfall retrieval technique has led to more channels at a wider range of frequencies. In 1972, the Electronically Scanned Microwave Radiometer (ESMR) on the Nimbus satellite relied on a single 19 GHz channel with a footprint size of 25 km (Wilheit and Chang 1977), whereas DMSP satellite, which was launched in 1987, has seven channels at four frequencies of 19 GHz, 22 GHz, 37 GHz, and 85.5 GHz. The horizontal resolutions range between
69 km × 43 km at 19.35 GHz and 15 km × 13 km at 85.5 GHz (Kidder and Vonder Harr 1995). The TMI on the TRMM satellite has nine channels at five frequencies (10 GHz, 19.35 GHz, 21.3 GHz, 37 GHz, and 85 GHz). The EFOVs of TMI are 9.1 km × 63.2 km at 10 GHz and 4.6 km × 7.2 km at 85 GHz (Table 1.1).

The EFOV of 19 GHz channel in TMI is as big as 9.1 km × 30 km, but the EFOV of 85 GHz channels are much smaller (4.6 km × 7.2 km). Due to the high spatial resolution of the 85 GHz channel, combining several channels may enable the TMI to produce rainfall observations with sufficient resolution to support mesoscale atmospheric research.

**General strategy** While many algorithms estimate rainfall using satellite data, there are few studies concerned with retrieving spatial variability of the precipitation field. Harris and Foufoula-Georgiou (2001) recently found that the variability in cloud modeled hydrometeor fields is known to have an important effect on simulated brightness temperatures. Harris and Foufoula-Georgiou focused solely on the effect of cloud model resolution on the microwave algorithm rainfall retrievals. Besides the resolution of a cloud model, there may be other factors that affect the algorithm’s ability to retrieve high resolution rainfall fields showing reasonable spatial variability. Some of these factors will be introduced in Section 1.5.2

This study attempts to evaluate the ability of the GPROF algorithm (V5) to retrieve rainfall at resolutions down to 0.1° (units of degree are used instead of km for easier data processing) by examining the factors which will be introduced in subsequent sections. Some error sources inherent in the GPROF algorithm are identified by comparing the retrieved rainfall with Kwajalein Radar (KR) observations with several resolutions between 0.1° to 2.5°. Methods to decrease the errors will also be
sought and tested by modifying the current GPROF algorithm to retrieve rainfall fields which are more consistent with the KR observations at high resolution. Specific strategies for the problems which this study addresses are introduced in the next section.

1.5.2 Factors that have been considered in this study

Factors that are problematic for microwave scanning retrieval algorithms are: the effect of surface type, scanning gap effect, melting layer, beamfilling effect, vertical hydrometeor profiles, the effect of size and age of a precipitation system, drop-size distribution, and satellite scan angle effect (3D effect). Among these factors, only the effect of surface type, scanning gap effect, melting layer effect, beamfilling effect, the validity of vertical hydrometeor profiles (GPROF database), and the effect of size and age of a precipitation system will be examined in this study.

**Is Kwajalein atoll oceanic or land?** The current GPROF algorithm (version 5) considers Kwajalein atoll as land and applies the coastal algorithm for much of the Kwajalein ground validation region (Fig. 1.3). However, the islands of Kwajalein and neighboring atolls are extremely small so this surface type defined in the algorithm has been in debate. The next version of the GPROF (version 6) will probably be corrected with the surface type of this area as open ocean. This study demonstrates how badly the coastal algorithm works and whether the assumption of open ocean is truly correct for rainfall retrieval over this region by comparisons with KR observations.

**Contiguity** The TMI antenna rotates about a nadir axis at a constant speed of 3.16 rpm **. The rotation traces a circle on the earth’s surface. Only 130° of the forward sector of the complete circle is used for taking data. The rest is used for

**revolutions per minute**
Figure 1.3: Surface classification used by GPROF for the Kwajalein region. Areas in red (blue) correspond to land (oceanic) grid boxes.
calibration and other instrument house keeping purposes (Kummerow et al. 1998). The radiometer sees the spacecraft so it cannot observe rain. From the TRMM orbit, the $130^\circ$ scanned sector yields a swath width of 758.5 km. During each complete revolution, the subsatellite point advances a distance of 13.9 km. Since the 85 GHz channels have a small footprint size of 6.9 km (down-track direction) by 4.6 km (cross-track direction), there is a gap of 7.0 km between successive scans (Fig. 1.4). Thus the GPROF algorithm retrieved profile field also has a spatial gap of 7 km across the scan line. This effect of the scanning gap on retrieved precipitation has not yet been examined and it is an important issue for designing microwave instruments on next generation satellites such as the GPM. The uncertainty related to the scanning gap effect will be calculated in this study by modifying ground-based radar data to have data gaps commensurate with those between TMI scan lines.

**Melting layer**  Although melting hydrometeors typically occupy a thin layer of about 500 m, the microwave absorption and emission by the melting layer can account for a significant portion of the emission observed by space borne passive radiometers, especially for light rainfall. By not considering the melting layer, the algorithm attributes the portion of emission from the melting layer to liquid precipitation. This results in overestimation of rainfall rates over regions of stratiform precipitation. The current (version 5) GPROF algorithm has no melting layer physics in it because there is not enough observational evidence to suggest how the bright band should be modeled. Recent studies of Schols et al. (1999), Bauer et al. (1999), and Olson et al. (2001a) address this issue. It will, no doubt, be included in subsequent version of GPROF algorithm. A simplified melting layer parameterization suggested by Klaassen (1990) will be employed to make the rainfall retrieval in this study more realistic.
Figure 1.4: Plot showing the footprint size and a gap between two scan lines in TMI 85 GHz channel
Beamfilling problems  Satellite fields of view (FOV) are seldom covered completely by rain or cloud and the rainfall rate is hardly ever uniformly distributed over the rainy region. The relation between rainfall rate and brightness temperature is linear only for light rainfall (Fig. 1.5). The rainfall rate, which corresponds to the mean brightness temperature of the FOV, may be quite different from the mean rainfall rate over the FOV for heavy rainfall. An error is thus introduced in estimating rainfall rates from brightness temperature of the FOV filled with non-uniform rainfall rates. This error is referred to as beamfilling error (Chiu et al. 1990, Wang 1996, and Kummerow 1998).

In the GPROF algorithm, the beamfilling problem associated with finer resolution of rainfall structure than cloud model resolution is handled by simulating the antenna-pattern response to calculate upwelling radiances. To consider the rainrate variability inside a FOV, convective precipitation fractions are calculated with cloud model profiles and used as a variable in the GPROF database. The observed area fraction of convection within a TMI footprint is measured by the merged polarization-texture methods (Olson et al. 2001b). The algorithm seeks an optimized profile that must also match this convective fraction. The GPROF algorithm estimated convective area fraction will be evaluated in this study. In addition, the beamfilling effect caused by the emission channels’ large size footprints which may be partially filled with rain at the edge of a large precipitation system (Fig. 1.6), will be addressed in this study.

Vertical hydrometeor profiles  Although microwave radiance are known to be sensitive to rain drops, they are also affected by cloud liquid and ice hydrometeors above the surface. The emission by cloud liquid water and melting ice increases brightness temperature while the scattering effect of ice hydrometeors like snow, hail, and graupel decreases brightness temperatures especially at 85 GHz. But the upper
Figure 1.5: Solid lines show the calculated brightness temperature (vertically polarized) at 19 GHz as a function of rain rate for freezing levels between 1 km and 5 km (Wilheit et al. 1991, Wang 1996). Linear approximations between brightness temperature and rain rate, which is given by $TB = a + bR$ are shown as dashed lines for reference. $a = 176.85, 185, 196.45, 211.2, \text{ and } 229.25$ for freezing levels of 1-km, 2-km, 3-km, 4-km, and 5-km, respectively. $b = 2 \times$ freezing level(km).
Figure 1.6: Plot illustrating the beamfilling effect in the edge of a large precipitation system.
level cloud liquid water or ice hydrometeor amount is not directly related to rain rates near the surface. To overcome this problem, the GPROF algorithm uses a lookup table, referred as the GPROF database, consisting of vertical hydrometeor profiles provided by the cloud models and brightness temperatures calculated by radiative transfer model from these profiles. However, the ability of that database to provide reasonable rainfall retrievals for various brightness temperatures and different geolocations is questionable. This study will evaluate the current GPROF database by comparing the retrievals with ground-based radar observations.

Impact of 85 GHz channels  GPROF algorithm uses all TMI channels for rainfall retrievals. However, upper level ice information, which is detected by 85 GHz channels, is not strongly correlated to the rainfall intensity near the surface. The poor correlation between upper level ice amount and surface rainfall rate may actually contaminate rainfall retrievals. This study will examine the impact of 85 GHz channels on rainfall retrievals.

1.5.3 Factors excluded in this study

Drop size distributions  The radiative transfer model calculations depend on the size distributions of hydrometeors. The drop size distribution (DSD) most commonly used in passive radiometer models is Marshall and Palmer’s (1948) exponential distribution. In the TMI algorithm, the Marshall-Palmer DSD is assumed for the precipitation size hydrometeors, while a uniform diameter of 100 \( \mu \text{m} \) is assumed for liquid and ice cloud droplets. Other DSDs have been suggested by Sekhon and Srivastava (1971), Willis and Tattelman (1989), and Feingold and Levin (1986). Coppins and Haddad (2000) quantified the effect of variations in DSD on calculated brightness temperatures and showed that the standard deviation of brightness temperature at
10 GHz, due to DSD variability, reaches 17 K at vertical (10 K at horizontal) polarization when rain rate averages 23 mm/h. At 37 GHz it remains near 7 K. They also showed that the effect was smallest between 16 GHz and 19 GHz, where the standard deviation was only 3.7 K. This study will not examine the DSD effect because the 19 GHz channels, which are the main emission channels reacting to liquid phase precipitation, are not especially sensitive to DSD assumption according to Coppens and Haddad (2000).

3D effect Since the scan angle of the TMI is 53°, the radiance from the upper level atmospheric layer (location A in Figure 1.7), which is used to retrieve rainfall near the surface, do not coincide with the retrieved rainfall location (location B in Figure 1.7). The 85 GHz signal, which strongly depends on the upper level ice structure, is the primary cause of this offset. This so-called 3D effect, which is the difference of brightness temperature over a finite cloud and a horizontally infinite cloud, can be attributed to geometric and physical problems. This effect causes a larger brightness temperature patterns than rainfall pattern. In addition, radiation from the side walls of a finite cloud and the reflected image of cloud by the surface distorts the brightness temperature pattern from the surface rain field (Hong et al. 2000; Bauer et al. 1998).

Bauer et al. (1998) presented a simple method to correct for the horizontal displacement caused by the 3D effect. They calculated the centers of gravity of the brightness temperature weighting to determine the position of effective radiance contribution along the line of sight. This provides a measure for the displacement of radiation origin with respect to the footprint location. The displacement correction estimated for the TMI ranges from 0 - 5.5 km at 37 GHz frequency and 0 - 11 km at 85.5 GHz frequency.
The correction method suggested by Bauer et al. (1998) is simple. However, practical problems occur in applying it to the current GPROF algorithm. Considering the footprint size of 37 GHz and the distance between two 85 GHz data across the scan line (Fig. 1.4), it is hard to apply displacements less than the distance between two scan lines. How to fill the empty pixel is also an open question. Moreover, the ice distribution in the upper layer, such as anvil, also depends on the upper level wind direction. The Bauer et al. (1998) correction method will therefore be omitted from this study.
Figure 1.7: Plot showing the 3D effect. The radar reflectivity shown in this figure was measured by the KR at 09:13 in July 28 1999.
DATA AND METHODS OF ANALYSIS

2.1 Kwajalein validation site

The GPROF algorithm is divided into three algorithms depending on the surface type (land, ocean, and coast). This is because the emissivity values of ocean and land are different (Section 1.3.3). This study focuses on the GPROF algorithm for oceans so the validation site should be located in the open ocean.

Kwajalein island is an ideal site for this purpose since Kwajalein and neighboring atolls are composed of tiny islands surrounding large lagoons in the open ocean (Fig. 2.1). The Kwajalein Experiment (KWJEX), which was the only TRMM field campaign over the open ocean (Yuter 1999), has provided the remote sensing community with a unique validation product. The validation area is defined as the 150 km radius around the radar which is located on Kwajalein island (8.72°N, 167.73°E). The red inner circle in Figure 2.1 shows 15-km range from the KR. The KR data inside of this circle are not used to avoid clutter caused by the ocean surface.

According to the Kwajalein gauge climatology (Schumacher 2000), Kwajalein receives over 200 mm/h of rain per month for eight months of the year (May-December). Figure 2.2 shows the monthly average rainfall accumulation estimated by rain gauges. Average monthly sea surface temperatures for the Kwajalein validation area range between 27 and 30°C. Lower SSTs occur during months (January-April) of low rain (Schumacher 2000).
Figure 2.1: Map of the Kwajalein area centered on the KR. The geography of the Kwajalein Atoll and neighboring atolls are indicated by dashed lines. The interior of each atoll is a giant lagoon. Rain gauge locations are indicated by the key for each network.
Figure 2.2: Kwajalein area averaged rain accumulation estimate with gauges (bars). The solid line shows the Kwajalein Island's gauge climatology. (From Schumacher (2000))
2.2 Kwajalein radar

The KR is a three-dimensionally scanning S-band dual-polarization, Doppler weather radar (Table 2.1). The scan strategies employ between 17 and 22 elevation angles (Fig. 2.3). KR data is quality controlled using an algorithm developed by the Mesoscale Group at the University of Washington. A comprehensive description of rainmap products and the sources of uncertainty are found in Houze et. al (2002). A brief summary of the document is introduced here.

Because Kwajalein is an atoll and has limited locations for rain gauges, operating KR is more difficult than other sites on land. Nevertheless, the uniqueness of the site makes it invaluable for long-term oceanic ground-validation for satellites. The four sources (the calibration of the radar, the vertical profile of reflectivity below the lowest beam of the radar, the Z-R relation implied by the drop size distribution, and gaps in the data collection) of uncertainty inherent in KR are taken into account independently (Houze et al. 2002) in the new University of Washington Ground Validation products which are summarized in Table 2.2.

Since data from the approximately 10 rain gauge/radar pixel pairs usually available from the atoll region are inadequate for statistical monitoring of the calibration, the TRMM PR is used for KR calibration (Houze et al. 2002. The calibration correction has been determined to make the area covered by echo > 17 dBZ at 6-km level (ice region) consistent between the PR and KR reflectivity. In this study, the instantaneous surface rainmaps, which provide the best estimated rainrates at the surface, are compared with the TMI surface rainfall products.

The height of the lowest scan (typically 0.4° elevation angle) of the KR reaches almost 2.5 km above sea level 150 km away from the radar. Since the drop-size spec-
trum continues to evolve by coalescence, breakup, and sedimentation below the lowest elevation angle, estimating surface rain rate from radar requires consideration of this effect. The best estimate rainfall product of the University of Washington has taken this effect into account by extrapolating the observed reflectivity from the lowest elevation angle to the surface using a climatological convective or stratiform reflectivity correction value. In addition to calibration uncertainty correction and vertical profile correction, the University of Washington Mesoscale Group used a disdrometer-based Z-R relationship from 2 wet seasons at Kwajalein and fitted the Z-R relationship to maximize the accuracy of the monthly accumulation over the entire radar-viewed area. Temporal radar data gaps (if the time interval between two consecutive volume scans are greater than 20 min) were also corrected by filling with interpolated data (Houze et al. 2002).

In this study, the instantaneous rainmaps (Table 2.2) applied with vertical profile correction are used for comparisons with TMI rainfall rainfall product. In addition, the convective/stratiform index (0=clear air, 1=stratiform, 2=convective) determined from KR reflectivity measurements by the method of Steiner et al.(1995) is used to validate the GPROF algorithm retrieved convective area fraction.

### 2.3 Data processing method

The main data used in this study are TMI measured brightness temperatures, GPROF retrieved rainfall products, and KR estimated rainrates for 80 TRMM satellite overpasses with significant rain over Kwajalein between August 1998 and December 1999 (Table 2.3 and Table 2.4). The rainfall amount over the validation area is calculated for each overpass. Those 80 overpasses are divided into two groups with similar rainfall amount distributions. First group of 40 overpasses (Table 2.3) is used to improve the algorithm by modifications and the other group of 40 overpasses (Ta-
Figure 2.3: An example of the KWAJEX KR scan strategy for non-polarized data collection (Yuter 1999)
Table 2.1: Characteristics of the KR (From Schumacher and Houze (2000))

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Table 2.4) is used to test validity of the modifications. The number of pixels per each scan in 10 GHz, 19.35 GHz, 21.3 GHz, and 37 GHz channels is 104. The 85 GHz channels provide twice as many pixels (208) as the other channels due to their small (4.6 km X 6.9 km) footprint size (Fig. 2.4).

The GPROF algorithm products have the same horizontal resolution as the TMI 85 GHz channels because the retrieved rainrates are calculated by combining brightness temperature information from all the channels and the finest resolution the final product can have is the resolution of the 85 GHz channels which have the smallest footprint size.

GPROF retrieved and KR estimated rainfall data are compared at several resolutions (2.5°, 1.0°, 0.5°, 0.25°, and 0.1°) in this study. Figure 2.5 illustrates the grid
Table 2.2: The summary of University of Washington ground validation data product set. Field names: DZ—reflectivity, CZ—corrected reflectivity, VR—radial velocity, maxdx—reflectivity, rainr—rainrate, convsf—indicator of whether echo is convective or stratiform, raccumbest—overall best estimate of accumulated rainfall, raccumgaplo/hi—lower and upper limits owing to gap filling uncertainty, raccumzlo/hi—lower and upper limits owing to Z-R relation uncertainty, raccumcallo/hi—lower and upper limits owing to calibration uncertainty, raccumvpllo/hi—lower and upper limits owing to vertical profile uncertainty. (From Houze et al. (2002))

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Figure 2.4: Plot showing the difference of FOVs in 19 GHz and 85 GHz channels.
boxes at each resolution defined in this study. Area-averaged rainrates are calculated with GPROF retrieved rainrates and 6-km area-averaged KR rainrates inside grid boxes for each resolution. The GPROF rainfall products are created along the scan line and depend on the direction of the satellite overpass while the KR rainfall products are gridded in a latitude-longitude grid. The differences between the grid shapes of the original KR data and GPROF rainfall products are neglected in this study. The KR rain products are created operationally at 2-km horizontal resolution. However, KR rainrates were averaged into 6-km horizontal resolution from the 2-km rain-rate maps to avoid discrepancies caused by the differences in raw resolution between GPROF and the KR in the analysis. Raw resolution of GPROF rainfall rates and the nearest neighboring area-averaged KR rainrates at a raw resolution are also compared in the analysis of gaps in 85 GHz channel information (Sections 1.5.2 and 3.3). resolution.

Since the KR is calibrated by the PR and the minimum detectable signal of the PR is 17 dBZ (≈ 0.5 mm/h) (Schumacher and Houze 2000) and the insensitivity of the TMI to rainrates less than 0.5 mm/h due to the large field of views, KR and GPROF rainrates less than 0.5 mm/h at 6-km resolution are treated as nonraining in this study. The 3 % of KR rain amount and 0.3 % of GPROF rain amount are neglected by this limitation.

2.4 Can effect of the islands in the Kwajalein atoll be neglected?

The current GPROF algorithm categorizes the Kwajalein atolls as “coast” and applies the coastal GPROF algorithm for the red region in Figure 1.3. Figure 2.6 shows plots of GPROF retrieved surface rainrates versus TMI observed brightness temperatures with commensurate resolution with rainfall retrievals at the resolution of 85-GHz channels. The blue and red dots in this figure show the rainfall retrievals
Figure 2.5: Plot illustrating grid boxes at each resolution. The shaded region shows the KR covered Kwajalein validation area in Figure 2.1.
by the oceanic and coastal GPROF algorithms, respectively. This figure shows that the relation of brightness temperature and surface rainrate retrieved by the coastal algorithm is apparently different from the oceanic algorithm.

A similar exercise comparing KR nearest neighbor rainrates and TMI observed brightness temperatures (Fig. 2.7) shows that there is no difference between rainrate distributions from the GPROF defined ocean and coast regions. The TMI observed brightness temperature and KR observed rainrate distribution is more similar to oceanic algorithm retrieved Tb-rainrate distribution (blue dots in Figure 2.6) over whole validation site.

This demonstrates that the coastal algorithm behaves incorrectly and employing oceanic GPROF algorithm over the whole Kwajalein validation site is valid.
Figure 2.6: TMI observed brightness temperatures versus GPROF algorithm retrieved surface rainrates in the region defined as ocean (blue dots) and coast (red dots) in Figure 1.3. brightness temperatures.
Figure 2.7: TMI observed brightness temperatures versus KR observed surface rainrates in the region defined as ocean (blue dots) and coast (red dots) in Figure 1.3.
Table 2.3: 40 TRMM overpasses for the first group which are analyzed in this study. AvgRR, RainF, and StF show the area-averaged rainrate, rainy area fraction, and stratiform rain area fraction, respectively. Date is in the format of yymmdd.

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Table 2.4: 40 TRMM overpasses for the second group which are used to test the validity of the modified GPROF algorithm developed in this study. AvgRR, RainF, and StF show the area-averaged rainrate, rainy area fraction, and stratiform rain area fraction, respectively. Date is in the formate of yymmdd.

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Chapter 3

COMPARISON OF RAINFALL RETRIEVED FROM THE TMI WITH KR OBSERVATIONS

3.1 Rainrate comparisons

3.1.1 Biases

GPROF retrieved rainrates are compared with KR estimated rainrates at 2.5°, 1°, 0.25°, and 0.1° resolutions (Fig. 3.1). The axes have been stretched in the light/moderate rain range by the relations $X = \frac{\text{Rainrate}_{\text{GPROF}}}{\text{Rainrate}_{\text{KR}}} + A$, where $A$ is 0.5 for 2.5° resolution, 1 for 1° resolution and 2 for 0.25° and 0.1° resolutions, because the occurrence of light rainrates is greater than occurrences of heavy rain rates. The fitted lines in Figure 3.1 were calculated by minimizing the least-square differences in both KR and GPROF rainrates. The result indicates that GPROF underestimates (overestimates) rainfall at light (heavy) rainrates at 2.5° and 1° resolutions (Fig. 3.1(a)(b)). In contrast, GPROF overestimates rainfall at light rainrates at 0.1° resolution (Fig. 3.1(d)). The correlation coefficients between GPROF and KR rainrates are 0.88, 0.76, 0.80, and 0.65 at 2.5°, 1°, 0.25°, and 0.1° resolutions, respectively.

It is hard to tell the degree of bias at 0.1° resolution with a scatter plot since GPROF versus KR rainrates at 0.1° in Figure 3.1(d) show much spread. For a better presentation of the GPROF’s bias pattern at 0.1° resolution, histograms of the number of rainrate occurrences have been produced (Fig. 3.2). Numbers of the GPROF and KR pixels observed at this resolution are 12,111. At a raw resolution (6-km for KR in this study), rainrates equal or less than 0.5 mm/h were considered no-rain
Figure 3.1: Scatter plots of GPROF retrieved and KR estimated rainrates. Dashed line shows 1:1 relation. Solid lines were calculated by minimizing the least-square differences in both KR and GPROF rainrates.
both for GPROF and KR due to the insensitivity of the TMI less than this rainrate. Because of the frequency of the GPROF rainrates between 0 mm/h \sim 0.5 mm/h is small, only rainrates above 0.5 mm/h were counted both for GPROF and the KR. Numbers of GPROF and KR pixels with rainrate greater than 0.5 mm/h were 1,657 and 1,357, respectively for all 40 overpasses. This means that the GPROF measures rainy (Rainrate > 0.5 mm/h) pixels more than KR observations. The histogram comparison in Figure 3.2 demonstrates that GPROF overestimates rainfall at rainrates less than 5 mm/h while it underestimates rainfall at rainrates between 5 mm/h and 11 mm/h. At rainrates greater than 11 mm/h, rainfall retrieved by GPROF are apparently unbiased.

3.1.2 Significance of biases

Considering the logarithmic scale of the y axis in Figure 3.2, the degree of overestimation of GPROF rainfall at light rainrates (R \leq 5 mm/h) is significant. However, the significance of underestimation at rainrates (5 mm/h < R \leq 11 mm/h) and the trend at rainrates greater than 11 mm/h needs to be checked since heavy rainrates are rare.

To illustrate the significance of GPROF’s bias at each rainrate, the expected uncertainty range of the KR rainrate occurrence is calculated in the following way:

1. the cumulative distribution of frequency (CDF) ranging from 0 to 1 is calculated from 1,357 non-zero precipitation KR data at 0.1° resolution (Fig. 3.3(a)).

2. 80 sets of 1,357 random numbers are generated with MATLAB. These random numbers are uniformly distributed in the interval of 0 and 1.
Figure 3.2: Histogram for rainrates estimated by the GPROF algorithm and KR at 0.1° resolution.
(3) Applying these random numbers to CDF of (1), 80 sets of randomly generated KR data are calculated. Each set has 1,357 rainrate data.

(4) Using these 80 sets of randomly generated KR data, the mean (solid line) and \( \pm 1 \) (dashed lines) and \( \pm 2 \) (dotted lines) standard deviations of the rainrate occurrence are calculated for each rainrate (Fig. 3.3(b)).

(5) Differences between GPROF and KR histograms shown in Figure 3.2 can be determined as significant if the bias is bigger than one or two standard deviations calculated in (4).

The histograms shown as bars in Figure 3.2 are presented by asterisks (KR) and circles (GPROF) in Figure 3.3(b). These histograms are compared with expected uncertainty range of the KR rainrate occurrence represented as dashed and dotted lines in Figure 3.3(b). Most of the difference between the GPROF and KR histograms at rainrates less than 11 mm/h were larger than \( \pm 1 \) standard deviation of the KR rainrate occurrence. Even at rainrates where the difference was smaller than \( \pm 1 \) standard deviation, GPROF retrieved rainrates were negatively biased not positively biased at rainrates between 5 mm/h and 11 mm/h and positively biased at rainrates greater than 11 mm/h. As a result, the overestimation (underestimation) of rainfall at light (heavy) rainrates by the GPROF algorithm appears to be significant.

3.1.3 Total rainfall comparison

The sum of rainrates for all KR and GPROF rainy pixels for the 40 cases are 3,234 mm/h and 4,028 mm/h, respectively. This suggests that the total rainfall amount retrieved by the GPROF at 0.1° resolution was overestimated by 25% (794 mm/h) (Fig. 3.4(a)). This 25% overestimation, however, is the net effect of overestimation by 17.4% at light rainrates, underestimation by 6.7% at rainrates between 5 mm/h and 11
Figure 3.3: (a) Cumulative Distribution of Frequency (CDF) of KR rainrates and (b) comparisons of histogram difference between GPROF and KR rainrates with expected uncertainty ranges of the occurrence at each KR rainrates.
mm/h, and overestimation by 11.9% at rainrates greater than 11 mm/h (Fig. 3.4(b)).

### 3.2 Spatial variability of rainfall

**Rainrate variance in a rainmap** The spatial variability of rainfall is compared between GPROF retrievals and KR observations at each resolution. The mean and standard deviation of non-zero precipitation in each rainmap were calculated for a given resolution (Fig. 3.5). The GPROF estimated rainmaps show less variability than KR retrieved rainmaps at 0.1° resolution. At 0.25° resolution, the variability is almost same for both GPROF and KR. At resolutions coarser than 0.25°, GPROF retrieved rainmaps show greater variability than KR rainmaps.

The rainrate-averaging process over the large area reduces the KR variance more than GPROF rainfall variance. This result suggests that the KR resolves more small-scale systems with intense rain than the GPROF.

**Comparison of power spectral density (PSD)** The variability of two 0.1° resolution rainmaps on 25 July 1999 (Fig. 3.6) and 28 July 1999 (Fig. 3.7), which have 0.1° resolution, were investigated by power spectrum analysis. The Fourier power spectra of the GPROF retrieved and KR estimated rainmaps are shown in Figure 3.8. In this analysis, spectral slope is an indicator of smoothness, with high spectral slopes characteristic of a smoother structure. The spectra have been normalized by their respective mean spectral energies. A falloff in variability at small scales (high wavenumbers) is evident in GPROF retrieved precipitation field in comparison with the observed KR rainfall field. The fall-off scale is estimated to be approximately 30 km ~ 40 km.

To generalize the PSD comparison between GPROF and KR rainmaps, ratios of
Figure 3.4: Comparisons of (a) cumulative rainrates between GPROF and KR and (b) the bias distribution of GPROF rainfall at each rainrate.
Figure 3.5: Mean and standard deviation of non-zero rainrate in each rainmap of 40 cases. The blue (red) line shows the minimized least-square fitting relation between mean and standard deviation of rainrates in each KR (GPROF) rainmap.
Figure 3.6: GPROF and KR surface rainfall fields in 25 July 1999.
Figure 3.7: GPROF and KR surface rainfall fields in 28 July 1999.
Figure 3.8: Spatial Fourier power spectral density for GPROF retrieved (dashed lines) and KR observed (solid lines) surface rainrates at 0.1° resolution.
the normalized PSDs for GPROF and KR were calculated at each wavenumber for all of the 40 cases (Table 2.3). The mean and one standard deviation ranges at each wavenumber are shown in Figure 3.9. The GPROF retrieved rainmaps show less spatial variability at wavenumbers greater than 0.018 (wavelength~54 km) in the mean and greater than 0.031 (wavelength~33 km) in +1 standard deviation (upper dashed line) suggesting GPROF rain areas are smoother and bigger than KR.

Figure 3.9: Ratios of the normalized PSDs for GPROF and KR rainmaps. The solid and dashed lines show the mean and one standard deviation of the ratios for 40 cases. The ratio of one is shown as a green line.
3.3 Do scanning gaps in the 85 GHz scan pattern affect rainfall variability?

Unlike the other factors mentioned in Section 1.5.2, the scanning gap effect comes from the mechanical design of the TMI instrument itself and it is not related to the assumptions in the GPROF algorithm. Related to the gap effect, the number of horns in the proposed radiometer antenna has been debated in designing the GPM satellite. However, the significance of the scanning gap effect has not been examined by comparison with observations.

The scanning gap effect (Fig. 1.4) is examined here, before going on to investigate physical factors of GPROF algorithm causing positive biases at light rainrates, negative biases at heavy rainrates, and underrepresentation of rainfall spatial variability.

**Rainrate variance in a rainmap** To test the effect of a 7-km gap between two scan lines of the TMI, 6-km resolution of KR data have been modified as having no-data every other line, horizontally or vertically (Fig. 3.10). These modified KR data have similar spatial gaps (6.0 km) to GPROF retrieved data.

In the same way as was shown in Figure 3.5, the mean and standard deviation of non-zero precipitation data in each rainmap were calculated for a given resolution using these original and modified KR data (Fig. 3.11). Considering the arbitrary scanning direction of TMI, the mean and standard deviation of KR data with the gap effect were calculated by averaging the KR data with vertical gaps and horizontal gaps.

The result shows that the standard deviation of a KR rainmap with data gaps (i.e. simulated scanning gaps) are smaller than a KR rainmap without data gaps at 0.1° resolution (Fig. 3.11(a)). However, the gap effect introduces little difference of rainfall
Figure 3.10: Schematic diagram showing fake gaps in 6-km resolution of KR data. (a) Original KR data at 6km resolution, (b) 6-km KR data simulating GPROF data with north-south scan lines, and (c) 6-km KR data simulating GPROF data with east-west scan lines.
variance in a rainmap at resolutions greater than 0.25°.

**PSD comparison** To examine the scanning gap effect on the rainfall variability at each spatial scale, the PSDs were compared between KR rainmaps with and without spatial gaps. Figure 3.12 shows the PSDs of KR data on 17 December 1998 and 25 July 1999. The solid lines show original KR data without the gap effect and the dashed lines show KR data with the gap effect. Compared with Figure 3.8, in which GPROF showed underrepresentation of small scale systems, the power spectra comparisons in Figure 3.12 show little difference of a slope between original KR rainfall map and modified KR rainfall map.

To generalize the PSD comparison between KR rainmaps with and without scanning gaps, ratios of the normalized PSDs were calculated at each wavenumber for 40 cases. The mean and one standard deviation ranges at each wavenumber are shown in Figure 3.13. In contrast to the ratio of PSDs for GPROF and KR rainmaps (Fig. 3.9), Figure 3.13 shows that KR rainmaps with scanning gaps, which are simulating the GPROF retrieved rainmaps, have bigger PSDs at high wavenumbers.

This result suggests that the scanning gap effect do not contribute to the underrepresentation of spatial variability of GPROF precipitation at the surface. In contrast, the scanning gap increases PSDs at high wavenumbers (small spatial scale). This is because the localized intense rainrate is emphasized more as a peak in averaging 6-km resolution data over a grid box with a 0.1° resolution for rainmaps with data gaps than for rainmaps without gaps. About four pixels are counted in the averaging process for rainmaps without gaps while about two pixels are counted in averaging for rainmaps with data gaps.
As a result, underestimated surface rainfall at heavy rainrates, overestimated surface rainfall at light rainrates, and underrepresentability of small scale structures in GPROF surface rainfall retrievals appear not to be caused by the scanning gap but caused by the assumptions in the algorithm and database.
Figure 3.11: Mean and standard deviation of non-zero rainrate in each rainmap of 40 cases. The blue (red) line shows the minimized least-square fitting relation between mean and standard deviation of rainrates in each KR rainmap without (with) the scanning gap effect.
Figure 3.12: PSDs for original KR rainfall maps (solid lines) and modified KR rainfall maps to have the gap effect at 0.1° resolution.
Figure 3.13: Ratios of the normalized PSDs for KR rainmaps with and without scanning gaps. The solid and dashed lines show the mean and one standard deviation of the ratios at each wavenumber for 40 cases. The ratio of one is shown as a green line.
Chapter 4

MELTING LAYER

4.1 Melting layer in stratiform precipitation

Stratiform precipitation is defined as a precipitation process in which the vertical air motion is small compared to the fall velocity of ice crystals and snow (1-3 m/s). Stratus and stratocumulus may produce drizzle but the bulk of stratiform precipitation falls from nimbostratus that reaches well above 0°C level (Houze 1993). In nimbostratus cloud, the ice particles grow by deposition of water vapor but they cannot be suspended for a long time due to the weak air motions (Fig. 4.1). When the ice particles that fall and grow by deposition descend to within about 2.5 km of the 0°C level, the particles begin to aggregate and form large snowflakes. The aggregation becomes more frequent within about 1 km of the 0°C level. Aggregation concentrates the condensate into large particles, which upon melting become large, rapidly falling raindrops. This layer in which the large snowflakes melt is marked on radar images by a bright band of intense echo in a horizontal layer about 500 m thick located just below the 0°C level.

Figure 4.2 shows the reflectivity detected by the Airborne Rain Mapping Radar (ARMAR) over Kwajalein. The melting layer represented by the bright band has a depth of about 500 m. This can be estimated from the figure if the flight altitude (~12 km) is considered. This figure supports the existence of aggregates and melting ice precipitation in stratiform precipitation over the Kwajalein.
4.2 Effect of the melting layer on passive microwave rainfall retrieval

The scattering and absorption characteristics of a particle are governed by the complex index of refraction and radius of the particle (Battan 1973). The refractive index is a complex number,

\[ m = n - ik \]  

(4.1)

where \( n \) and \( k \) are real and imaginary parts of the refractive index and they determine the scattering and absorption effects in the medium.

Table 4.1 gives the values of \( n \) and \( k \) for water and ice tabulated by Gunn and East (1954). Considering the range of \( n \) and \( k \) values from ice to water (Table 4.1), melting snow not only enhances microwave scattering, it also enhances emission that increases brightness temperatures measured by a microwave radiometer. Although such enhanced emission layers may only be 0.5 to 1 km thick, their emission can be comparable to that of as much as 2-4 km of comparable rainfall (Schols et al. 1999).

4.3 Klaassen’s (1990) melting layer parameterization

To avoid complex assumptions and computations, the parameterization suggested by Klaassen (1990) is used in this study to insert the melting layer effect in the current GPROF algorithm.

Klaassen (1988) developed a realistic melting layer model and its main features are:

(a) The average dielectric constant of a melting snowflake is calculated by assuming that the melted water surrounds the elliptical needles and plates that form the flake. This is in contrast to previous models where the water was assumed to surround the flake as a whole.
Table 4.1: The components of the complex index of refraction for water and ice. (From Gunn and East (1954)).

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Temperature ($^\circ$C)</th>
<th>Wavelength (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>10   3.21 1.24 0.62</td>
</tr>
<tr>
<td>n (water)</td>
<td>20</td>
<td>8.88 8.14 6.15 4.44</td>
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<tr>
<td></td>
<td>10</td>
<td>9.02 7.80 1.24 0.62</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>8.99 7.14 4.75 3.45</td>
</tr>
<tr>
<td></td>
<td>-8</td>
<td>.... 6.48 4.15 3.10</td>
</tr>
<tr>
<td>k (water)</td>
<td>20</td>
<td>0.63 2.00 2.86 2.59</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>0.90 2.44 2.90 2.37</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1.47 2.89 2.77 2.04</td>
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<tr>
<td></td>
<td>-8</td>
<td>.... .... 2.55 1.77</td>
</tr>
<tr>
<td>n (ice)</td>
<td>All temperature</td>
<td>1.78</td>
</tr>
<tr>
<td></td>
<td>when $\rho = 0.82 \text{ g/cm}^3$</td>
<td></td>
</tr>
<tr>
<td>k (ice)</td>
<td>0</td>
<td>$2.4 \times 10^{-3}$</td>
</tr>
<tr>
<td></td>
<td>-10</td>
<td>$7.9 \times 10^{-4}$</td>
</tr>
<tr>
<td></td>
<td>-20</td>
<td>$5.5 \times 10^{-4}$</td>
</tr>
</tbody>
</table>
(b) The density of the ice particles is allowed to vary over the complete range from snow to hail. In this way the simulated brightness of the melting layer is adapted to the radar observations.

(c) The air temperature, and thus the melting rate, is calculated from the energy balance. The cooling by melting and heating by incoming air result in an almost isothermal layer on top of the melting layer. In this way the depth of the simulated melting layer is made in agreement with the radar observations.

Klassen’s (1990) parameterizations were derived statistically from 50 measurements of the Delft Atmospheric Research Radar (DARR), which is an S-band radar, and attenuation excess simulated by the realistic melting layer model (Klaassen 1988) at 12, 20, and 30 GHz, corresponding to the frequency bands of the Olympus satellite. The study shows that the simulated attenuation excess appears to be proportional to the rain intensity and increases with the maximum reflectivity excess in the bright band (Fig. 4.3).

Using these statistical results, Klaassen (1990) shows that

\[ A_e(F) = \alpha R^\beta \]  \hspace{1cm} (4.2)

where \( R \) is the rain rate (mm/h) just below the melting layer and \( A_e \) (dB) represents the attenuation excess caused by the absorption and scattering in the melting layer at frequency \( F \) (GHz). The estimated constants are given in Table 4.2.

If the source term source term in Eq. 1.3 is excluded,

\[ I = I_o e^{-\Delta k \Delta z} \]  \hspace{1cm} (4.3)

where \( I_o \) and \( I \) are radiation absorbed (i.e. emitted) in cases without and with a melting layer, respectively. \( \Delta k \) is excess extinction coefficient and \( \Delta z \) is the depth of
Figure 4.1: Plot describing characteristics of stratiform precipitation. (From Houze (1993))

Table 4.2: Statistical relations for the attenuation excess at 12, 20, and 30 GHz given by Klaassen (1990). Constants for 37 GHz channels are estimated by extrapolating these given values to apply to the TMI emission channels in this study.

<table>
<thead>
<tr>
<th>Frequency (GHz)</th>
<th>12</th>
<th>20</th>
<th>30</th>
<th>37</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.0456</td>
<td>0.0707</td>
<td>0.0733</td>
<td>0.075</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.85</td>
<td>0.75</td>
<td>0.65</td>
<td>0.57</td>
</tr>
</tbody>
</table>
Figure 4.2: Reflectivity measured by ARMAR on NASA DC-8 over Kwajalein atoll in 3 August 1999. From KWAJEX website (Yuter et al. 1999)
Figure 4.3: Simulated attenuation excess in melting layer at 20 GHz against radar measured rain intensity just below the bright band. The dashed line shows the relation $A_e(20) = 0.0707R^{0.75}$. (From Klaassen (1990))
a melting layer.

Since the $A_e$ is in dB units,

$$10 \log_{10} I = 10 \log_{10} I_o + 10 \log_{10} e^{-\Delta k \Delta z}$$  \hspace{1cm} (4.4)

$$A_e = 10 \log_{10} I_o - 10 \log_{10} I = -10 \log_{10} e^{-\Delta k \Delta z} = 4.34 \Delta k \times \Delta z$$  \hspace{1cm} (4.5)

If rain rates just below the melting layer are assumed to be known from the GPROF database, the $\Delta k$ can be calculated by Eq. 4.2.

The current GPROF database consists of cloud model produced hydrometeor profiles and radiative transfer model calculated brightness temperatures. To calculate brightness temperatures for each hydrometeor profile, the radiative transfer model calculates the total extinction coefficient which is given by Eq. 1.5.

This study examines the melting layer effect in stratiform precipitation profile of the GPROF database by adding $\Delta k$ to $k^{tot}$ in Eq. 1.5 in calculating emission channels' brightness temperatures for each stratiform precipitation profile. Calculated brightness temperatures at 85-GHz in the GPROF database were excluded in the melting layer parameterization of this study. The depth of the melting layer is assumed uniformly as 500 m based on radar observations over Kwajalein (Fig. 4.2). Surface rainrates were used for $A_e$ calculations for simplicity since the GPROF database provides rainfall information just in water content amount for all levels while it provides the rainrate additionally at the surface.

Due to this increase of $k^{tot}$ by the melting layer effect, the modified GPROF database has higher brightness temperatures for a given rain rate profile. This makes the GPROF algorithm retrieve less rainfall over the stratiform region. This melting layer corrected GPROF algorithm is referred to as ML GPROF, hereafter.
4.4 Results

4.4.1 Changes in brightness temperatures

The increment of calculated brightness temperature after the melting layer correction versus surface rainrate is plotted in Figure 4.4 for stratiform precipitation from one of the GCE model simulations (TOGA1, Appendix B). The 85 GHz brightness temperature is relatively insensitive to the emission from liquid particles so the brightness temperature change by a melted particle at this frequency is neglected in this study. The result shows that brightness temperature increments by melting layer increase with rainrate for each frequency. The brightness temperature increments after melting layer corrections are up to 20 K, 15 K, 6 K, and 8 K at 10 mm/h for 10 GHz, 19 GHz, 21.3 GHz, and 37 GHz, respectively. For a given rainrate, the brightness temperature difference gets bigger as frequency increases except for 21.3 GHz at which the water vapor absorption band exists.

Even for the same rainrate at a certain frequency, the brightness temperature difference before and after melting layer correction varies. To show the reason for this, the original brightness temperatures (without the melting layer effect) are shown in different colors depending on their scale in Figure 4.4. The higher, original brightness temperature is less affected after the melting layer effect is considered. The brightness temperature at a certain rainrate can be different depending on the vertical structure of hydrometeors (e.g., liquid cloud depth, liquid cloud amount). For a hydrometeor profile with a thick liquid cloud, brightness temperatures in emission channels are already high, so brightness temperature changes by melting particles contribute less to the brightness temperature increment.

Results from the comprehensive analysis of the melting layer conducted by Bauer et al. (1998) are compared to Klaassen’s simplified parameterization. Their study
compared two different approaches for calculating the effective permittivity of mixed particles. The first approach assumes graupel as ice-in-water mixtures and snow as the average between the results for air-ice-in-water and water-in-air-ice using a constant weight. Brightness temperature differences between including and excluding melting effects shown in Figure 4.5 depending on rainrates and frequencies are similar to the results of Klaassen’s parameterization shown in Figure 4.4.

Bauer et al. (1999) showed that the melting layer effect is most obvious at 10.7 GHz and diminishes at higher frequencies for precipitation over the ocean. They also suggested that the weighted average of the air-ice-in-water and water-in-air-ice mixtures (filled circles in Figure 4.5) would provide better representation of the radiative properties for snow while an ice-in-water mixture (open circles) provides a better results for graupel particles. Since the melting layer correction in this study is applied mainly to melting aggregates in stratiform precipitation, only the filled dots should be compared with Figure 4.4.

This comparison demonstrates that the Klaassen’s method used in this study represents the melting layer effect to a reasonable degree at frequencies greater than 10 GHz, even though the method is simple and the observations for the parameterization were taken at a different place (Netherlands) from the tropical oceans.

4.4.2 Histogram comparison

The histogram of the GPROF retrieved surface rainrates for 40 cases (Section 2.3) after applying the melting layer correction is shown in Figure 4.6(a). It still shows positive biases at light rainrates less than 4 mm/h. Figure 4.6(b) shows the percentage of rainfall change at each rainrate after the melting layer correction.
The percentage of rainfall is defined as

\[
100 \times \left( \frac{GPROF_{\text{no melting layer}} - GPROF_{\text{with melting layer}}}{\sum GPROF_{\text{no melting layer}}} \right)
\]  

Rainfall retrievals have been reduced over a wide range of rainrates after ML correction. Especially, rainfall retrievals at rainrates between 2 mm/h and 8 mm/h are reduced by up to 6.2 %. Figure 4.6(b) shows that the frequency of rainrate occurrence was decreased even at heavy rainrates up to 25 mm/h after melting layer correction. The reason for this decrement is that many FOVs in the GPROF database contain a mixture of stratiform and convective precipitation because the database was made by area-averaging the GCE model results with resolutions between 1-3 km over \( \sim 10 \) km\( \times 10 \) km area. The increased frequencies at 0-2 mm/h, 16-18 mm/h and 25-32 mm/h are due to the replacement of the rainy pixels with rainrates decreased by the melting layer correction. The sum of rainrates for all KR and the melting layer corrected GPROF rainy pixels of 40 cases are 3,234 mm/h and 3,711 mm/h, respectively (Fig. 4.7). Considering the sum of the original GPROF retrieved rainrates (4,028 mm/h), the melting layer correction reduced the retrieved rain amount by 7.9 %.

Even after the melting layer was considered, the overestimation of GPROF rainfall at light rainrates is still significant and the GPROF algorithm overestimates the total accumulated rainfall amount by 15 %. Since this study used the Klaassen parameterization which was derived with empirical results in a different region (Netherlands) not over the tropical oceans, there may be uncertainty caused by the simplified method. How much a more sophisticated treatment of the melting layer, which will be employed in the next version of GPROF, will improve the results is an open question.
Figure 4.4: Increments of brightness temperatures after melting layer correction versus surface rainrates. The melting layer correction was applied to hydrometeor profiles from TOGA1 (after 180 min model integration) simulation at 1-km resolution. (See Appendix B for further information about GCE model simulations)
Figure 4.5: Simulated brightness temperature differences (horizontal polarization) between including and excluding melting effects in graupel particles for ice-in-water mixtures (open circles) and for snow in weighted mixtures (filled circles) at (a) 10.7 GHz, (b) 19.35 GHz, (c) 37.0 GHz, and (d) 85.5 GHz. (From Bauer et al. 1999) The weighted results can be compared to those in Fig. 4.4
Figure 4.6: (a) Histogram of the GPROF retrieved rainrates after melting layer correction and (b) the difference of histograms between after and before the melting layer correction.
Figure 4.7: Comparisons of (a) cumulative rainrates between ML GPROF retrievals and KR observations and (b) the bias distribution of ML GPROF retrieved rainfall at each rainrate.
Chapter 5

BEAMFILLING PROBLEM: CONVECTIVE AREA FRACTION

As introduced in Section 1.5.2, the beamfilling problem is caused by inhomogeneity of precipitation in a satellite FOV. Methods to separate convective/stratiform precipitation using microwave radiometer data have been developed by Hong et al. (1999) and by Olson et al. (2001). The GPROF algorithm employs these methods to solve the beamfilling problem by distinguishing convective and stratiform precipitation.

5.1 Characteristics of convective precipitation

In contrast to stratiform precipitation, which was discussed in Section 4.1, the convective precipitation is defined as a precipitation process in which the vertical air motion (1-10 m/s) is strong enough to sustain dense ice crystals and snow (Houze 1993). Figure 5.1 shows the convective precipitation process.

The growth of precipitation particles in convective precipitation is short (30 min to a few hours) since the growth is dependent on updraft in convective precipitation strong enough to carry the growing particles upward. These particles become heavy enough to overcome the updraft and begin to fall relative to the ground. The microphysical mechanism which plays a role in the quick growth of precipitation particles in a convective cloud is accretion of liquid water which is carried along by the strong convective updraft. It is observed that the strong updraft in convective clouds are usually narrow (typically ∼1 km or less in width) so radar echoes from precipitation
associated with active convection form well-defined vertical cores with large reflectivity (Fig. 5.1). In the dissipating stages of precipitating convective clouds, strong upward motions cease and no longer carry precipitation particles upward or suspend them aloft. The fallout of the less dense snow particles left aloft by the dying updraft can take on a stratiform character, including a radar bright band (Houze 1993).

5.2 Why should convective/stratiform be separated in a microwave rainfall retrieval?

Since measured brightness temperatures at the top of the atmosphere are vertical integrals of the radiatively active hydrometeors, retrieving vertical profiles of hydrometeors from the observed brightness temperatures suffers uncertainty (referred to as the inversion problem). Cloud structure in convective and stratiform precipitation (such as cloud liquid water amount, cloud depth, ice particle size, and melting layer) are different for each case so retrieving surface rainfall without discriminating convective/stratiform precipitation may result in significant uncertainty. To erroneously use the convective (stratiform) precipitation database for stratiform (convective) rainfall retrievals results in the overestimation (underestimation) of rainfall.

5.3 Convective-stratiform separation in the GPROF algorithm

Since the footprint sizes of TMI are bigger than the general scale of localized convective cells, the convective area fraction, instead of classification of a TMI footprint as convective or stratiform, is determined by the algorithm. In addition to brightness temperatures, the convective area fraction retrieved by the algorithm is also used in the rainfall retrieval by seeking the best-fit convective area fraction stored in the GPROF database.
The convective area fraction within a TMI footprint is retrieved by the GPROF algorithm by combining the local horizontal gradients of brightness temperatures (texture-based method, Hong et al. 1999) and the polarization of 85.5-GHz scattering signatures (polarization-based method, Olson et al. 2001). The description of these methods is summarized in Appendix A.

5.4 Validation of the GPROF retrieved convective area fraction with KR observations

The convective area fraction retrieved by the GPROF algorithm is compared with the KR estimated convective area fraction at 0.1° resolution. The KR convective area fraction was calculated from convective/stratiform indices at 2-km resolution. These indices were generated by the University of Washington with the method based on Steiner et al. (1995). The criteria for identifying convective precipitation suggested by Steiner et al. (1995) are summarized in Appendix C. The modified version of these criteria was applied to KR and these modifications are described in the Appendix B of Yuter et al. (1997).

Convective area fractions retrieved by the GPROF algorithm for the 40 cases used in this study (Table 2.3) are plotted as a function of GPROF retrieved surface rainrates in Figure 5.2(a). Generally, convective area fraction increases with surface rainrate, but the result shows significant spread between 1 mm/h and 10 mm/h rainrates. The plot for KR convective area fraction also shows much spread (Fig. 5.3(a)).

For a better comparison, the median values of GPROF and KR convective area fraction at each rainrate are presented as asterisks in Figure 5.2(a) and as circles in
Figure 5.3(a), respectively. They were calculated with data points in 1 mm/h rainrate intervals. The result shows that GPROF algorithm retrieved convective area fraction was underestimated (overestimated) relative to KR estimates, which are shown as circles in Figure 5.3(a)), at rainrates less (greater than) than 5 mm/h. This shows that high rainrates estimated by KR can occur over regions with less convective area fraction whereas large convective area fraction is a necessary condition for the high rainrate retrievals by the GPROF algorithm. Note that there are many KR data points showing zero convective area fraction at rainrates less than 5 mm/h.

The histogram comparison between Figure 5.2(b) and Figure 5.3(b) shows that the GPROF estimated frequency at convective area fractions between 0 and 0.1 was greater than the KR estimated frequency while KR shows a greater frequency at convective area fractions between 0.1 and 0.5 than GPROF.

Figure 5.4 shows a comparison between the GPROF and KR convective area fraction at 0.1° resolution for two TMI overpasses. The general patterns of GPROF and KR convective area fraction in these maps agree well with each other. The GPROF algorithm generally misses localized pixels at which KR shows significant convective area fraction.

Note that there is an exceptional area, which is marked with “A”, in Figure 5.4(a) where the GPROF overestimated the convective area fraction relative to the KR estimates. The reason for this overestimation of convective area fraction by GPROF is related to the upper level ice existing in the fully developed mesoscale convective system.

Because this rainfall system has been fully developed, there is much ice to scatter radiation in the upper level (Fig. 5.5) while surface rain rates have weakened (Fig. 3.6(b)). When the ice scattering is strong, the polarization-based method plays a main role
(See Appendix A) and it retrieves a significant convective area fraction.

The issue of the impact of the upper level ice to GPROF rainfall retrievals will be treated in detail in the next chapter.
Figure 5.1: Characteristics of convective precipitation. Shading shows higher intensities of radar echo, with hatching indicating the strongest echo. The cloud is shown at a succession of time $t_0, \ldots, t_n$. A growing precipitation particle is carried upward by strong updraft until $t_2$ and then falls to the ground. The dashed boundary indicates an evaporating cloud. (From Houze (1993))
Figure 5.2: (a) Distribution of GPROF retrieved convective area fraction for the 40 cases of this study (Table 2.3) as a function of GPROF retrieved surface rainrate. Asterisks show the median values of GPROF convective area fraction at each rainrate. For the comparison, the median values of KR convective area fraction (circles) were overlapped. (b) The histogram of occurrence number of convective area fraction at each rainrate.
Figure 5.3: (a) Distribution of KR observed convective area fraction for the 40 cases of this study as a function of KR observed surface rainrate. Circles show the median values of KR convective area fraction at each rainrate. (b) The histogram of occurrence number of convective area fraction at each rainrate.
Figure 5.4: Comparisons of representative convective area fraction map between GPROF retrievals ((a) and (c)) and corresponding KR measurements ((b) and (d)).
Figure 5.5: KR observed (a) reflectivity at 8-km altitude and (b) TMI 85-GHz vertically polarized brightness temperature in 25 July 1999.
Chapter 6

IMPACT OF 85 GHZ CHANNELS ON RAINFALL RETRIEVALS

6.1 Roles of 85 GHz channels

The emission effect of liquid phase hydrometeors increases brightness temperatures in the low frequency channels (10 GHz, 19.35 GHz, 21.3 GHZ, and 37 GHz) and the scattering effect caused by ice phase hydrometeors decreases brightness temperatures in high frequency channels. The 37 GHz channels are sensitive both liquid and ice phase hydrometeors while 85 GHz channels are mainly sensitive to ice scattering. Therefore, cold brightness temperature at 85 GHz channels plays main role in matching ice phase hydrometeor profiles in the GPROF database and affects rainfall retrievals.

Figure 6.1 shows brightness temperature maps at 19 GHz and 85 GHz. Note that the region “A” where heavy rainfall was overestimated by the GPROF algorithm agrees well with the the region with cold brightness temperatures at the 85 GHz frequency.

This shows that the GPROF retrieval of heavy rainfall is significantly sensitive to the ice scattering signal captured by the 85 GHz channels. The GPROF algorithm tends to generate heavy rainfall as long as brightness temperatures at 85 GHz are low.

Unfortunately, the upper level ice amount is not strongly proportional to rainfall rate near surface. It depends on the stage of convective systems and geolocational
Figure 6.1: Vertically polarized brightness temperatures (a) at 19 GHz in 25 July 1999, (b) at 85 GHz in 25 July 1999, (c) at 19 GHz in 28 July 1999, and (d) at 85 GHz in 28 July 1999.
characteristics of systems. Wind shear altering the vertical shape of a convective cloud reduces the correlation between upper level ice amount and surface rainrate.

Figure 6.2 shows the occurrence percentage of KR rainrate at 3-km altitude for a given KR reflectivity at 7-km altitude. The freezing level over the Kwajalein validation site is about 5-km so the reflectivity at 7-km represent the upper level ice amount.

The result shows that the range of KR rainrate at 3-km for a given 7-km KR reflectivity is large. If we could predict a rainrate as 3.5 mm/hr with the reflectivity of 20-dBZ at 7-km altitude, the range of surface rainrates is between 1 mm/h and 6 mm/h with 50% probability. The other 50% is beyond this range and even worse. This suggests that using upper level ice information in rainfall retrieval near surface contributes little quantitative information over Kwajalein.

In addition to using 85 GHz brightness temperature information in seeking the best-fit profile in the GPROF database, the GPROF algorithm employs 85 GHz channels to estimate convective area fraction (Chapter 5). Considering beamfilling effect on passive microwave rainfall retrievals, the role of 85 GHz channles to estimate convective area fraction is significant.

To examine the impact of 85 GHz channels on the rainfall retrievals, this study modifies the GPROF algorithm to employ 85 GHz channels only to estimate convective area fraction and to neglect 85-GHz brightness temperatures in seeking the best-fit brightness temperature set in the GPROF database for rainfall retrieval.
Figure 6.2: Occurrence percentage of KR rainrate at 3-km altitude for a given KR reflectivity at 7-km altitude for 40 cases.
6.2 Results

The histogram of the GPROF retrieved surface rainrates for 40 cases (Table 2.3) after neglecting brightness temperatures at 85-GHz is shown in Figure 6.3(a). The rainfall at light rainrates has been reduced but the histogram still shows positive biases at light rainrates. Figure 6.3(b) shows the percentage of rainfall change at each rainrate after neglecting 85-GHz channels.

The percentage of rainfall change here is defined as

\[
100 \times \left( \frac{GPROF_{\text{without \ 85\text{-GHz} Tbs}} - GPROF_{\text{with \ 85\text{-GHz} Tbs}}}{\sum GPROF_{\text{without \ 85\text{-GHz} Tbs}}} \right)
\]  

(6.1)

Rainfall retrievals have been increased at rainrates between 3 mm/h and 11 mm/h by up to 1.5 % and decreased at rainrates greater than 11 mm/h after neglecting 85-GHz brightness temperatures in rainfall retrievals. This change reduces the biases between GPROF rainfall retrievals and KR rainfall observations considering the positive biases at light rainrates (R < 5 mm/h) and heavy rainrates (R > 11 mm/h) in the original GPROF algorithm rainfall retrievals.

The sum of rainrates for all KR and the 85-GHz brightness temperature neglected GPROF rainy pixels of 40 cases are 3,234 mm/h and 3,598 mm/h, respectively (Fig. 6.3). Considering the sum of the melting layer corrected GPROF retrieved rainrates (3,674 mm/h), neglecting 85-GHz brightness temperatures reduced the retrieved rain amount by 2 %.

Rain map comparisons in Figure 6.4 and Figure 6.5 show that the general distribution of rainfall and rainy area has not been changed by neglecting 85-GHz brightness temperatures. Heavy rainfall overestimated by the original GPROF in convective region “A” in Figure 6.4 has been reduced, which is more consistent with the KR observations after the modification. Localized small-scale cell underestimated by the
Figure 6.3: (a) Histogram of the GPROF retrieved rainrates after neglecting 85-GHz channels’ brightness temperatures and (b) the difference of histograms between after and before neglecting 85-GHz brightness temperatures.
original GPROF in convective region “B” has been resolved better after the modifications.

As a result, employing the 85-GHz channels’ brightness temperatures only to estimate convective area fraction and neglecting them in seeking the best-fit profiles in the GPROF database improve the rainfall retrievals over the Kwajalein.

Figure 6.4: Rainfall maps estimated by (a) KR, (b) original GPROF, and (c) 85-GHz brightness temperature neglected GPROF algorithms in 25 July 1999.
Figure 6.5: Rainfall maps estimated by (a) KR, (b) original GPROF, and (c) 85-GHz brightness temperature neglected GPROF algorithms in 28 July 1999.
Chapter 7

SUFFICIENCY OF THE GPROF DATABASE

7.1 The GPROF database

The GPROF database was generated by the GCE model and the Eddington radiative transfer model (Sec. 1.4.2). The GCE model is three-dimensional, nonhydrostatic, cloud-resolving numerical model (Tao and Simpson 1993). Four major classes of cloud model simulations (TOGA, COHMEX, HURRICANE, and FEB22-2D) serve as input to the GPROF database for the ocean region. The case simulation settings and model produced data fields are described in Appendix B.

Horizontal resolutions of the hydrometeor profiles from the GCE model and Eddington radiative transfer model calculated brightness temperatures vary between 1 km and 3.3 km depending on the resolution of each cloud model simulation. Generating the GPROF database after these model simulations is a two-step process. The first step is to merge the results from cloud model simulations and radiative transfer model simulations into a new output file. Cloud model results are averaged into about 10 km resolution and brightness temperatures resulting from the Eddington radiative transfer model are averaged over the area commensurate with each TMI channel’s FOV. The second step is to take a series of these files, and select only the frequencies of the TMI channels. The number of profile layers are then reduced from 28 to 14. Four ice species (cloud ice, snow, graupel, and hail) are reduced to cloud ice and precipitable ice. Identical profiles are combined and the final database files are generated.
The contents of the data fields include the number of identical profiles combined into one profile, surface temperature, layer height for layer 1 to 14, surface rainrate, convective rainrate, rain coverage, convective rain coverage, surface wind, and cloud liquid water, rain water, cloud ice water, and ice water at each layer.

Figure 7.1 shows brightness temperatures in the GPROF database plotted as a function of the surface rainrate at each frequency at 85-GHz channel’s resolution.

7.2 Inversion method in the GPROF algorithm

It is possible to calculate a brightness temperature with a radiative transfer model in a known atmospheric structure and a hydrometeor profile. This can be done by integrating the emission and scattering effects from all atmospheric layers (forward problem). However, to retrieve hydrometeor profiles from brightness temperature observations suffers uncertainty since there are lots of possible hydrometeor profiles that can give those observed brightness temperatures (inversion problem). To solve this inversion problem, the GPROF algorithm uses the GPROF database and employs a probability method based on Bayesian theory to retrieve rainfall.

Conditional probability As seen by a Venn diagram (Fig. 7.2), probability that A will occur, given that B has occurred is given by

\[ P(A \mid B) = \frac{P(A \cap B)}{P(B)} \quad (7.1) \]

This definition of conditional probability yields

\[ P(A \cap B) = P(A \mid B)P(B) = P(B \mid A)P(A) \quad (7.2) \]

This leads to the following relation which shows the common form of Bayes theorem.

\[ P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} \quad (7.3) \]
Figure 7.1: Plot showing brightness temperatures and surface rainrates stored in the GPROF database at 85-GHz channel’s resolution.
Figure 7.2: Venn diagram
Bayes theorem (From Hartmann 1999) Let $E_1, E_2, \ldots, E_n$ be a set of $n$ events, each with positive probability, that partition a set $S$, in such a way that

$$\bigcup_{i=1}^{n} E_i = S \quad \text{and} \quad E_i \cap E_j = \emptyset \quad \text{for} \quad i \neq j \quad (7.4)$$

This means the events include all the possibilities in $S$ and the events are mutually exclusive. For any event $B$, also defined on $S$, with positive probability $P(B) > 0$, then

$$P(E_j \mid B) = \frac{P(B \mid E_j)P(E_j)}{\sum_{i=1}^{n} P(B \mid E_i)P(E_i)} \quad (7.5)$$

since $P(B) = \sum_{i=1}^{n} P(B \mid E_i) \cdot P(E_i)$.

Bayesian approach in the GPROF algorithm retrieval If the $TB_0$ represents the set of observations (brightness temperatures at each frequency and convective area fraction) and the vector $X$ represents all of the hydrometeor profiles to be retrieved, the best estimate of $X$ given the set of observations $TB_0$ can be expressed as

$$X_{\text{best}} = \sum_{i=1}^{n} X_i \cdot pdf(X_i = X_{\text{true}} \mid TB = TB_0) \quad (7.6)$$

where $pdf(X)$ is the probability density function. This is proportional to the conditional probability that profiles $X$ represents the true atmospheric profiles, $X_{\text{true}}$ when $TB = TB_0$. That is

$$pdf(X_i = X_{\text{true}}) \propto P(X_i = X_{\text{true}} \mid TB_i = TB_0) \quad (7.7)$$

But it is hard to tell $P(X = X_{\text{true}} \mid TB = TB_0)$ due to the inversion problem. Using Bayes theorem, this can be rewritten as
\[ pdf(X_i = X_{\text{true}}) \propto P(TB_i = TB_o \mid X_i = X_{\text{true}})P(X_i = X_{\text{true}}) \quad (7.8) \]

Here \( P(TB_i = TB_o \mid X_i = X_{\text{true}}) \) is the probability that a given set of \( TB_i \) in database equals a set of observed \( TB_o \) when a given set of hydrometeor profiles in database \( (X_i) \) is assumed to be same as a true hydrometeor profiles in the atmosphere\( (X_{\text{true}}) \). In the GPROF algorithm, this probability is assumed as

\[ P(TB_i = TB_o \mid X_i = X_{\text{true}}) \propto \exp\left\{ -\frac{(TB_i - TB_o)^2}{2\sigma^2} \right\} \quad (7.9) \]

\( P(X_i = X_{\text{true}}) \) in Eq. 7.8 is the probability that a given set of hydrometeor profiles in database \( (X_i) \) is the true state of the atmosphere. The GPROF algorithm assumes that profiles in the GPROF database occur with nearly the same relative frequency as those found in nature, or at least with the same frequency as those found in the region where the inversion method is to be applied (Kummerow et al. 1996). Under this assumption, \( P(X_i = X_{\text{true}}) \) is represented simply by the number of similar profiles.

Using these assumptions, the GPROF algorithm calculates the best estimated profile \( X_{\text{best}} \) as

\[ X_{\text{best}} = \sum_{i=1}^{n} X_i \cdot W_{\text{channel}} \cdot \exp\left\{ -\frac{(TB_i - TB_o)^2}{2\sigma^2} \right\} \cdot N_i \quad (7.10) \]

Here \( W_{\text{channel}} \) is the weighting assigned for each channel depending on the relative intensity of scattering and emission signals, \( \sigma \) is the width of the Gaussian distribution used to assign weights to individual profiles. It is assumed to be 8 K in the entire GPROF algorithm. \( N_i \) is the relative number of occurrence of a given profile \( X_i \), and \( A \) is the normalization factor given by

\[ A = \sum_{i=1}^{n} W_{\text{channel}} \cdot \exp\left\{ -\frac{(TB_i - TB_o)^2}{2\sigma^2} \right\} \cdot N_i \quad (7.11) \]
7.3 Effect of $\sigma$ on rainfall retrievals

Eq. 7.10 says that as the deviation of a given $TB$ (of the database) from the observed $TB_o$ is smaller and as the number of occurrences of a given $TB$ in the database is greater, the hydrometeor profiles are weighted more. The exponential term in the numerator in Eq. 7.10 also plays a role of giving weight to a hydrometeor profile.

The $\sigma$ determines how significant a given weighting is to each profile. Smaller $\sigma$ will guarantee that only the true profile is weighted in the final result. As $\sigma$ gets larger, more dissimilar profiles are weighted into the final structure and the results become less correct. However, as $\sigma$ gets smaller, the possibility of nonexistence of the true set of brightness temperatures in the database get bigger. The original GPROF algorithm assumes $\sigma$ as 8 K for that reason. The algorithm may be unable to find any similar profiles in the database and results in “missing” values if $\sigma < 8$K.

To examine the $\sigma$ value effect on the retrieved rainrate distributions, the GPROF algorithm has been implemented with various minimum $\sigma$ values of 2 K, 4 K, 6 K, and 8 K. Figure 7.3 compares the histograms at each rainrate. The result shows that the frequency of the light rainfall (heavy rainfall) occurrences increases (decreases) as a $\sigma$ value increases. As the $\sigma$ value gets bigger, the heavy (light) rainfall retrievals are contaminated with light (heavy) rainfall profiles in the database.

Figure 7.3 shows that the GPROF algorithm with a small $\sigma$ of 2 K will overestimate (underestimate) rainfall at rainrates greater (less) than 5 mm/h. Ideally, using a small $\sigma$ value should improve the result at all rainrates. This result suggests that surface rainrates of light rainfall in stratiform profiles (heavy rainfall at convective profiles) in the GPROF database are underestimated (overestimated).

Comparisons with KR observations (a red line in Figure 7.3) show that results
from minimum $\sigma$ value of 4 K agree with KR observations at rainrates less than 4 mm/h and results from minimum $\sigma$ value of 6 K are close to KR observations at rainrates between 4 mm/h and 8 mm/h. At rainrates greater than 8 mm/h, GPROF rainfall retrievals with a minimum $\sigma$ value of 8 K agree well with KR observations.

![Sigma Effect](image)

**Figure 7.3:** The histogram for rainrates retrieved by the modified GPROF algorithm with various $\sigma$ values. The heavy lines show the range where the various $\sigma$ values were utilized.

This study modified the GPROF algorithm to have different $\sigma$ values depending on the rainrates from a retrieval with a $\sigma$ 4 K. If retrieved rainrates are between 4
mm/h and 8 mm/h, the algorithm seeks a best-fit profile again with a $\sigma$ value of 6 K. If there is no profile available with a $\sigma$ of 6 K, the algorithm changes a $\sigma$ value to 8 K. If retrieved rainrates from a $\sigma$ value 4 K are greater than 8 mm/h, the algorithm seeks a best-fit profile again with a $\sigma$ value of 8 K.

### 7.4 Results

**Histogram comparison**  Figure 7.4(a) compares the histogram of the $\sigma$ adjusted GPROF algorithm retrieved rainfall and KR observations. Comparing with the original GPROF rainfall retrievals shown in Figure 3.2, $\sigma$ adjusted GPROF has reduced biases for both light and heavy rainrates. The $\sigma$ value modification implemented in this study reduced retrieved rainfall at light rainrates less than 5 mm/h as shown in Figure 7.4(b).

**Total rainfall comparison**  The sum of rainrates for all KR and $\sigma$ adjusted GPROF rainy pixels of 40 cases are 3,234 mm/h and 3,292 mm/h, respectively. This suggests that the total rainfall amount retrieved by the $\sigma$ adjusted GPROF algorithm at 0.1° resolution has been underestimated by 1.7 % (Fig. 7.5(a)). Considering the result from the original GPROF algorithm which overestimated total rainfall amount for 40 cases by 25 %, the modification of $\sigma$ values significantly improved the result.

Compared with KR observations, rainfall retrievals show positive bias (8 %) at rainrates less than 5 mm/h, negative bias (4.1 %) at rainrates between 5 mm/h and 11 mm/h, and negative bias (2.2 %) at rainrates greater than 11 mm/h after adjusting $\sigma$ values depending on a rainrate. Considering the biases shown in the original GPROF rainfall retrievals (Fig. 3.4), the modifications applied to the GPROF algorithm in this study have improved the rainfall retrievals over whole range of rainrates.

In Figure 7.6 and Figure 7.7, comparison of KR rainmaps with the rainmaps retrieved by the original GPROF algorithm shows that the original GPROF algorithm
Figure 7.4: (a) The histogram for the rainrates retrieved by the $\sigma$ adjusted GPROF algorithm and (b) difference of histograms between $\sigma$ adjusted GPROF and 85-GHz brightness temperature neglected GPROF algorithms.
Figure 7.5: Comparisons of cumulative rainrates between σ adjusted GPROF and KR. in (a) cumulative rainfall rates and (b) bias distribution of σ adjusted GPROF rainfall retrievals at each rainrate.
retrieved rainmaps have larger rainy area than KR observations especially for large-scale precipitation system. This overestimation of rainy area by the passive microwave algorithm is caused by the beamfilling effect at the edge of large precipitation systems. This beamfilling effect is caused by the emission channels’ large size footprints which may be partially filled with rain at the edge of large precipitation systems as shown in Figure 1.6.

Figure 7.6(d) and Figure 7.7(d) show that $\sigma$ adjusted GPROF algorithm improves this partial beamfilling problem. The $\sigma$ adjusted GPROF algorithm, which uses a small $\sigma$ value of 4 K, retrieves lower rainrates at light rainrates than the original GPROF algorithm. Due to this lower rainrate retrieval by the $\sigma$ adjusted GPROF algorithm, the light rainrates at the edge of a large precipitation system are reduced to rainrates less than 0.5 mm/h, the threshold of no rain.

To examine the effect of modifications on the rainfall variability at each spatial scale, ratios of the normalized PSDs for $\sigma$ adjusted GPROF and KR estimated rainmaps were calculated at each wavenumber for 40 cases. The result in Figure 7.8 shows that modifications implemented in this study improved the spatial variability of rainfall rates about 20 % when compared with results from the original GPROF (red curves).
Figure 7.6: Rainfall maps estimated by (a) KR, (b) original GPROF, (c) 85-GHz Tb neglected GPROF, and (d) σ adjusted GPROF algorithms in 25 July 1999.
Figure 7.7: Rainfall maps estimated by (a) KR, (b) original GPROF, (c) 85-GHz Tb neglected GPROF, and (d) $\sigma$ adjusted GPROF algorithms in 28 July 1999.
Figure 7.8: Ratios of the normalized PSDs for the σ adjusted GPROF and KR rainmaps. The solid and dashed lines show the mean and one standard deviation of the ratios for 40 cases. For the comparison, the ratios of the normalized PSDs for original GPROF and KR rainmaps are shown in red lines.
Chapter 8

SUMMARY AND CONCLUSIONS

Providing high-resolution rainfall products for mesoscale atmospheric research has become a concern of the satellite remote sensing community especially over oceans where ground based observations are not generally available. This study attempts to evaluate the ability of the GPROF algorithm, which is the passive microwave rainfall retrieval algorithm of the TRMM program, to retrieve rainfall at resolutions down to 0.1° by examining the effects of the surface type, the melting layer effect, the sufficiency of vertical hydrometeor profiles in the database, the beamfilling effect, the impact of 85-GHz channels, and the scanning gap effect (Section 1.5.2) by comparisons with KR observations.

Comparisons of the GPROF retrieved rainfall with the KR observations show that GPROF overestimated rainfall by 17.4% at rainrates less than 5 mm/h, underestimated rainfall by 6.7% at rainrates between 5 mm/h and 11 mm/h, and overestimated rainfall at rainrates greater than 11 mm/h by 12%. The GPROF algorithm has been modified in this study to reduce biases of the retrieved rainfall and to improve the spatial variability in rainfall distributions compared to KR observations at 0.1° resolution. Figure 8.1 shows the flow chart for the final modified GPROF algorithm developed in this study. The features cited below are addressed by those modifications.
Figure 8.1: Flow chart for the oceanic GPROF algorithm modified in this study.
8.1 Results and modifications of the GPROF algorithm

No single factor stands out as a dominant improvement in the GPROF modifications. All of the following were introduced into the revised algorithm.

Are Kwajalein atolls oceanic or land? The current GPROF algorithm categorized the Kwajalein atolls as “coast” and applied the coastal GPROF algorithm for the red region in Figure 1.3. Comparing the retrieved rainfall with nearest neighbor KR observations (Fig. 2.7) shows that the oceanic algorithm (blue dots in Figure 2.6) retrieves a distribution of rainfall that is similar to the KR observations while the coastal algorithm results (red dots in Figure 2.6) behave incorrectly. The first step of the modified GPROF developed in this study therefore employed the oceanic GPROF algorithm over the whole Kwajalein validation site (Section 2.4).

Melting layer The current GPROF algorithm neglects the melting layer effect. This appeared to have resulted in an overestimation of rainfall rates over stratiform precipitation systems (Section 1.5.2). This study employs Klaassen’s (1990) parameterization to represent the melting layer effect in stratiform precipitation. The brightness temperature increments after melting layer corrections show changes up to 20 K, 15 K, 6 K, and 8 K at 10 mm/h for 10 GHz, 19 GHz, 21.3 GHz, and 37 GHz, respectively. This melting layer correction reduced the rain amount retrieved by the GPROF algorithm by 8% (Section 4.4).

Beamfilling effect (Convective-stratiform separation) The GPROF algorithm estimated the convective area fraction to overcome the beamfilling problem, which is caused by the inhomogeneity of rainfall distribution inside a FOV (Section 5.3). The general patterns of GPROF and KR convective area fraction in these maps agreed well with each other. The GPROF algorithm generally missed localized
pixels at which KR showed a significant convective area fraction. The GPROF overestimated the convective area fraction relative to the KR estimates in MCSs where the ice scattering was strong (Section 5.4). Omission of small scale warm convective clouds by the current GPROF algorithm was caused by the large FOVs of the TMI and appears to be as a limit which no algorithm can overcome. The rainfall retrieval biases caused by the overestimated convective area fraction and strong ice scattering signals in the middle of large-scale MCSs are improved by modifying the GPROF algorithm to neglect 85-GHz channels’ brightness temperatures in Bayesian approach.

**Impact of 85-GHz channels** This study modifies the GPROF algorithm to employ 85-GHz channels only to estimate convective area fraction and to neglect 85-GHz brightness temperatures in seeking the best-fit brightness temperature set in the GPROF database for rainfall retrieval. The general distribution of rainfall and rainy area has not been changed by neglecting 85-GHz brightness temperatures. Heavy rainfall overestimated by the original GPROF algorithm in convective region where ice scattering is strong have been reduced. Localized small-scale convective cells underestimated by the original GPROF have been resolved better after the modifications.

**Vertical hydrometeor profiles in the GPROF database** In addition to rain drops, microwave radiances are affected by cloud liquid and ice hydrometeor profiles. The GPROF algorithm considered the effects by using the GPROF database (Section 7.1) to calculate the best-fit profile with Eq. 7.10. In this equation, smaller $\sigma$ will guarantee that only profiles that are nearly the same as the actual profile are weighted in the final result. As $\sigma$ gets larger, more dissimilar profiles are weighted into the final structure and the results become less correct. The original GPROF algorithm assumed $\sigma$ to have a fixed value of 8 K in case the algorithm was unable to find similar profiles in the database that would have resulted in “missing” values
if $\sigma < 8$K. The modified GPROF algorithm has been run with various minimum sigma values of 2 K, 4 K, 6 K, and 8 K (Fig. 7.3). It shows that the GPROF algorithm with a small sigma of 2 K will overestimate rainfall at rainrates greater than 5 mm/h. This suggests that surface rainrates of convective profiles calculated by the GCE cloud model in the GPROF database are overestimated. Based on Figure 7.3, this study modified the GPROF algorithm to have different sigma values depending on the sufficiency of the database and rainrates from a retrieval with a sigma 4 K. If retrieved rainrates are between 4 mm/h and 8 mm/h, the algorithm seeks a best-fit profile again with a sigma value of 6 K. If there is no profile available with 6 K sigma, the algorithm changes a sigma value to 8 K. If retrieved rainrates from a sigma value of 4 K are greater than 8 mm/h, the algorithm seeks a best-fit profile again with a sigma value of 8 K. The modified GPROF algorithm improves the rainfall retrievals by 9.4 % at light rainrates and 9.9 % at heavy rainrates when compared to the original GPROF algorithm (Section 7.4). In addition, this modified GPROF algorithm reduces the light rainfall rates at the edge of a large precipitation system and improves the beamfilling problem over the regions. resolves the small scale convective system better than the original GPROF algorithm (Fig. 7.7).

8.2 Comparisons of rainfall retrievals between the final modified GPROF algorithm and the original GPROF algorithm

Comparison of Figure 7.4(a) with Figure 3.2 shows that the modifications implemented in this study reduced the biases of rainfall retrieval compared to the KR for all rainrates at a 0.1° resolution. The modified algorithm retrieves less rainfall at rainrates less than 5 mm/h and more rainfall at rainrates between 5 mm/h and 11 mm/h when compared to the the original GPROF rainfall retrievals (Fig. 7.4(b)).
Comparison of Figure 3.4(a) and Figure 7.5(a) shows that the total rainfall amount retrieved by the modified GPROF algorithm was underestimated by 1.7% whereas the total rainfall retrieved by the original GPROF algorithm was overestimated by 25%. The 25% was net effect of overestimation by 17.4% at light rainrates (R ≤ 5 mm/h), underestimation by 6.7% at rainrates (5 mm/h ≤ R < 11 mm/h), and overestimation by 12% at rainrates greater than 11 mm/h (Fig. 3.4(b)). The 1.7% underestimate by the modified GPROF algorithm is the net effect of overestimation by 8.0% at rainrates less than 5 mm/h and underestimation by 6.3% at rainrates greater than 5 mm/h (Fig. 7.5(b)). This shows that the modified GPROF algorithm reduced the biases of the retrieved rainfall by 18% (4%) at light (heavy) rainrates when compared with the original GPROF algorithm.

An example of the effect of the modified algorithm can be seen in the comparison of Figure 7.6(b) and (d). These figures show that the modified GPROF algorithm successfully reduces the overestimated heavy rainfall caused by the oversensitivity of the original GPROF algorithm to strong ice scattering.

Figure 7.8 compares the ratios of the normalized PSDs for the modified GPROF algorithm and the KR estimated rainmaps with the ratios of the normalized PSDs for the original GPROF algorithm and the KR estimated rainmaps at each wavenumber for 40 cases listed in Table 2.3. The result shows that the modifications implemented in this study improved the spatial variability of rainfall rates about 20% when compared with results from the original GPROF algorithm.
8.3 Verification of GPROF modifications in this study

To test the validity of the modifications applied the GPROF algorithm in this study, the modified GPROF algorithm is employed for 40 independent overpasses listed in Table 2.4. Figure 8.2 shows the histograms of surface rainrates retrieved by the original and modified GPROF algorithms. The biases shown in the original GPROF algorithm retrieved rainfall distribution have been improved both at light and heavy rainrates. The cumulative rainfall distribution has been improved after the modifications applied to the GPROF algorithm in Figure 8.3. The sum of rainrates for all KR and the modified GPROF rainy pixels for these independent 40 cases are 3,814 mm/h and 4,057 mm/h, respectively. This suggests that the total rainfall amount retrieved by the GPROF at 0.1° resolution was overestimated by 6%. Considering the result from the original GPROF algorithm which overestimated total rainfall amount for the 40 cases by 32 % as shown in Figure 8.3(a), the modification of σ values significantly improved the result significantly.

8.4 Comparison of statistics from the modified GPROF and the original GPROF rainfall retrievals

To show the improvement of the GPROF algorithm by the modifications implemented in this study, the false alarm ratio (FAR), the probability of detection (POD), the skill score (SS) (Panofsky and Brier 1965, Ebert and Manton 1998), odds ratio (OR) (Goeber and Milton 2002), the bias score, the rms errors (Mass et al. 2002), and the correlation coefficient have been computed. Categorizations shown in the contingency table (Table 8.1) were employed for these evaluations.

The FAR gives the fraction of rainfall retrievals that were actually nonraining:
Figure 8.2: Verification of the modified GPROF algorithm with independent 40 cases listed in the Table 2.4
Figure 8.3: Verification of the modified GPROF algorithm with independent 40 cases listed in the Table 2.4.
Table 8.1: Contingency table for rainfall retrievals

<table>
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<td>Total</td>
</tr>
<tr>
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<td>a</td>
<td>b</td>
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<td></td>
<td>Yes</td>
<td>c</td>
<td>d</td>
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<tr>
<td>Total</td>
<td>a+c</td>
<td>b+d</td>
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\[ FAR = \frac{b}{b+d} \quad (8.1) \]

The POD measures the fraction of the pixels with KR observed rain for which rain was also retrieved by the algorithm:

\[ POD = \frac{d}{c+d} \quad (8.2) \]

The SS is the number of correct retrievals divided by the expected number correct due to chance:

\[ SS = \frac{a + d - E}{a + b + c + d - E} \quad (8.3) \]

where \( E = \{(a + b)(a + c) + (c + d)(b + d)\}/(a + b + c + d) \).

The odds is the ratio of the probability of an event occurring to the probability of the event not occurring. The OR is the ratio of the odds of making a detection to the odds of a false alarm:

\[ OR = \frac{ad}{bc} \quad (8.4) \]
The bias score is defined as

\[ Bias = \frac{NR}{NO} \]  

(8.5)

where \( NR \) is the number of retrievals with precipitation equal to or exceeding a given threshold amount, and \( NO \) is the number of occurrences in which the observations meet or exceed the threshold. Bias scores greater (less) than 1 mean that the retrieved rainfall was overestimated (underestimated) at rainrates greater than a certain threshold.

The rms error is defined as

\[ RMS = \sqrt{\frac{\sum_{n=1}^{NOBS} (P_n - X_n)^2}{NOBS}} \]  

(8.6)

and the correlation coefficient is given by

\[ Correlation \ coefficient = \frac{\sum_{n=1}^{NOBS} (\bar{P}_n - P_n)(\bar{X}_n - X_n)}{\sqrt{\sum_{n=1}^{NOBS} (P_n - P_n)^2} \sqrt{\sum_{n=1}^{NOBS} (X_n - X_n)^2}} \]  

(8.7)

where \( NOBS \) is the number of observations reaching a certain rainrate threshold, \( X_n \) is the observed rainrate, and \( P_n \) is the algorithm retrieved rainrate.

Figure 8.4 compares FAR, POD, SS, and OR between the modified GPROF rainfall retrievals and the original GPROF rainfall retrievals at a 0.1° resolution.

The modified GPROF algorithm shows smaller FARs and PODs than the original GPROF algorithm for the whole rainrate rates (especially at rainrates greater than 5 mm/h). This change is caused by the fact that the modifications reduce the retrieved rainfall at light rainrates less than 5 mm/h and at rainrates greater than 11 mm/h (Fig. 7.4(b)). The results of the SS and OR comparisons (Fig. 8.4(c) and (d)) show that the modified algorithm is better than the original GPROF algorithm
at retrieving rainrates greater than 6 mm/h.

Figure 8.5 compares the bias score, the rms error, and the correlation coefficient between the modified GPROF rainfall retrievals and the original GPROF rainfall retrievals at a $0.1^\circ$ resolution. The modified GPROF algorithm shows better (i.e. closer to one) bias scores than the original GPROF algorithm both for light and heavy rainfall thresholds (Fig. 8.5(a)). The rms errors for the modified GPROF algorithm were smaller than the rms errors for the original GPROF algorithm almost over the whole rainrate range (Fig. 8.5(b)). The correlation coefficients for the modified GPROF algorithm were not obviously improved (Fig. 8.5(c)).

8.5 Scanning contiguity and its impact on the design of the GPM radiometers (Scanning gap effect)

Because the GPM radiometer under consideration could have gaps between scan lines of the 85.5 GHz radiometer if only one feed horn is used, the following simulation was undertaken:

The 85.5-GHz brightness temperature field has a spatial gap of 7 km between successive scans (Fig. 1.4). KR data at 6-km resolution were modified by removing every other line, horizontally or vertically (Fig. 3.10) to simulate this scanning gap effect. Results show that the standard deviation of a KR surface rainmap with data gaps (i.e. simulated scanning gaps) are smaller than a KR rainmap without data gaps at a $0.1^\circ$ resolution (Fig. 3.11(a)). However, the gap effect introduces little difference in rainfall variance in rainmaps at resolutions greater than $0.25^\circ$. The PSD analysis shows that the scanning gap effect does not contribute to the underrepresentation of large-scale spatial variability of GPROF precipitation. In contrast, scanning gaps er-
Figure 8.4: (a) FARs, (b) PODs, (c) skill scores, and (d) odds ratios for the rainfall retrievals by the original GPROF algorithm and the final modified GPROF algorithm.
Figure 8.5: (a) Bias scores, (b) rms errors, and (c) correlation coefficients for the rainfall retrievals by the original GPROF algorithm and the final modified GPROF algorithm.
ronously increased PSDs at high wavenumbers (small spatial scale) (Fig. 3.13). The problem is more acute for determining rainfall over land because those algorithms depend more on the 85.5-GHz channels. It would therefore be best to use dual high frequency feed horns in future radiometers if the cost can be accepted.

8.6 Discussion and future study

**GPROF database issue** With the current GPROF database, using small sigma values improved the GPROF algorithm rainfall retrievals at light rainrates while it worsened the heavy rainfall retrievals. This suggests that GPROF database needs to be improved, especially for heavy rainrate profiles. At a given brightness temperature set, the current GPROF database overestimated heavy rainrates compared with the KR observations. The modifications applied to the original GPROF algorithm in this study have been examined just for the Kwajalein validation site which is located in the open ocean. The best-fit sigma values tuned in this study may be different for other TRMM validation sites (Texas, Florida, Darwin, Thailand, Guam, and Hawaii) and other types of precipitation (e.g., hurricane).

**Impact of 85-GHz channels** Comparisons of GPROF retrieved rainfall with KR observations show that heavy rainfall retrieval by the original GPROF algorithm depends too much on signals from 85.5-GHz channels. The algorithm considers the ice scattering as necessary condition not as a sufficient condition. The bias caused by the oversensitivity of the GPROF algorithm to the ice scattering information detected by 85-GHz channels contributes significantly to total rainfall amount biases over the Kwajalein validation site. The correlation between upper level ice and lower level rain depends on the age of a convective system, geolocational characteristics, and wind shear effect. Those relationships should be well taken into account in the GPROF database to improve rainfall retrievals.
Hydrometeor profile retrievals  The final goal of the GPROF algorithm is to retrieve the latent heating profiles which are related to hydrometeor profiles. However, this study only addressed the retrieval of surface rainfall derived from the GPROF algorithm. Changes in retrieved profiles after the modifications and comparisons with available observations such as radar reflectivity aircraft data are worthy of further study.

Scanning gap effect on hydrometeor profile retrievals  Since 85-GHz channels are sensitive to ice and they are the channels which have scanning gaps. The scanning gap effect may not be negligible for the frozen hydrometeors. Recalling that the main role of 85-GHz in rainfall retrieval over the Kwajalein validation site suggested in this study is to estimate convective area fraction, improving gap effect may be improving the Tb gradient calculation and the estimation of convective area fraction. In that way, reducing the scanning gap effect may improve surface rainfall retrievals. This study analyzed the surface rainfall retrievals. Therefore, the scanning gap effect on the hydrometeor profile retrievals are also worthy of further study to provide practical information for designing radiometeors in future.

Coastal and land GPROF algorithm  This study has been focused on just the oceanic GPROF algorithm. The behavior and error sources of a passive microwave rainfall retrieval algorithm may be different for rainfall over land. Because fewer channels contribute to the retrieval of rainfall over land, more careful analysis will be needed for those cases.
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Appendix A

CONVECTIVE/STRATIFORM SEPARATION IN THE GPROF ALGORITHM (FROM OLSON ET AL. 2001)

a. Texture-based method

Due to localized intensive precipitation (with strong vertical velocity) in the convective cloud, substantial horizontal gradients of precipitation characterize convective regions. The texture-based method empirically relates the horizontal variation of microwave radiances to the fraction of the TMI footprint area covered by convective precipitation (Olson et al. 2001).

Hong et al. (1999) developed a convective-stratiform index (CSI) that combined the local maximum variation and relative magnitude of radiances from the 19.35, 37.0, and 85.5 GHz horizontal polarization channels of TMI.

\[
CSI_e = VM_{37h} + 0.5 VM_{19h} + 0.25(TB_{19h} - TB_{19h-back}) \quad (A.1)
\]

\[
CSI_s = VM_{85h} + (TB_{85h-back} - TB_{85h}) \quad (A.2)
\]

\[
CSI = (1 - w_s)CSI_e + w_sCSI_s \quad (A.3)
\]

where \(TB_{vp}\) and \(TB_{vp-back}\) are the microwave radiance and background “clear-air” radiance, respectively, at frequency \(v\) and polarization \(p\).

The variable \(VM_{vp}\) is the local maximum variation of a measured radiance with respect to its neighbor defined by
where the subscript \( j \) refers to any of the eight neighboring TMI footprints surrounding the footprint being analyzed.

Since convection is generally associated with heavy precipitation, the relative magnitude of the radiance with respect to a background radiance is added to the CSI on the right-hand side of Eq. A.1 and Eq. A.2. The background radiance is defined as the average of clear-air radiances from the eight neighboring TMI footprints surrounding the footprint being analyzed. A footprint is classified as clear air if the mean cloud water content below the freezing level, retrieved using the algorithm of Karstens et al. (1994), is less than 0.06 g/m\(^3\).

The final index, CSI, is a weighted sum of the emission and scattering indices (eq. A.3). The weighting factor \( w_s \) is defined as

\[
w_s = \begin{cases} 
0, & TB_{85h} > TB_{85h-back} \\
(TB_{85h-back} - TB_{85h})/80, & TB_{85h-back} - 80 < TB_{85h} < TB_{85h-back} \\
1, & TB_{85h} < TB_{85h-back} - 80 \end{cases}
\]

(A.7)

Hong et al. (1999) related CSI to the convective area fraction by matching the cumulative distribution of convective area fractions derived from the TOGA COARE shipboard radar data to the cumulative distribution of synthesized TMI CSI measurements. The resulting empirical relationship is approximated by
b. Polarization-based convective area fraction

It has been found that differences between the vertically and horizontally polarized 85.5 GHz radiances in stratiform precipitation regions are significant on the order of 5 K or greater, whereas regions of strong convection were nearly unpolarized at 85.5 GHz in SSM/I observations by Spencer et al. (1989) and Heymsfield and Fulton (1994a,b). The physical basis of these polarization differences has been hypothesized that precipitation-sized ice particles such as snow or aggregates would tend to become oriented as they fall through the relatively weak updrafts or downdrafts of stratiform regions, resulting preferential scattering in the horizontal polarizations (Olson et al. 2001). Roberti and Kummerow (1999) suggested that in addition to ice particle orientation, the relative amounts of asymmetric snow and non spherical graupel in convective and stratiform precipitation regions could contribute to the observed polarization differences.

In the GPROF algorithm, the results of 85.5 GHz TMI polarization data are used to infer the convective area fraction within the TMI footprint by the method suggested by Olson et al. (2001).

Figure A.1 shows TMI-observed 85.5 GHz polarization differences versus average 85.5 GHz radiances from 10 organized convective systems over ocean sampled from the first three years of the TRMM mission. The congregation of observations along an approximate 45° diagonal line in Figure A.1 indicates increasing 85.5 GHz polariza-
tion difference with decreasing average 85.5 GHz brightness temperatures. These observations generally correspond to stratiform areas in mesoscale convective systems (Olson et al. 2001).

If it is assumed that TMI 85.5 GHz polarization differences are essentially zero in purely convective regions, and that they follow a quasi-linear relationship with average 85.5 GHz radiances in stratiform regions, then an estimate of the convective area fraction within the sensor footprint is given by

Figure A.1: Polarization differences at 85.5 GHz plotted vs average 85.5 GHz radiances over ocean surfaces. TMI observations are plotted as points (nonraining areas) and open circles (raining areas). Diamonds represent radiative transfer simulations for atmospheres containing oriented, aspherical liquid and ice-phase precipitation. Dashed lines are approximate curves representing purely stratiform and purely convective precipitation conditions. From Olson et al. (2001).
\[ f_{POL} = \begin{cases} 
0, & POL > POL_{strat} \\ 
1 - \frac{POL}{POL_{strat}}, & POL_{strat} \geq POL \geq 0 \\ 
1, & POL < 0 
\end{cases} \]  

(A.9)

where

\[ POL = TB_{85v} = TB_{85h} \quad \text{and} \quad POL_{strat} = a \frac{TB_{85v} + TB_{85h}}{2} + b \]

In the empirical linear relationship relating the polarization difference to the average 85.5 GHz brightness temperature in stratiform regions, the constants \(a(-0.192)\) and \(b(-52.4 \text{ K})\) have been adjusted to obtain a best fit with the cluster of TMI observations. Here, it was assumed that the polarized emission from the ocean surface does not contribute significantly to the total observed brightness temperature (Olson et al. 2001).

c. Merger of the two methods

Olson et al. (2001) found that the polarization-based method generally yields less biased estimates of convective area fraction in regions of significant ice scattering than ground radar observations. The texture-based convective fraction tends to vary in proportion to the depression of 85.5 GHz radiances in scattering regions, even if these scattering depressions are produced by ice-phase precipitation that has been detrained into stratiform regions. So the polarization-based method discriminates better in regions with strong ice scattering whereas the texture-based method works better if ice scattering is weak. Thus

\[ f_{COM} = \frac{f_{CSI} \text{var}_{CSI}}{\text{var}_{CSI} + \text{var}_{POL}} + \frac{f_{POL} \text{var}_{POL}}{\text{var}_{CSI} + \text{var}_{POL}} \]  

(A.10)
where \( var_{CSI} \) and \( var_{POL} \) are the error variances of the texture-based and polarization-based estimates of convective fraction, respectively.

The error variance of texture-based convective fraction estimates were derived from synthesized TMI data generated from TOGA COARE radar measured rain distributions. The difference between the TMI texture-based estimate of the convective area fraction and the true convective fraction were derived from a TOGA COARE radar data (Short et al. 1997). An empirical fit to the error variances of texture based convective fraction estimates is given by

\[
var_{CSI} = \gamma_0 + \gamma_1 CSI + \gamma_2 CSI^2
\]

(A.11)

where \( \gamma_0, \gamma_1, \) and \( \gamma_2 \) are 0.246653, 6.667 \( \times \) 10\(^{-3} \), and \(-4.762 \times 10^{-5} \), respectively.

The error of polarization-based convective area fraction estimates is a function of the 85.5 GHz scattering depression.

\[
var_{POL} = \frac{2POL_{strat}^2 + [(aPOL)^2] var_{TBS5}}{POL_{strat}^4} + var_f
\]

(A.12)

where \( var_{TBS5} \) is the variance of noise in the TMI 85.5 GHz raicance measurements (assumed to be 1 \( K^2 \)), and \( var_f \) is the error variance of the polarization-based estimate in the absence of noise (approximately 0.1). If the ice-scattering depression at 85.5 GHz is small, then the expected polarization differences in stratiform regions, \( POL_{strat} \) is also small. Therefore, errors in polarization-based estimates of convective area fraction are expected to be large where ice scattering is weak.
Appendix B

GCE MODEL SIMULATIONS

The GCE model was initialized using National Oceanic and Atmospheric Administration (NOAA) P-3 flight-level data and rawinsonde observations of the environment in immediate advance of a tropical squall line, which occurred 22 February 1993, during TOGA COARE. A 1-km resolution GCE squall line simulation (called TOGA1) on a 128 km $\times$ 128 km domain and a subsequent 3-km resolution squall line simulation on a 384 km $\times$ 384 km domain (called TOGA3) exhibited storm structure similar to TOGA 1, but initiation by a more extensive cool pool resulted TOGA 3 appears to be more consistent with aircraft observations.

Two additional simulations were performed. A tropical cyclone simulation (called HURRICANE) was initiated using atmospheric observations made a Kingstone, Jamaica, 36 hr prior to the passage of Hurricane Gilbert (1988). The final 6 hr of the HURRICANE simulation utilized a 3.3 km resolution, 205 km $\times$ 205 km inner nest, from which atmospheric parameters were extracted for the current analysis. A second simulation included in the GPROF database for rainfall retrieval over the ocean is a thunderstorm complex observed during Cooperative Huntsville Meteorological Experiment (COHMEX), which was performed on a 1-km resolution, 50 km $\times$ 50 km grid.

The Model produced data fields include layer heights (28 layers), temperature, relative humidity, cloud liquid water amount, rain water amount, cloud ice water amount, snow amount, graupel amount, hail amount, and convective/stratiform flag and surface rain rate. More details for HURRICANE and COHMEX simulations are described in Panegrossi et al. (1998).
Appendix C

THE CRITERIA FOR SEPARATING STRATIFORM AND CONVECTIVE RADAR ECHOES (FROM STEINER ET AL. 1995)

- Intensity: Any grid point in the radar reflectivity field with reflectivity of at least 40 dBZ ($\sim 15 mm/hr$) is automatically labeled as a convective center, since rain of this intensity could practically never be stratiform.

- Peakedness: Any grid point in the radar reflectivity field not identified as convective center in the first step, but which exceeds the average intensity taken over the surrounding background by at least the reflectivity difference depicted in Figure C.1(c) is also identified as a convective center. The background intensity is determined as the linear average of the nonzero radar echoes ($mm^6m^{-3}$) within a radius of 11 km around the grid point (Fig. C.1(a)). The area covered by the circles is roughly 400 $km^2$.

- Surrounding area: For each grid point identified as a convective center by one of the above two criteria, all surrounding grid points within an intensity-dependent convective radius around that grid point are also included as convective area (Fig. C.1(b)).
Figure C.1: (a) Schematic diagram showing how convective grid points are identified. (b) The convective area radius as a function of the mean background reflectivity (measured by radar observations). (c) Reflectivity difference between the grid point and mean background used for convective center identification. From Steiner et al. (1995).
Appendix D

**ABBREVIATIONS**

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<th>Page</th>
<th>Abbreviations</th>
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<tr>
<td>60</td>
<td>ARMAR Airborne Rain Mapping Radar</td>
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<tr>
<td>6</td>
<td>AMSR-E Advanced Microwave Scanning Radiometer for EOS</td>
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<tr>
<td>42</td>
<td>CDF Cumulative Distribution of Frequency</td>
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<td>3</td>
<td>CERES Clouds and Earth’s Radiant Energy System</td>
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<td>COHMEX Cooperative Huntsville Meteorological Experiment</td>
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<td>136</td>
<td>CSI Convective Stratiform Index</td>
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<td>3</td>
<td>DMSP Defense Meteorological Satellite Program</td>
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<td>EFOV Effective Field Of View</td>
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<td>6</td>
<td>EOS Earth Observing System</td>
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<td>ESMR Electronically Scanned Microwave Radiometer</td>
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<td>115</td>
<td>FAR False Alarm Ratio</td>
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<td>GCE Goddard Cumulus Ensemble</td>
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<td>GPM Global Precipitation Measurement</td>
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<td>GPROF Goddard Profiling</td>
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<td>IFOV Instantaneous Field Of View</td>
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<td>IFOV-CT Instantaneous Field of View in the Cross-Track</td>
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